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The Ethical Dilemma of AI-Generated Videos: A Hybrid PLS-SEM, ANN, and fsQCA Study of Purchase Intention in E-commerce

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ABSTRACT

AI-generated video advertising combines rapid affective cues with more deliberate assessments of usefulness, privacy, and trust. This study evaluates two ethics-related interactions within a Dual-System framework using 491 Vietnamese consumer responses and a sequential PLS-SEM–ANN–fsQCA design. SmartPLS bootstrap estimates show that Trust predicts purchase intention ($\beta = 0.466$, $p < 0.001$), while AI Personalization has a positive direct association ($\beta = 0.344$, $p < 0.001$). Ethics attenuates the AP–purchase intention relationship ($\beta = -0.354$, $p < 0.001$) and the PU–Trust relationship ($\beta = -0.165$, $p < 0.001$). Ten-fold ANN validation yields mean held-out RMSE values of 0.713 for purchase intention and 0.696 for Trust; the former does not outperform a linear ridge benchmark. Configurational analysis identifies four conservative sufficient pathways to high purchase intention (solution consistency = 0.919; coverage = 0.439). None of the tested single conditions reaches conventional necessity consistency. Together, the analyses support a conditional rather than universal personalization benefit: trust and low privacy concern can accompany high purchase intention, while stronger ethics scores weaken the marginal role of personalization. Interpretation remains associational because the data are cross-sectional and self-reported.

KEYWORDS Dual-System Theory; AI-generated video; Ethics; Trust; Purchase Intention.

I. INTRODUCTION

In the modern e-commerce environment, the integration of artificial intelligence (AI) into advertising strategies has ushered in a new era, particularly with the emergence of AI-generated videos [1,2]. This approach enables retailers to personalize the consumer experience based on behavioral data and preferences in a flexible and cost-effective manner [3]. A recent industry survey indicates that 47% of online retailers are currently experimenting with AI technology in advertising, while 33% have fully implemented it, and 16% are assessing its effectiveness in Figure 1 [4]. However, with this rapid development comes a significant issue ***ETHICS***. This issue has become more pressing than ever, as it affects every individual involved in the e-commerce ecosystem, influencing the trust and behavior of consumers within the online shopping environment [5].

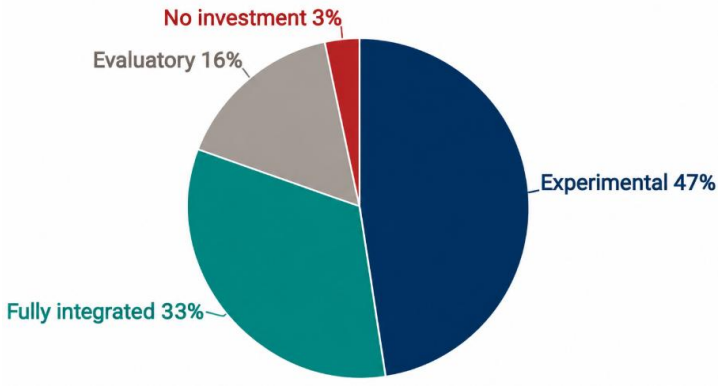


Figure 1. AI Adoption Rates for Optimization in E-Commerce [4]

AI-generated content and the continuous optimization of personalization capabilities have inevitably raised concerns about personal data exploitation [6]. This has created an emotional conflict between the technological convenience offered by AI and the growing ethical concerns associated with its use [7]. Consumers may appreciate the convenience, speed, and variety brought by AI-powered advertising; however, these benefits

also lead to skepticism and concerns about the transparency of data collection methods. The personalization process not only generates resistance from some consumers but also raises serious ethical issues, such as the replacement of human jobs by AI and the perception of being excessively manipulated or exploited by technology [7]. The rapid pace of AI development, which I refer to as *"development at the cost of neglect"* alongside the dual-system theory of human cognition affective and cognitive systems, presents a critical challenge that this study aims to address. Figure 2 illustrates the use of AI in replacing human involvement in advertising products.

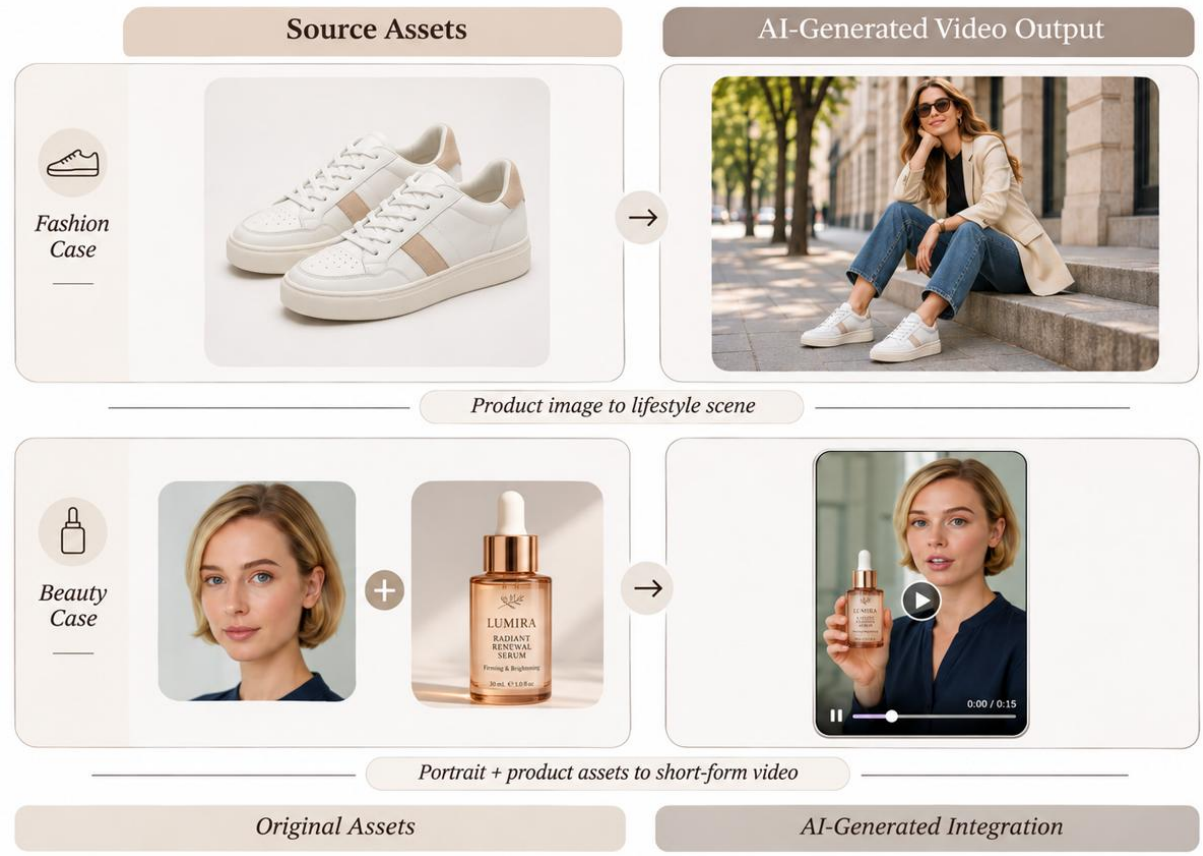


Figure 2. Illustrating Optimized Product through AI-Generated Video [8]

Although this is a novel study, several previous research works have explored the impact of generative AI in advertising and e-commerce. However, there are still many gaps that need to be addressed. Research by Rodgers and Nguyen (2022) has highlighted the importance of ethical factors in smart advertising but lacks detailed studies on how ethical elements, such as autonomy and transparency of AI, influence consumer trust and advertising effectiveness [9]. Additionally, while AI can enhance advertising effectiveness through consumer behavior-based algorithms, the research by Wasilewski et al. (2025) [10] has pointed out the lack of integration between diverse UI models and AI-generated content to create a more seamless e-commerce experience. This study also confirms that the personalization of user interfaces has not been widely implemented and requires more empirical research to demonstrate its practical effectiveness. Another notable gap is the ability to create advertising content tailored to different customer segments, which has not been deeply explored, as seen in Jung's (2025) [11] research on artificial creativity in luxury advertising, where the combination of trust in AI and human-like traits in AI advertising needs further exploration. Grewal et al. (2025) [12] also highlight certain limitations in the application of AI in marketing, especially in using generative AI to create advertising content and analyze consumer behavior data to optimize user experiences, but there is a lack of comprehensive research on the long-term impact of AI on brand perception and consumer loyalty. Therefore, this study aims to address these gaps by examining the impact of generative AI video on purchase behavior in e-commerce, especially when integrating ethical considerations and human-like qualities in the advertising process.

Three questions organize the inquiry. RQ1 asks how emotional attraction, social influence, AI personalization and trust relate to purchase intention. RQ2 asks whether the ethics score alters the AP→PI and PU→Trust relationships, as specified in Figure 3. RQ3 asks whether nonlinear predictive patterns and alternative

configurations qualify the average structural associations. These questions distinguish explanatory associations from out-of-sample prediction and set-theoretic sufficiency.

Through these questions, the study seeks to address the following objectives, with the main goal being to examine the impact of AI-generated videos in e-commerce on purchase intention, particularly when integrating ethical factors and human-like qualities in video advertisements. The specific objectives are as follows:

RO1: To explore the impact of AI-generated videos on consumer trust and purchase intention in e-commerce.

RO2: To assess the two hypothesized ethics interactions, namely Ethics × AI Personalization → Purchase Intention and Ethics × Perceived Usefulness → Trust.

RO3: To analyze the contradiction between emotional and cognitive factors in shaping consumer purchase intention when exposed to AI-generated videos in advertising.

The study combines linear structural estimation, cross-validated neural-network prediction and a conservative configurational solution. The approaches answer different questions: whether individual associations are statistically distinguishable from zero, how accurately the variables predict outcomes out of sample, and which combinations of conditions are sufficient for high purchase intention. This distinction is important because a statistically significant interaction need not improve prediction or imply a necessary condition.

The paper is structured as follows: Section 1 introduces the study's background, research gaps, and objectives. Section 2 reviews the relevant theories and develops hypotheses for the research model. Section 3 explains the research methodology, including data collection, survey design, and analysis methods. Section 4 presents the results from the data analysis, including the relationships between variables. Section 5 discusses the findings in relation to the research questions, theoretical framework, and practical implications, while also addressing limitations and future research. Finally, Section 6 concludes the paper, summarizing the contributions and providing recommendations for both practitioners and future research.

II. THEORETICAL FOUNDATION AND HYPOTHESIS DEVELOPMENT

To offer a more detailed understanding of the model and further strengthen the development of the hypotheses, this study applies Dual System Theory [29] to clarify and extend the model. However, it is important to recognize the continued relevance of traditional theoretical frameworks such as the Technology Acceptance Model (TAM) [19], Social Influence Theory, and Privacy Calculus Theory [22]. These foundational theories, along with various related studies, play a critical role in supporting, explaining, and rigorously developing the measurement scales for the model. Their integration, alongside relevant research, is vital for providing a comprehensive and nuanced perspective.

What distinguishes this research is its novel application of Dual System Theory. Unlike previous studies that typically treat the two systems (System 1: emotional and System 2: cognitive) as separate entities, this study explores their dynamic and contrasting relationship, emphasizing how they interact and influence each other throughout the decision-making process that leads to Purchase Intention [28,29]. This unique approach underscores the contradictory and complementary nature of emotional and cognitive responses in the context of AI-generated videos, presenting a more holistic view of consumer behavior.

The ethical dimension of AI-generated video is operationalized as a measured Ethics (E) construct. Figure 3 specifies two interactions only: E changes the AP→PI path and the PU→Trust path. The sign of each interaction must be interpreted relative to the item coding; a higher Ethics score should not automatically be equated with stronger objective transparency, consent or regulation. The two tested moderations are grounded in the arguments developed below [26,27].

Table 1. Theoretical frameworks and related hypotheses.

Theoretical Famework	Hypothesis	Theoretical Foundation	Source
Dual-System Theory (Affective System)	H1_Emotional Attraction (EA)	Affective Response Theory*	[13], [14]
	H2_ Social Influence (SI)	Social Influence Theory*	[15], [16]
	H3_AI Personalization (AP)	Personalization Theory*	[17], [18]
Dual-System Theory (Cognitive System)	H4_Perceived Usefulness (PU)	Technology Acceptance Model*	[19], [20]
	H5_ Privacy Concern (PC)	Privacy Calculus Theory*	[21], [22]

	H6_ Brand Recognition (BR)	Brand Trust Theory*	[23], [24]
Mediator	H7_Trust	Trust Theory	[25]
Moderator	H8a–H8b: E×AP → PI; E×PU → T	Ethical Behavior Theory*	[26], [27]

**The variables and hypotheses are further supported by related theories and research works.*

A. Dual System Theory - Affective System

The nature of every decision that leads to human behavior is always influenced and shaped by two factors: emotion and cognition. Unlike previous studies that treated these variables as mere regular influences, this study positions these variables as revolving around human factors, placing them within two contradictory and parallel dimensions. In an era where intelligence dominates and everything moves quickly, emotions or cognition have a stronger impact on purchase intention (PIE). This is why this study uses Dual-System Theory, with System 1 representing fast, intuitive, and effortless thought processes. This system is associated with immediate emotional reactions triggered by external factors that consumers are exposed to, especially in the e-commerce environment. Decisions made in System 1 are primarily based on emotion and intuition, without the need for deep thinking or analysis [28,30]. In this study, emotional variables are placed in System 1 because they reflect powerful factors that influence emotions and consumers' purchasing decisions, especially in the context of AI-generated video advertising, where aesthetics and attraction quickly trigger strong emotional responses. The variables Emotional Attraction (EA), Social Influence (SI), and AI Personalization (AP) are placed in System 1 because they directly impact the viewers' sense of excitement and enthusiasm, thereby influencing Purchase Intention (PIE).

Based on the S-O-R theoretical model, this model explains that external stimuli, such as the quality of sound, visuals, and engaging content, trigger internal psychological responses (organism), such as feelings of joy and excitement, which then lead to behaviors like purchase intention (response). Han et al. (2024) [31] argue that emotional states, such as pleasure and excitement, are significant mediators of purchase intention; environmental cues such as atmosphere, sound, images in videos stimulate emotional responses, which in turn drive purchasing behavior. Research by Luo et al. (2025) [32] on 372 Chinese users demonstrates that three content characteristics usefulness, ease of use, and entertainment positively affect trust and purchase intention. Entertainment is described as "the appeal and immersion capability of short video content, capturing attention and stimulating purchase motivation." The evidence suggests that high-quality, entertaining, and interactive video content triggers positive emotions (pleasure, excitement). According to the S-O-R model, these emotions increase trust in the presenter/brand and lead to purchasing decisions. Entertaining videos also reduce skepticism and enhance engagement [33]. From this evidence, we can develop Hypothesis 1 as follows:

H1*: Emotional Attraction (EA) positively influences Purchase Intention in E-commerce (PIE).*

In the current era, social presence and psychological companionship have a profound impact. Research on knowledge-based short videos suggests that social presence helps viewers feel accompanied in virtual spaces; engagement and empathy with content creators increase trust and purchase intention [34]. In the context of this study, market trends, hot topics on social media, and the FOMO (Fear of Missing Out) effect [35] make consumers feel left out if they do not keep up with current youth trends [36]. AI-generated videos serve this role; they not only trigger the FOMO effect but also tap into consumers' curiosity with novelty, keeping them engaged and increasing purchase intention [37]. Therefore, Social Influence (SI) positively influences Purchase Intention (PIE) because community and social interactions enhance trust and shopping enthusiasm.

H2*: Social Influence (SI) positively influences Purchase Intention in E-commerce (PIE).*

In digital marketing, Beyari & Hashem (2025) [38] analyze the role of artificial intelligence in personalizing social media marketing strategies. A survey of 893 users in the MENA region found that AI enhances content personalization, influencer selection, and real-time engagement, improving brand awareness, user experience, and purchase intention. AI tools like content optimization and customized messaging help capture user attention. Research on AI personalized short videos (Tong et al., 2025) [39] indicates that emotionally engaging and relevant experiences in AI-generated videos increase immersion, and this immersion significantly affects purchase intention. The study also found that this relationship is weakened by privacy concerns but strengthened by information quality. From the privacy paradox perspective, Gupta et al. (2025) [40] at Advances in Consumer Research highlight the dual nature of AI-driven personalization: on one hand, it provides convenience and

relevance to customers; on the other hand, it raises concerns about privacy loss, data manipulation, and algorithm transparency. To personalize, data extraction is required; the question arises, what happens when data is extracted for other purposes, especially with AI involvement? This ethical dilemma has sparked growing concerns. Research by Alzaidi and Agag (2022) [41] on 1,200 social media users shows that privacy concerns significantly reduce the use of social media for shopping; personalized ads make users aware of personal data exploitation, leading to negative attitudes and avoidance of purchases. Based on this, we can form two additional hypotheses:
H3*: AI Personalization (AP) positively influences Purchase Intention in E-commerce (PIE).*

H8a: Ethics (E) moderates the AI Personalization (AP) → Purchase Intention (PI) relationship.

B. Dual System Theory - Cognitive System

In Dual System Theory, System 2 represents the logical, slow, and conscious thinking system. Unlike System 1, which is driven by emotions and quick reactions, System 2 processes information through rational deliberation, weighing benefits and risks before making decisions [43]. In the context of AI-generated videos and e-commerce, viewers are not only drawn by the aesthetic appeal but also evaluate the perceived usefulness, privacy concerns, and brand reputation before placing trust and making purchase decisions. These perceptual factors (perceived usefulness, privacy concern, brand recognition) are considered components of System 2 because they require consumers to think, compare, and assess long-term benefits.

According to Technology Acceptance Models (TAM/UTAUT), perceived usefulness and ease of use are crucial elements in forming trust [19,20]. A study from Heliyon (2023) on chatbots argues that perceived usefulness, ease of use, and perceived enjoyment are fundamental factors in technology acceptance and trust [42] . This study highlights that when users perceive a system as useful saving time, offering flexible and personalized services they are more likely to develop initial trust. Moreover, the evaluation of a system's usefulness positively affects trust. Alongside usefulness, security risks and ethical concerns can diminish trust. Many study also indicates that concerns over privacy and data security negatively impact trust in chatbots, as users fear their data may be exploited or learned by algorithms [44]. Consumers are concerned about whether the usefulness of products presented through AI-generated videos might be exaggerated, leading to diminished purchase intention and a significant loss of trust [45]. Simultaneously, H8a suggests that Ethics [26,27] (primarily privacy concerns and transparency) moderates the relationship between PU and Trust. When ethical concerns are high, the positive impact of perceived usefulness on trust will decrease. Conversely, transparency and ethical assurance will strengthen this relationship Therefore, Hypothesis H4 is proposed:

H4: *Perceived Usefulness (PU) positively influences Trust, thereby increasing Purchase Intention in E-commerce (PIE).*

H8b: Ethics (E) moderates the Perceived Usefulness (PU) → Trust (T) relationship.

When discussing AI and e-commerce, we cannot overlook Privacy Concern (PC) [21,22], which directly impacts consumers' trust in online platforms [47]. The concern over personal data such as health, weight, or appearance information, when personalized through AI raises questions about how this data might affect consumers' lives and whether it could be exploited. According to research by Hermann, E (2022), a highly personalized ad campaign using AI made consumers feel monitored, significantly diminishing trust and raising ethical concerns [46]. This brings up a critical ethical dilemma: do these AI-generated ads inadvertently support illegal behaviors or other unethical practices? Imagine seeing your face on an advertisement without consent. This kind of experience undermines trust and severely reduces purchase intention. Based on this, the following hypotheses are formed:

H5: Privacy Concern (PC) negatively influences Trust (T), with an indirect association with Purchase Intention through Trust.

Brand Recognition (BR) has a direct effect on Trust in e-commerce [23,24]. When consumers recognize a reputable brand, they are more likely to trust its products or services. BR plays a crucial role in building consumer trust online. Studies on Brand Knowledge show that brand recognition is a key factor in establishing trust [48]. A strong, well-recognized brand helps consumers feel more secure when making purchases, thus strengthening their trust in that brand. High brand recognition increases credibility, and the appearance of a dedicated KOL (Key Opinion Leader) for a brand can further improve brand perception, as illustrated in Figure 1. However, from an ethical standpoint, consumers may feel disappointed if they perceive that supporting AI-generated ads is indirectly causing job losses, especially if they originally supported the brand for its social responsibility [49]. If the brand

shifts too drastically from its initial ethical position, it could reduce consumer trust and negatively impact purchase intention.

H6: Brand Recognition (BR) positively influences Trust (T), with an indirect association with Purchase Intention through Trust.

Trust is a decisive factor in driving Purchase Intention in e-commerce [25]. When consumers trust an e-commerce platform, they are more likely to engage in transactions and make purchase decisions. Chen & Zhang (2023) confirm that when consumers trust a platform, they are more inclined to engage in transactions faster and more frequently, thereby increasing Purchase Intention. This is well-documented across numerous studies that show the critical role of trust in the decision-making process, particularly in digital environments.

H7: *Trust (T) positively influences Purchase Intention in E-commerce (PIE).*

Figure 3 depicts the prespecified model. Emotional Attraction (EA), Social Influence (SI) and AI Personalization (AP) enter Purchase Intention directly; Perceived Usefulness (PU), Privacy Concern (PC) and Brand Recognition (BR) enter Trust, which in turn predicts Purchase Intention. Ethics moderates AP→PI and PU→Trust. Direct Ethics→PI and Ethics→Trust terms are included as lower-order controls for the interaction model. In the supplied SmartPLS files, Social Influence is labeled SP and Brand Recognition is labeled PR; these refer to the same SI and BR indicator blocks shown in the questionnaire. The SmartPLS interaction object labelled "E*PU->PI" in its export actually targets Trust (T), as shown by its path matrix and bootstrap row.

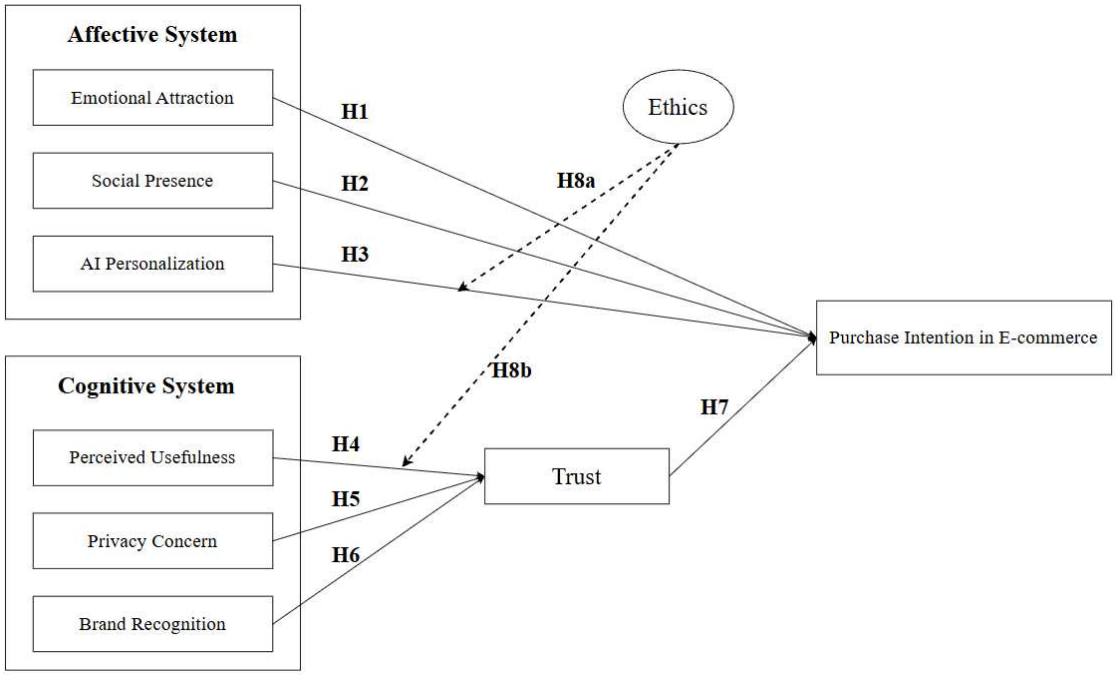


Figure 3. Research Model

III. RESEARCH METHODOLOGY

A. Research Design

A three-stage design was retained: PLS-SEM estimates the prespecified paths in Figure 3; ANN evaluates predictive relationships for the two endogenous constructs; fsQCA examines combinations sufficient for high purchase intention. These methods provide complementary, not interchangeable, evidence. The design uses 491 complete cases from the 34-item survey file and the case-level latent scores exported by SmartPLS 4. Claims are restricted to observed associations, prediction and set relations, not experimental causal effects.

First, SmartPLS 4 report files supplied the outer loadings, reliability and validity diagnostics, structural paths, model fit, R^2, f^2 and the bootstrap t statistics and p values. The direct and interaction paths follow Figure 3; the exported model also includes the lower-order Ethics main effects on PI and Trust. Indicator blocks were reconciled with the raw 34-column survey (AP5, PU5 and PI5 are retained; no PC4 is present).

Second, two feed-forward multilayer perceptron regressors were estimated from the SmartPLS standardized latent variable scores. The PI network uses AP, EA, SI, T, E and E×AP; the Trust network uses PU, PC, BR, E and E×PU. Both use eight tanh hidden neurons, L-BFGS optimization and L2 regularization ($\alpha = 10$). Ten shuffled outer folds (seed 2026) assess held-out RMSE and R^2; all input scaling is fitted on each training fold. Held-out permutation importance (20 shuffles per predictor/fold) ranks predictors on the basis of RMSE-independent increases in mean squared error. A ridge model evaluated on the same folds serves as a linear prediction benchmark. This analysis was run in Python (scikit-learn), not RapidMiner or SPSS.

Third, standardized SmartPLS scores were directly calibrated to fuzzy memberships using each variable's empirical 10th, 50th and 90th percentiles as the 0.05, 0.50 and 0.95 anchors. PI was the outcome; six theoretically proximal conditions (AP, EA, SI, T, E and PC) formed the truth table. The conservative solution retained observed rows with at least three cases, sufficiency consistency ≥ 0.80 and PRI consistency ≥ 0.65; no unobserved logical remainders were used for simplification. Scores equal to the crossover were assigned to the non-high category only for truth-table frequency assignment; fuzzy memberships were unchanged in consistency calculations. The computation was implemented in Python, with Boolean minimization, rather than claimed as an fsQCA 3.0 software run. Figure 4 retains the original conceptual workflow.

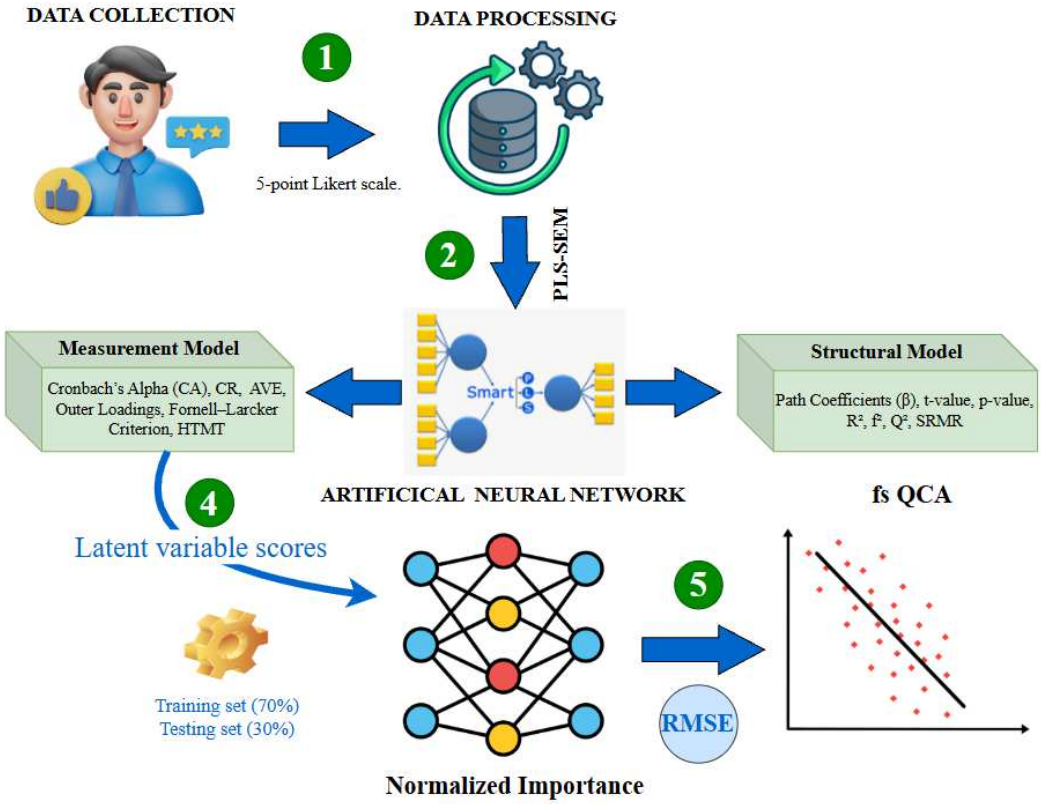


Figure 4. Flowchart

B. Sampling and Data Collection

The original manuscript reports purposive sampling of Vietnamese consumers familiar with AI-generated video ads, 800 questionnaires distributed and 491 valid responses (61.4%). The raw analytic file confirms 491 complete records and 34 Likert items, but does not contain survey invitations or demographic fields. The sampling totals and participant profile therefore remain survey-report information rather than independently revalidated properties of the supplied response matrix. As Table 2 includes respondents over age 50, the eligible age range is described as adults aged 18 and above.

Table 2 retains the demographic distributions recorded in the source manuscript (N = 491). These categories provide contextual information, but no demographic columns were supplied for independent verification or subgroup analysis. Counts are not used to infer that gender or education causes differences in purchasing behavior. The main analyses below use only the 34 observed measurement indicators and SmartPLS latent scores.

Table 2. Descriptive Analysis (*N = 491*)

Variable	Category	Frequency	Percentage (%)
Gender	Male	250	50.9
	Female	241	49.1
Age	18-24	110	22.4
	25-34	180	36.6
	35-44	100	20.4
	45-50	51	10.4
	Above 50	50	10.2
Education Level	High school	85	17.3
	Undergraduate	267	54.4
	Post-graduate	139	28.3
Occupation	Office employee	160	32.6
	Freelancer / Online seller	155	31.6
	Manager / Entrepreneur	105	21.4
	Student	71	14.4
Monthly Income (mil. VND)	Below 10 million	103	21.0
	10 – 20 million	213	43.3
	Above 20 million	175	35.7
Frequency of Viewing AI-Generated Advertising Videos	Rarely	91	18.5
	Occasionally	170	34.6
	Frequently	230	46.9
Main Platform Used	Shopee / Lazada	180	36.7
	TikTok	150	30.5
	Facebook	105	21.4
	YouTube / Instagram	30	6.1
	Other platforms	26	5.3
Region	Ho Chi Minh City	172	35.0
	Hanoi	126	25.7
	Other provinces	193	39.3

C. Measurement Intruments

To ensure the validity and relevance of the measurement model, this study used a set of multi-item reflective scales adapted from well-established instruments in behavioral and marketing research. The survey questionnaire was developed in both English and Vietnamese, utilizing a five-point Likert scale ranging from 1 = "strongly disagree" to 5 = "strongly agree." Each construct in the model was derived from validated scales in prior studies but was carefully refined in terms of wording and contextual framing to capture the unique characteristics of AI-generated video advertisements and consumer purchase intention within the e-commerce ecosystem, especially under the influence of ethical dilemmas.

The adaptation process was conducted in two stages. In the first stage, all the original items were assessed for their theoretical relevance and content validity in the context of online consumer decision-making, specifically with AI-generated video ads. In the second stage, the wording of each item was contextually adjusted to align with the Vietnamese digital advertising environment while maintaining conceptual consistency.

To ensure linguistic accuracy, the bilingual version of the questionnaire underwent a back-translation process following Brislin's (1980) method, ensuring semantic equivalence between the English and Vietnamese versions.

Table 3 reproduces the nine questionnaire constructs and their sources. Item counts were checked against the raw CSV (34 observed items in total). The source text of individual questions and the original language-validation audit were not provided; consequently, interpretation of the direction of the Ethics scale must remain cautious.

Table 3. Measurement Instruments

Construct	No. of items	Sources

Emotional Attraction (EA)	3	[52], [61]*
Social Influence (SI)	3	[53]*
AI Personalization (AP)	5	[54]*
Perceived Usefulness (PU)	5	[55]*
Privacy Concern (PC)	3	[56]*
Brand Recognition (BR)	3	[57]*
Trust (T)	3	[58]*
Ethics (E)	4	[59]*
Purchase Intention in E-commerce (PIE)	—	[60]*

**There has been additional reference and adjustments made to align it appropriately*

The supplied 34-item survey was rechecked for a dominant unrotated component. PCA on standardized indicators yields a first eigenvalue of 5.629 and 16.5% of total observed variance (Table 4). This is below the often-used 50% heuristic. It is a descriptive single-component diagnostic rather than proof that common method bias is absent; the original 44.2% figure and 32-item count were inconsistent with the supplied data and have been replaced.

Table 4. Common Method Bias

Statistical Indicator	Value
Total number of observed indicators	34
First eigenvalue (unrotated PCA)	5.629
Variance explained by first component	16.5%

IV. RESULT AND ANALYSIS

A. Measurement Model Assessment

Outer loadings were taken directly from the supplied SmartPLS 4 algorithm export and reconciled against all 34 questionnaire columns. Each indicator loads on its intended factor; the minimum is 0.757 (AP4). Measurement reporting here follows the nine substantive latent constructs and excludes the two product-indicator interaction objects from reliability tables.

$$AVE = \frac{\sum_{i=1}^{M} \lambda_i^2}{M} \tag{1}$$

Convergent validity is supported by AVE values of 0.629–0.737 for the nine substantive constructs, all above 0.50. These are construct-specific proportions of indicator variance, not evidence of predictive accuracy. The full outer-loading matrix and construct reliability estimates are provided in Table 5.λ_i^2

$$\alpha = \frac{K}{K-1} \times \left(1 - \frac{\sum_{i=1}^{K} \sigma_{Y_i}^2}{\sigma_X^2}\right) \tag{2}$$

Cronbach's alpha ranges from 0.768 (EA) to 0.876 (PI), while composite reliability ranges from 0.863 (EA) to 0.910 (PI). Values support acceptable internal consistency for the reported blocks. Privacy Concern has three items in the raw data, not four; Purchase Intention and Perceived Usefulness each have five.

$$CR = \frac{\left(\sum_{j=1}^{k} \lambda_j\right)^2}{\left(\sum_{j=1}^{k} \lambda_j\right)^2 + \sum_{j=1}^{k} \sigma_j^2} \tag{3}$$

The rho_A estimates range from 0.786 (SI) to 0.879 (PU). Retaining item-level results matters: an incorrect inventory would make later replication of both latent scores and reliability statistics impossible.

Table 5. Items Loadings and Reliability Measures

Latent variable	Obs. Var	Outer Loading	Cronbach's α	rho_A	CR	AVE
AP	AP1	0.787	0.853	0.856	0.895	0.629
	AP2	0.807				
	AP3	0.819				
	AP4	0.757				
	AP5	0.794				
E	E1	0.797	0.832	0.869	0.886	0.661
	E2	0.820				
	E3	0.866				
	E4	0.767				
EA	EA1	0.872	0.768	0.816	0.863	0.678
	EA2	0.786				
	EA3	0.809				
PC	PC1	0.832	0.783	0.793	0.873	0.697
	PC2	0.859				
	PC3	0.813				
PI	PI1	0.806	0.876	0.878	0.910	0.668
	PI2	0.846				
	PI3	0.804				
	PI4	0.806				
	PI5	0.824				
PR	BR1	0.873	0.800	0.809	0.882	0.714
	BR2	0.831				
	BR3	0.830				
PU	PU1	0.802	0.875	0.879	0.909	0.667
	PU2	0.798				
	PU3	0.822				
	PU4	0.813				
	PU5	0.847				
SP	SP1	0.827	0.774	0.786	0.869	0.688
	SP2	0.861				
	SP3	0.799				
T	T1	0.863	0.822	0.822	0.894	0.737
	T2	0.858				
	T3	0.855				

The measurement results support the use of the nine substantive latent scores in the structural and predictive stages. They do not by themselves establish that the constructs are free from all measurement error or common method effects.

Table 6. Cross Loadings for Main Constructs

Variable	AP	BR	E	EA	PC	PI	PU	SI	T
AP1	**0.787**	0.061	0.000	0.076	0.033	0.296	-0.079	0.060	-0.037
AP2	**0.807**	0.007	0.052	0.040	-0.026	0.271	-0.116	0.066	-0.052
AP3	**0.819**	0.013	0.047	0.062	-0.029	0.309	-0.054	0.034	-0.027
AP4	**0.757**	-0.005	0.002	0.122	0.014	0.254	-0.073	0.093	-0.088
AP5	**0.794**	0.005	0.033	0.115	0.002	0.268	-0.053	0.061	-0.042
BR1	0.031	**0.873**	0.030	0.015	0.007	0.187	0.005	0.005	0.350
BR2	0.010	**0.831**	0.030	-0.002	0.087	0.184	0.045	-0.010	0.306
BR3	0.011	**0.830**	0.036	-0.022	-0.022	0.142	-0.004	0.016	0.288
E1	0.026	0.077	**0.797**	0.008	0.052	-0.090	0.005	-0.025	0.009
E2	0.001	0.055	**0.820**	-0.045	-0.014	-0.101	-0.080	-0.092	-0.011
E3	0.051	-0.015	**0.866**	0.001	0.020	-0.127	-0.056	-0.081	-0.049
E4	0.027	0.024	**0.767**	-0.005	0.035	-0.078	-0.038	-0.040	0.028
EA1	0.060	-0.010	-0.042	**0.872**	-0.024	0.063	-0.011	0.057	-0.015

EA2	0.130	-0.006	-0.008	**0.786**	0.022	0.040	0.002	0.043	-0.024
EA3	0.082	0.015	0.033	**0.809**	0.001	0.043	0.052	0.006	-0.009
PC1	-0.008	0.005	-0.013	-0.005	**0.832**	-0.184	0.030	0.044	-0.284
PC2	-0.000	0.031	0.035	-0.005	**0.859**	-0.175	-0.019	0.030	-0.313
PC3	0.004	0.036	0.046	-0.002	**0.813**	-0.198	0.026	0.039	-0.245
PI1	0.256	0.173	-0.103	0.016	-0.229	**0.806**	0.201	0.166	0.368
PI2	0.315	0.178	-0.077	0.059	-0.190	**0.846**	0.225	0.220	0.387
PI3	0.297	0.193	-0.076	0.060	-0.138	**0.804**	0.193	0.164	0.306
PI4	0.292	0.110	-0.154	0.081	-0.156	**0.806**	0.202	0.213	0.322
PI5	0.283	0.180	-0.103	0.036	-0.188	**0.824**	0.181	0.161	0.357
PU1	-0.042	-0.007	-0.049	0.014	0.036	0.171	**0.802**	-0.011	0.276
PU2	-0.094	0.006	-0.027	0.032	0.046	0.149	**0.798**	-0.030	0.345
PU3	-0.055	0.061	-0.071	0.007	-0.024	0.215	**0.822**	-0.006	0.347
PU4	-0.092	-0.036	-0.045	-0.004	-0.035	0.222	**0.813**	-0.035	0.368
PU5	-0.091	0.046	-0.034	0.009	0.036	0.236	**0.847**	0.026	0.360
SI1	0.056	0.024	-0.086	0.054	0.047	0.175	-0.065	**0.827**	-0.022
SI2	0.103	0.022	-0.049	0.077	0.022	0.213	0.029	**0.861**	0.024
SI3	0.025	-0.040	-0.062	-0.025	0.045	0.174	-0.007	**0.799**	-0.026
T1	-0.039	0.322	0.009	-0.042	-0.290	0.377	0.358	-0.008	**0.863**
T2	-0.052	0.341	0.003	-0.013	-0.274	0.358	0.367	-0.004	**0.858**
T3	-0.065	0.301	-0.050	0.007	-0.310	0.366	0.354	-0.006	**0.855**

In Table 6, all 34 indicators have their largest loading on the associated substantive construct. The weakest target loading is AP4 (0.757); no item exceeds a competing-construct loading. Because the report uses PR/SP labels for BR/SI, these two indicator blocks were explicitly harmonized before reformatting the cross-loading matrix.

Table 7. Fornell-Larcker Criterion

Variable	AP	BR	E	EA	PC	PI	PU	SI	T
AP	**0.793**								
BR	0.022	**0.845**							
E	0.034	0.038	**0.813**						
EA	0.103	-0.002	-0.013	**0.823**					
PC	-0.002	0.028	0.026	-0.005	**0.835**				
PI	0.354	0.204	-0.125	0.062	-0.221	**0.817**			
PU	-0.094	0.018	-0.055	0.014	0.012	0.246	**0.817**		
SI	0.077	0.004	-0.078	0.046	0.044	0.227	-0.014	**0.830**	
T	-0.061	0.374	-0.014	-0.019	-0.339	0.427	0.419	-0.007	**0.859**

Table 7 gives the Fornell–Larcker matrix extracted from the current SmartPLS model. For every substantive construct, the diagonal square root of AVE exceeds the corresponding interconstruct correlations. This addresses discriminant validity under the reported criterion but does not substitute for the more stringent HTMT check.

Table 8. Heterotrait–Monotrait Ratio (HTMT)

Variable	AP	BR	E	EA	PC	PI	PU	SI	T
AP									
BR	0.035								
E	0.057	0.064							
EA	0.138	0.022	0.055						
PC	0.035	0.065	0.057	0.034					
PI	0.407	0.242	0.143	0.072	0.268				

PU	0.108	0.053	0.069	0.052	0.065	0.277		
SI	0.096	0.047	0.097	0.088	0.060	0.272	0.058	
T	0.074	0.459	0.054	0.030	0.419	0.502	0.489	0.038

All substantive-construct HTMT coefficients in Table 8 are below 0.85; the largest is approximately 0.502 for Trust–Purchase Intention. The interaction objects are excluded from HTMT because they are model products rather than independent multi-item constructs.

Table 9. Model Fit Evaluation

Model	SRMR	d_ULS	d_G	Chi-Square	NFI
Saturated Model	0.043	1.099	0.414	1236.954	0.827
Estimated Model	0.046	1.244	0.423	1260.138	0.823

The estimated-model SRMR is 0.046, compared with 0.043 for the saturated model. NFI is 0.823 for the estimated model, below the frequently cited 0.90 reference point. Therefore, these diagnostics do not warrant an unqualified claim of excellent global fit; PLS-SEM inference is based primarily on the measurement diagnostics, path uncertainty and predictive checks, not on NFI alone.

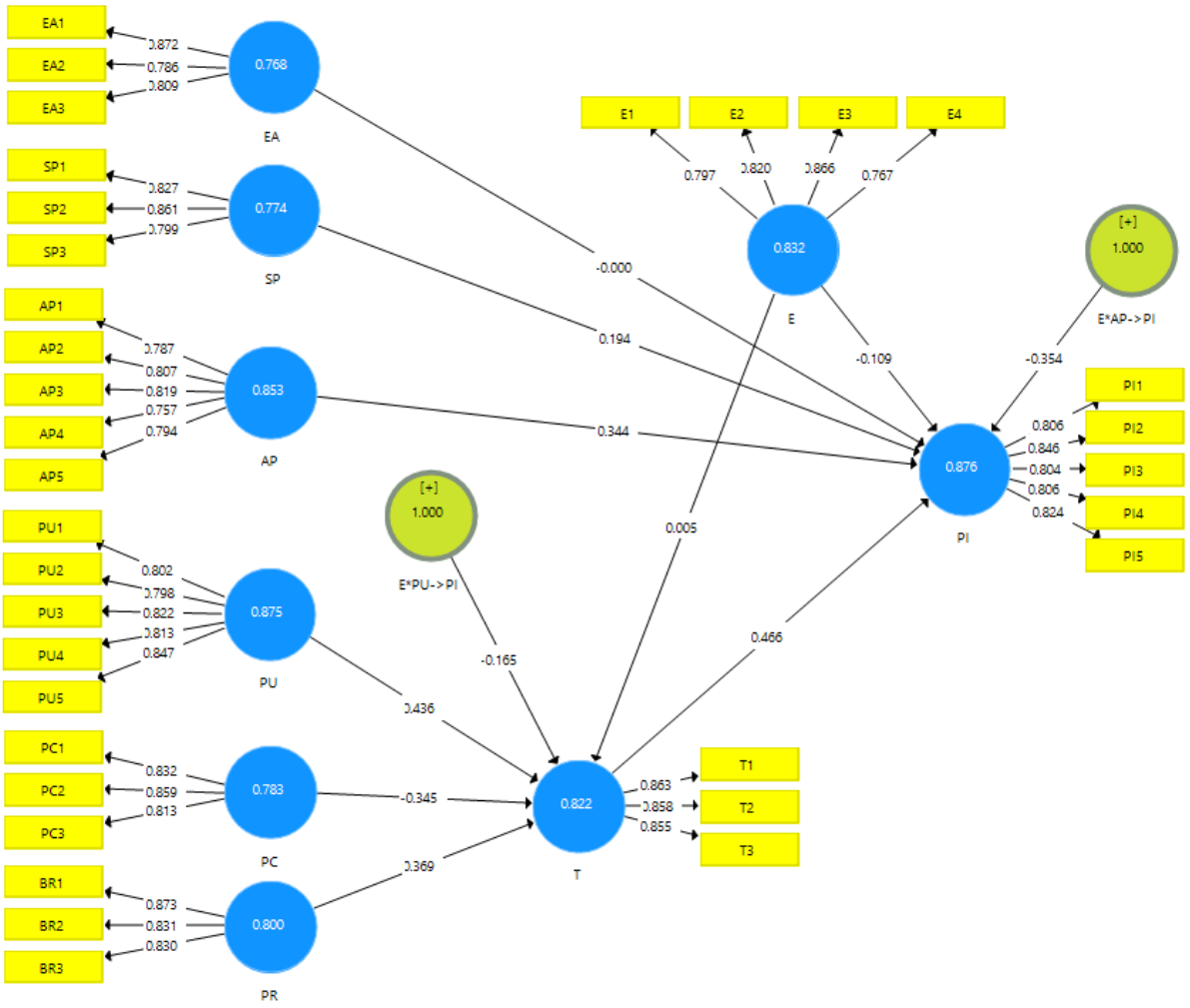


Figure 5. PLS Algorithms Analysis

Figure 5 is retained from the original submission and corresponds to the same two-moderator specification. Current SmartPLS output reports $R^2 = 0.508$ for Purchase Intention and $R^2 = 0.465$ for Trust. The prior statement that Trust had $R^2 = 0.547$ was inconsistent with the supplied algorithm report and has been corrected.

B. Structural Asessment Model

The structural model directly tests seven substantive links, two Ethics interaction terms and two Ethics main effects included for hierarchy. Table 10 reproduces the supplied bootstrap estimates rather than the coefficients printed in the earlier draft. Statistical significance is distinguished from effect magnitude; interaction coefficients describe conditional changes in slopes, not unconditional effects of Ethics.

The standardized model explains 50.8% of the variance in Purchase Intention and 46.5% in Trust. Inner VIF values are approximately 1.00–1.03, giving little indication of problematic collinearity among the modeled predictors. The model remains cross-sectional, so a significant coefficient should not be read as a causal treatment effect.

Table 10. PLS Structural Model Results

Relationships	Original (O)	Mean (M)	STDEV	t statistic	VIF	p value
AP → PI	+0.344	+0.342	0.037	9.313	1.026	<0.001
E → PI	-0.109	-0.108	0.036	3.053	1.008	0.002
E → T	+0.005	+0.003	0.047	0.108	1.005	0.914
E × AP → PI	-0.354	-0.338	0.058	6.153	1.012	<0.001
E × PU → T	-0.165	-0.157	0.043	3.796	1.018	<0.001
EA → PI	-0.000	+0.005	0.036	0.002	1.016	0.998
PC → T	-0.345	-0.347	0.036	9.606	1.005	<0.001
BR → T	+0.369	+0.369	0.032	11.598	1.005	<0.001
PU → T	+0.436	+0.434	0.034	12.972	1.016	<0.001
SI → PI	+0.194	+0.195	0.032	6.089	1.014	<0.001
T → PI	+0.466	+0.467	0.029	16.089	1.006	<0.001

Trust is the largest positive direct correlate of Purchase Intention ($\beta = 0.466$, $p < 0.001$). AI Personalization also has a positive direct coefficient ($\beta = 0.344$, $p < 0.001$), and Social Influence remains positive ($\beta = 0.194$, $p < 0.001$). Emotional Attraction has essentially no conditional linear association once the other predictors are held constant ($\beta \approx 0.000$; $p = 0.998$). These estimates suggest that visual appeal alone cannot be assumed to convert into purchase intention after trust and personalization are accounted for.

Within the cognitive route, Perceived Usefulness ($\beta = 0.436$, $p < 0.001$) and Brand Recognition ($\beta = 0.369$, $p < 0.001$) are positively associated with Trust, while Privacy Concern is negatively associated ($\beta = -0.345$, $p < 0.001$). Their estimated indirect associations with purchase intention via Trust are +0.203, +0.172 and −0.161, respectively. Such mediation is statistical, not longitudinal proof of an intervening psychological mechanism.

The two prespecified interactions are both negative: Ethics × AP → PI ($\beta = -0.354$, $p < 0.001$) and Ethics × PU → Trust ($\beta = -0.165$, $p < 0.001$). At Ethics scores one standard deviation below, at, and above the mean, the implied AP slopes are approximately 0.699, 0.344 and −0.010, respectively; the corresponding PU slopes are approximately 0.601, 0.436 and 0.271. This shows slope attenuation, not a uniform negative effect of either predictor.

Ethics itself has a negative main effect on Purchase Intention ($\beta = -0.109$, $p = 0.002$) but no detectable main effect on Trust ($\beta = 0.005$, $p = 0.914$) at the centering point of the interacting predictors. Item-level wording for Ethics was not supplied. It is therefore more defensible to report conditional score patterns than to assert that better ethical governance directly reduces trust or purchase intentions.

The bootstrap confidence intervals exclude zero for both interactions and for all substantive paths except EA→PI and E→Trust. Table 10 reports the individual path VIFs; Figure 6 summarizes the corrected structural coefficients, while Figure 7 visualizes the conditional slopes implied by the moderation terms.

The E × AP moderation is material in the specified standardized model ($f^2 = 0.257$). The E × PU moderation is smaller ($f^2 = 0.055$), but still detected by bootstrap inference. These f^2 values evaluate incremental explained variance within this model; they do not establish effects of actual advertising policy interventions. The findings do not establish a simple opposition between emotion and cognition. Trust, which operationalizes a deliberative assessment, is central to the average PI association; Social Influence and Personalization still matter. The nonsignificant EA direct coefficient narrows claims about affective appeal, even though configurational and predictive methods can reveal patterns that do not appear in a single linear slope.

Figure 7 displays the model-implied marginal slopes at three Ethics values. It is a visualization of the fitted interaction equations, not an experiment or a segmentation analysis. The Ethics × AP effect can offset the average

positive personalization slope at high E scores, whereas the PU–Trust slope stays positive within the illustrated ±1 SD range.

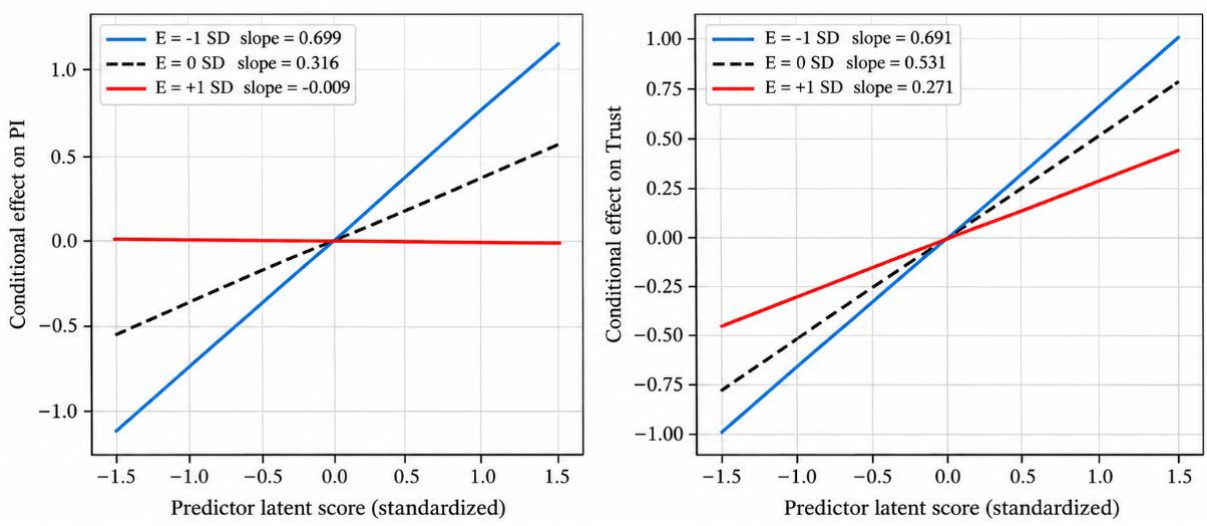


Figure 7. Conditional effects of Ethics on AP–PI and PU–Trust

C. Indirect Effects and Model Diagnostics

The main cognitive predictors connect to Purchase Intention through Trust. Standardized indirect coefficients are +0.203 for PU, +0.172 for BR and −0.161 for PC. The conditional E×PU term also has an indirect coefficient of −0.077. This mediation summary is a compact account of modeled pathways, not evidence of temporal ordering.

Together, the path and indirect-effect estimates show why focusing only on direct responses to AI-generated video would omit much of the model's cognitive component. The stronger managerial signal is to assess usefulness and consumer trust alongside personalization. Causal wording is deliberately avoided because both mediators and outcomes were self-reported at one time point.

The original draft's IPMA graphic was not supported by an IPMA-specific export in the supplied files; Figure 8 therefore reports verifiable indirect effects instead. A valid IPMA would require separate construct-performance scores and explicit target-construct effect definitions.

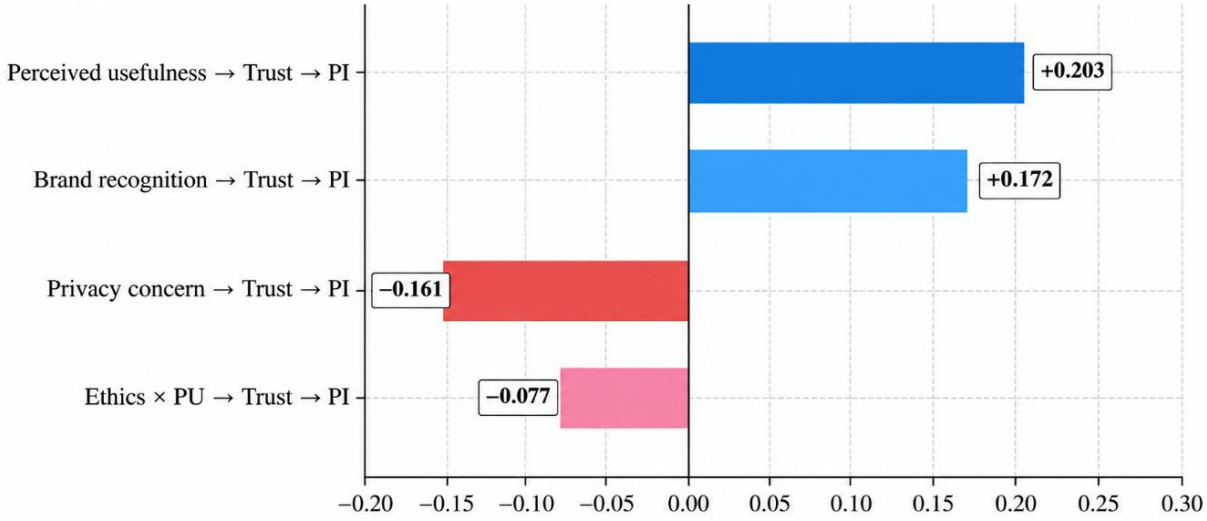


Figure 8. SmartPLS specific indirect associations through Trust

D. Artificial Neural Network (ANN)

Two networks were trained to match Figure 3 rather than allowing every questionnaire scale to predict every endpoint indiscriminately. Network A predicts PI from EA, SI, AP, T, E and the E×AP score. Network B

predicts Trust from PU, PC, BR, E and E×PU. This staged predictive setup is consistent with the direct-parent structure, though it should not be interpreted as causal identification.

The models use the same single-hidden-layer architecture (8 tanh neurons, L-BFGS, α = 10); the feature scales are fitted separately within each training fold. Unlike the original draft, there is no unverified claim of scaled conjugate-gradient optimization or a separate 70:30 split. Ten-fold cross-validation provides exactly ten held-out partitions; permutation importance is calculated on the held-out partitions, not on the training data.

The ANN results are compared against ridge regression on identical folds. For PI, mean testing RMSE is 0.713 for ANN versus 0.711 for ridge; nonlinear modeling does not improve this predictive benchmark. For Trust, ANN has lower mean testing RMSE (0.696) than ridge (0.740). The mixed result limits broad claims that ANN universally outperforms linear methods in this dataset.

Table 11. ANN Parameters and Configuration

Parameters	Function
Network design	Two MLP regressors, PI (6 inputs) and Trust (5 inputs); one hidden layer with 8 neurons
Source	SmartPLS 4 standardized latent scores, N = 491; 34-item survey cross-checked
Resampling	10-fold shuffled CV, random_state = 2026; preprocessing fitted within each fold
Loss / evaluation	Training loss: squared error + L2 penalty; held-out RMSE and R^2; ridge comparison
Activation	tanh hidden layer; linear regression output
Optimizer	L-BFGS; α = 10; max_iter = 1200; seed = 2026 + fold

Ten-fold results for the PI network are reported in Table 12; mean train/test RMSE are 0.692/0.713, with fold-to-fold test RMSE SD = 0.062. The mean held-out R^2 is 0.468. The separate Trust network obtains mean train/test RMSE of 0.669/0.696 and mean held-out R^2 = 0.484. RMSE units are standard deviations of the SmartPLS latent scores, not purchase probabilities.

Table 12. ANN Ten-Fold Training and Testing RMSE (PI Network)

Fold	Training RMSE	Testing RMSE
1	0.699	0.638
2	0.687	0.758
3	0.703	0.605
4	0.692	0.707
5	0.690	0.741
6	0.684	0.786
7	0.696	0.696
8	0.686	0.771
9	0.688	0.763
10	0.697	0.662
Mean	0.692	0.713
SD	0.006	0.062

Held-out permutation importance identifies Trust as the leading PI predictor (normalized 100%), followed by E×AP (56.7%) and AP (51.1%). The E×AP score is treated as one prediction feature in this exercise, not as proof of causal moderation. EA carries almost no incremental test-set information, matching its weak structural path. Predictive importance cannot be interpreted as a standardized SEM coefficient.

In the Trust network, PU ranks first (100%), with BR (88.4%) and PC (83.5%) close behind; E×PU has lower importance (15.6%). This partly corroborates the PLS-SEM ordering but also shows that the empirical importance of an interaction can be modest even when its bootstrap coefficient differs from zero. The signed direction of an association must still be read from the SEM estimates, because permutation importance is unsigned.

Table 13a. Purchase Intention (PI)

Fold	AP	EA	SI	T	E	E×AP
1	0.288	0.002	0.065	0.293	0.008	0.171
2	0.206	-0.001	0.093	0.467	0.063	0.348
3	0.061	0.004	0.051	0.481	0.020	0.123
4	0.223	-0.006	0.113	0.442	0.033	0.184
5	0.080	0.008	0.020	0.489	-0.008	0.195
6	0.189	0.004	0.094	0.375	-0.001	0.182
7	0.275	-0.001	0.041	0.363	0.052	0.440
8	0.310	0.010	0.047	0.306	0.005	0.231
9	0.093	0.001	0.084	0.355	0.043	0.052
10	0.242	-0.001	0.115	0.284	0.007	0.258
Mean ΔMSE	0.197	0.002	0.072	0.385	0.022	0.218
Norm. (%)	51.1	0.5	18.7	100.0	5.8	56.7

Table 13b. Trust (T)

Fold	PU	PC	BR	E	E×PU
1	0.314	0.367	0.279	0.082	0.031
2	0.427	0.275	0.106	0.107	0.085
3	0.335	0.314	0.285	0.099	0.071
4	0.484	0.221	0.196	0.012	0.080
5	0.413	0.311	0.493	0.034	0.125
6	0.347	0.309	0.380	0.118	0.068
7	0.163	0.205	0.390	0.077	-0.011
8	0.476	0.230	0.175	0.061	-0.008
9	0.220	0.300	0.416	0.101	0.078
10	0.280	0.357	0.335	0.059	0.019
Mean ΔMSE	0.346	0.289	0.306	0.075	0.054
Norm. (%)	100.0	83.5	88.4	21.7	15.6

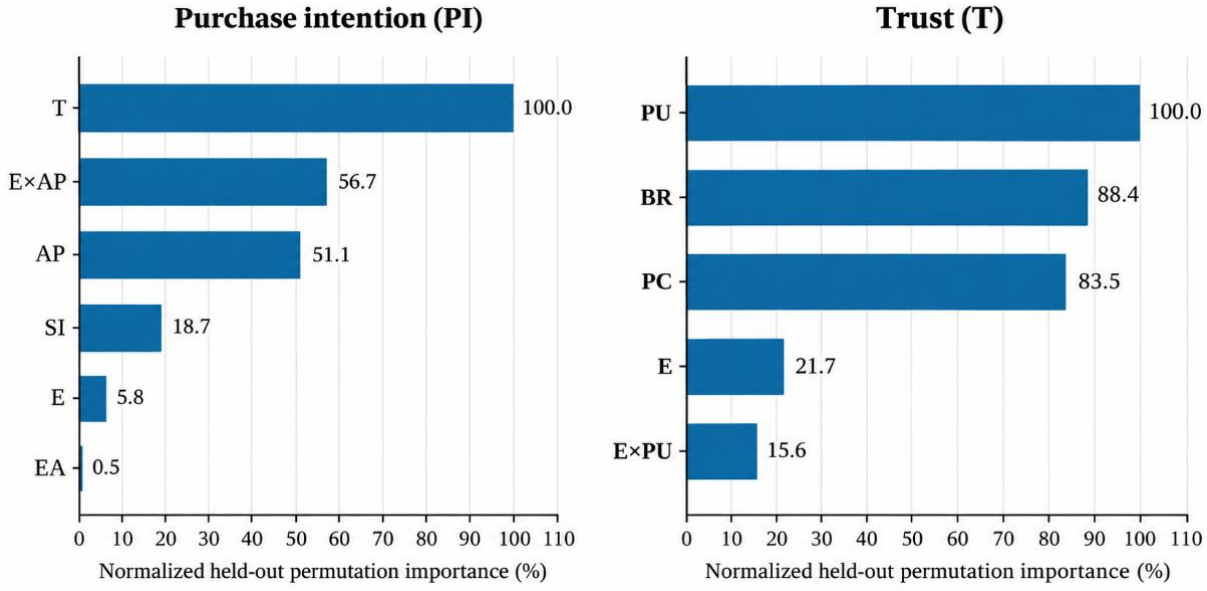


Figure 10. ANN predictor rankings in the two endogenous models

The combined methods provide a restricted interpretation of Dual-System Theory. Social Influence remains useful for predicting PI, but the average direct EA coefficient is almost zero. Cognitive assessments become most

visible through Trust and its upstream predictors; the ANN adds evidence about predictive ordering, not an alternative estimate of the causal mechanism.

The contrast with ridge regression also matters. An ANN is not validated simply because it fits the training sample. PI prediction is almost identical to the linear benchmark and the sample is limited to one national, self-reported survey. A claim of universal nonlinear superiority would overstate these results.

E. fuzzy-set Qualitative Comparative Analysis (fsQCA)

The configurational analysis uses six conditions tied to Figure 3: AP, EA and SI represent outcome-proximal affective and social inputs; T and PC capture the trust/privacy component; E represents the ethics score. PU and BR are not added to the PI truth table because their modeled relationship is routed through Trust and adding every predictor would create severe limited diversity. Six conditions yield 64 logically possible truth-table rows, of which 50 have at least three observed cases.

Direct fuzzy-set calibration uses the empirical 10th/50th/90th percentiles of each standardized latent score, corresponding to memberships 0.05/0.50/0.95. A truth-table frequency cutoff of 3, consistency cutoff of 0.80 and PRI cutoff of 0.65 yielded seven eligible rows. Conservative Boolean minimization of those observed rows produced four configurations. The result is sensitivity-dependent: empirical-percentile thresholds define relative high and low sets in this sample, not externally validated policy benchmarks.

Table 14. fsQCA Sufficient Configurations for High Purchase Intention

Condition	C1	C2	C3	C4	Nec. cons.	System
AI Personalization (AP)	●	●	●	●	0.693	S1
Trust (T)	●	●	–	●	0.676	S2
Privacy Concern (PC)	⊗	–	⊗	⊗	0.617	S2
Ethics (E)	⊗	⊗	⊗	–	0.585	E
Emotional Attraction (EA)	–	●	●	⊗	0.682	S1
Social Influence (SI)	–	●	●	⊗	0.685	S1
Raw coverage	0.302	0.274	0.274	0.222	–	Sufficiency
Consistency	0.947	0.956	0.941	0.931	–	Sufficiency
Unique coverage	0.021	0.050	0.049	0.039	–	Incremental
Support (n)	6	9	11	4	–	Illustrative

Note: ● = condition present; ⊗ = condition absent; – = condition not constrained in the minimized term. Conservative solution consistency = 0.919; coverage = 0.439; frequency ≥ 3; raw consistency ≥ 0.80; PRI ≥ 0.65. The last two columns report condition-level necessity consistency and system classification (S1 = affective/social; S2 = cognitive; E = Ethics).

Four distinct sufficient configurations satisfy the stated thresholds, although they explain only 43.9% of calibrated high-PI membership. Across the minimized terms, AP is present and high Trust appears repeatedly; several pathways also require the absence of high Ethics and/or Privacy Concern scores. A high solution consistency indicates that the selected combinations are mostly subsets of high PI, but a coverage of 0.439 prevents claiming that they explain the bulk of high purchase intention.

C1 combines AP and Trust with low E and low PC (consistency = 0.947, raw coverage = 0.302). C2 adds high EA and SI to high AP and Trust under low E (consistency = 0.956, raw coverage = 0.274). The latter is compatible with a jointly affective-and-cognitive route, but it is not evidence that emotional reactions mechanically precede trust.

C3 combines high AP, EA and SI with low E and PC, while leaving Trust unrestricted (consistency = 0.941; raw coverage = 0.274). C4 combines AP and Trust with low EA, SI and PC while leaving E unrestricted (consistency = 0.931; raw coverage = 0.222). This asymmetry matters: some high-intention cases are consistent with trust-led decision making even when affective and social cues are weak.

No individual condition or its absence approaches the conventional necessity consistency threshold of 0.90; the highest is absence of E at 0.698. Thus, the data support equifinality within a limited portion of the sample rather than a universal gatekeeper condition. Because all conditions are derived from the same cross-sectional survey, the configurations should be viewed as descriptive sufficient set relations that require replication under alternative calibration anchors.

V. DISCUSSION

The central finding is conditional personalization, not a claim that personalization is inherently ethical or unethical. AP has a positive average PI coefficient, yet its marginal association weakens as the measured Ethics score rises. Likewise, PU supports Trust but its conditional slope diminishes at higher E. The two interactions are consistent with an ethical-friction interpretation, but without the exact E item wording and experimental manipulation, the study cannot identify whether the mechanism is perceived risk, scrutiny, transparency, or another correlated attitude.

Dual-System Theory gains a more discriminating empirical interpretation. The positive SI and AP coefficients show that socially salient and personally relevant cues can shape purchase intention, while EA has no detectable average direct slope after controls. The cognitive route runs through Trust: usefulness and brand recognition increase it, privacy concern decreases it, and its link to PI is the strongest among modeled direct paths. This pattern favors a conditional integration of affective and cognitive responses rather than a claim that either system dominates all users.

The predictive and configurational evidence does not simply repeat SEM. ANN shows that Trust has the largest out-of-fold predictive contribution to PI, but it also fails to outperform ridge regression for that endpoint. Its improvement for Trust suggests nonlinear structure may matter more for the upstream cognitive model. fsQCA identifies multiple high-PI pathways, several requiring low privacy concern, yet overall coverage is 0.439 and no single condition is necessary. Hence SEM, ANN and fsQCA converge on the relevance of Trust and personalization while differing in what they can substantiate.

The practical implication is to evaluate AI video campaigns on more than immediate content attraction. Platforms can test whether ads are useful, whether audiences recognize the advertised brands, and whether disclosure and data practices are understandable to users. Personalization should be monitored alongside privacy concern and trust rather than treated as a universal conversion lever. Because the outcomes measure intention rather than transactions, the present coefficients should not be used as guaranteed sales uplifts.

Limitations include a single-country purposive survey, common-source measurement, observational cross-sectional data, absent demographic records in the supplied analytic file, and lack of a detailed Ethics item-codebook. Percentile-calibrated fsQCA solutions are relative to this sample and sensitive to the selected cutoff and set of conditions. ANN rankings are predictive and model dependent, while SEM interactions identify conditional associations only. Future work should validate the measurement wording, preregister alternative set calibrations, and test observed purchase behavior using longitudinal or experimental designs.

VI. CONCLUSION

The reconciled PLS-SEM results identify Trust ($\beta = 0.466$) and AI Personalization ($\beta = 0.344$) as positive direct correlates of purchase intention, with Social Influence also significant and Emotional Attraction not significant. Ethics attenuates both the AP→PI and PU→Trust slopes. This conclusion is based on the two-moderator structure displayed in the original Figure 3 and the accompanying SmartPLS algorithm and bootstrap exports.

Using SmartPLS case-level scores, two cross-validated neural networks provide separate predictions for PI and Trust. ANN improves held-out accuracy over ridge only for Trust, not for PI. A six-condition fsQCA yields four conservative high-PI configurations, with substantial consistency but limited coverage. The combined results do not justify claims that every consumer uses the same pathway or that personalization necessarily causes purchasing behavior.

Responsible AI advertising should therefore integrate relevance with verifiable communication about privacy and trust. The immediate research priority is to test whether the measured ethics-related slope attenuation persists when AI disclosure and consent practices are manipulated directly and actual transactions, rather than stated intention, are observed.

Declarations

Funding: This research received no financial support.

Ethics: This study used consumer survey data. All participants provided informed consent, and no conflicts of interest were identified.

Author Contributions: The author was responsible for conceptualization, research design, data processing, data analysis, and manuscript preparation.

AI Declaration: Grammarly AI was used solely for language editing. The author reviewed the text and takes full responsibility for the final content of the manuscript.

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