AI NARRATION IN E-COMMERCE VIDEOS: THE MEDIATING ROLES OF TRUSTWORTHINESS AND PERCEIVED DIAGNOSTICITY IN SHAPING CONSUMER BEHAVIORAL INTENTION

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Abstract. This study investigates the influence of AI narration in e-commerce videos on consumer behavioral intention via information processing mechanisms in Vietnam. The study, based on the Cognition–Affect–Behavior (CAB) paradigm and the Elaboration Likelihood Model (ELM), suggests that the perceived quality and informativeness of AI narration affect behavioral intention through perceived trustworthiness and diagnosticity. Data were collected from 400 consumers in Ho Chi Minh City and analyzed using PLS-SEM. The results reveal that AI narration quality and informativeness are significant drivers of consumer behavioral intention, both directly and indirectly through trustworthiness and perceived diagnosticity. Perceived diagnosticity emerged as the stronger behavioral driver and mediating mechanism, suggesting that consumers respond more strongly to decision-relevant information than to credibility alone. On a theoretical level, the study applies CAB and ELM to AI-narrated e-commerce videos, using CAB to organize the direct and mediated relationships from narration-related cognitions to behavioral intention and ELM to explain systematic message processing. Managerially, AI narration should emphasize clarity, comparability, and decision-supporting information to facilitate consumer decision-making.

Keywords. AI narration, behavioral intention, e-commerce videos, elaboration likelihood model, information processing, perceived diagnosticity, trustworthiness.

1 INTRODUCTION

The rapid development of digital technologies has had a substantial impact on the way consumers acquire, evaluate, and process information in online settings. With the proliferation of digital platforms [1], [2], consumers are faced with large amounts of product-related information, which is often inconsistent, ambiguous and redundant. In information-rich environments, consumers may feel overwhelmed, confused, or less confident in their decisions if they cannot determine which information is credible, relevant, or useful for product assessment. To address these issues, a new digital communication form, artificial intelligence-generated content (AIGC), has been introduced to support consumers' access to structured, timely, and personalized product information.

The modes of information delivery are also changing. In addition to conventional text communication, audio and voice content have gained prominence in short-form videos, livestream commerce, and social media platforms. Voice, as a sensory and nonverbal signal, can influence consumer perceptions by communicating clarity, fluency, naturalness, competence, and sincerity [3], [4]. Previous research indicates that vocal and auditory cues can affect consumer engagement, perceived trustworthiness, and reactions to digital content. Nevertheless, a significant portion of this research has focused on emotive or behavioral consequences, providing scant insight into how voice-based AI communication influences consumers' cognitive evaluation of product information during decision-making.

In this study, AI narration refers specifically to an AI-generated or AI-synthesized voice track embedded in an e-commerce video to deliver product-related information. It differs from human narration, which is recorded by a human speaker and may naturally convey human identity, emotion, and spontaneity, whereas AI narration is algorithmically produced and can be standardized and scaled across content [5]. AI narration is also narrower than AI-generated video, which may include AI-created visuals, avatars, scripts, editing, and audio; the present study isolates the narrated voice component rather than the entire video-production process [6], [7]. Unlike AI chatbots, which engage users through adaptive and turn-based interactions, AI narration predominantly delivers information in a one-way, non-conversational format [8]. It also differs from AI voice assistants, which respond to user commands, conduct dialogue, and perform requested tasks [9]. These distinctions position AI narration as a specific voice-based message-delivery mechanism rather

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than a general form of AI-generated or conversational media.

This distinction is especially significant in digitally saturated e-commerce contexts. Consumers' decision-making challenges stem not only from the abundance of information but also from deficiencies in information processing, particularly when they struggle to analyze, compare, and assess product-related data efficiently [10], [11]. In these settings, consumers must evaluate not just the credibility of information but also its utility for product assessment and decision-making. Perceived trustworthiness denotes the legitimacy and reliability of information, while perceived diagnosticity indicates the degree to which information aids consumers in assessing product quality, appropriateness, and purchase relevance [12], [13]. Despite the growing use of AI-generated speech in video commerce, few studies have investigated how AI narration, as a distinct one-way, voice-based message-delivery mechanism embedded in e-commerce videos, influences these two cognitive evaluation processes. Evidence derived from human narration, fully AI-generated videos, chatbots, or voice assistants may not adequately explain how consumers evaluate the credibility and decision usefulness of AI-narrated product information.

This study redirects focus from emotional and behavioral responses to the cognitive processes involved in AI-mediated communication. This study uses the CAB framework to conceptualize consumer responses as a sequential process, where cognitive evaluations of external stimuli generate internal evaluative appraisals, that subsequently affect behavioral intention. In this study, the key cognitive inputs are identified as the perceived AI narration quality and the perceived AI narration informativeness. The former relates to consumers' perceptions of the clarity, fluency, and effectiveness of the delivery of information, and the latter relates to the perceived relevance, adequacy, and utility of the information provided. These cognitive inputs are expected to influence two main evaluative mechanisms, including perceived trustworthiness and perceived diagnosticity. Both concepts relate to information evaluation, but they refer to different aspects of consumer judgment, such as believability and decision utility.

In addition, the Elaboration Likelihood Model (ELM) provides another theoretical framework for understanding how consumers perceive AI narration as persuasive communication. In video-based commerce, AI narration is a primary informational signal to facilitate consumers' engagement in message-relevant processing. Consumers will be able to judge the product and the seller based on the clarity, consistency, relevance, and informational value of the narration, rather than on peripheral cues. In central-route processing, narration quality and informativeness are expected to affect consumers' evaluations of the reliability and diagnosticity of product information delivered through AI narration [14], [15], [16].

Building on this theoretical foundation, this study proposes a process-based model in which AI narration influences consumer behavioral intention both directly and indirectly through perceived trustworthiness and perceived diagnosticity. By integrating the CAB framework with ELM, the study explains not only whether AI narration affects behavioral intention, but also how such effects are transmitted through cognitive evaluation mechanisms. This approach allows the study to clarify whether consumers respond more strongly to the perceived credibility of AI narration or to its usefulness for decision-making.

This research makes several contributions to the literature. First, it contributes to emerging research on AIGC in e-commerce by applying CAB and ELM to examine the cognitive mechanisms through which AI narration influences consumer behavioral intention. Second, it contributes to the auditory and sensory marketing literature by showing that voice-based AI stimuli can shape information evaluation processes, rather than merely producing affective or engagement-related responses. Third, it contributes to information processing research by distinguishing trustworthiness from perceived diagnosticity as two related, but conceptually distinct evaluative mechanisms. Accordingly, the theoretical value of the study lies in contextualizing established CAB and ELM mechanisms within AI-narrated e-commerce videos and empirically distinguishing credibility from decision usefulness. From a managerial perspective, the findings provide practical guidance for designing AI narration in e-commerce videos. They indicate that effective AI narration should focus on clarity, comparability, and decision-supporting information, rather than relying primarily on credibility cues or promotional appeal.

2 THEORETICAL BACKGROUND AND HYPOTHESIS DEVELOPMENT

2.1 Theoretical Foundations

In this study, we integrate the Cognition–Affect–Behavior (CAB) framework and the Elaboration Likelihood Model (ELM) to explain the impact of AI narration on consumer behavioral intention in e-commerce videos. Within this framework, AI narration is conceptualized as a one-way, AI-generated or AI-synthesized voice-based message-delivery mechanism embedded in e-commerce videos, functioning as both a delivery cue and an informational cue rather than as the entire AI-generated video or an interactive conversational agent such as a chatbot or voice assistant. The CAB framework conceptualizes the consumer response as a sequential process in which cognitive evaluations influence internal appraisal states, which in turn influence behavioral outcomes, describing the major structural logic of the model [17], [18]. This viewpoint is important for AI-mediated commerce because consumers do not respond automatically to communicated product information. They first evaluate the clarity, fluency, usefulness, and relevance of the narration before making judgments and behavioral intentions.

In the present model, perceived AI narration quality and perceived AI narration informativeness represent the cognitive stage. These constructs capture consumers' initial evaluation of how information is delivered and how useful the narrated content is for understanding the product. Trustworthiness and perceived diagnosticity represent appraisal-based evaluative states. Trustworthiness reflects whether AI narration is perceived as credible, reliable, and dependable, whereas perceived diagnosticity reflects whether the narrated information helps consumers evaluate product quality, compare alternatives, and make more confident decisions. Consumer behavioral intention represents the behavioral outcome. Accordingly, CAB is used to organize the proposed relationships from narration-related cognition to evaluative appraisal and then to behavioral intention. This logic is consistent with prior studies showing that cognitive evaluations influence behavioral outcomes through internal evaluative mechanisms in digital and AI-mediated consumption contexts [19], [20].

ELM complements CAB by explaining how consumers process AI narration as persuasive information. According to ELM, persuasion may occur through a central route, where individuals systematically evaluate message content, or through a peripheral route, where they rely on heuristic cues when motivation or cognitive effort is limited [14], [21]. In AI-narrated e-commerce videos, narration can function as a central informational cue because it conveys product claims, usage explanations, comparisons, and evaluative content. When narration is clear, coherent, relevant, and informative, consumers are more likely to process the message systematically and assess whether it is credible and useful for decision-making.

This study applies CAB as the organizing framework for the proposed sequence from narration-related cognition to evaluative appraisal and behavioral intention [17], [18], while using ELM as a complementary explanatory lens for how narration quality and informativeness support systematic message processing [14], [15], [16]. CAB describes the progression from cognitive evaluation to appraisal and behavioral intention, whereas ELM explains how clear, relevant, and useful narration can strengthen trustworthiness and perceived diagnosticity. Together, these established perspectives provide the theoretical basis for examining consumer responses to AI narration in e-commerce videos.

2.2 Hypothesis development

a. Effects of AI Narration Quality

The CAB paradigm suggests that consumers' evaluations of product information delivered through AI narration are influenced further by their cognitive evaluation of the quality of AI narration. High-quality narration, characterized by clarity, coherence, fluency, and natural prosody, can increase processing fluency and reduce information ambiguity, and this in turn signals expertise and professionalism in digital communication [22]. Such quality cues are important heuristic cues from the ELM perspective, which consumers use to evaluate the credibility and reliability of the communication. In AI-mediated e-commerce videos, where consumers might have limited access to directly verify the seller, product, or information source, clear and natural narration can increase the perceived reliability and trustworthiness of product information [5], [9]. Therefore:

H1: Perceived AI narration quality positively influences trustworthiness.

Perceived diagnosticity is the extent to which information is perceived by consumers as being valuable

for the assessment of products and the making of informed decisions. Improved AI narration may increase perceived diagnosticity by helping consumers comprehend, process, and utilize product-relevant knowledge. Desirable pronunciation, a steady rate of speech and natural voice delivery reduce cognitive load and improve consumers' ability to process product descriptions. In the ELM perspective, narration quality improves access to information and decreases interpretative ambiguity, thereby facilitating central-route processing [22]. Narration in e-commerce videos helps consumers evaluate product features, imagine product use, and assess product suitability more efficiently [23], [24]. Therefore:

H2: Perceived AI narration quality positively influences perceived diagnosticity.

In addition to its effect on trustworthiness and perceived diagnosticity, the narration quality can also directly influence consumer behavioral intention. When AI narration is well articulated, smooth, and authentic, consumers can absorb product information more easily and may form more positive evaluations of the video, product and seller. In online shopping scenarios where consumers are unable to physically touch the products, high-quality narration may alleviate uncertainty and enhance the confidence of consumers to make decisions, thus raising behavioral intention [9], [24], [25]. Therefore:

H3: Perceived AI narration quality positively influences consumer behavioral intention.

b. Effects of AI Narration Informativeness

The perceived informativeness of AI narration is the extent to which AI narration provides product information that is relevant, valuable, adequate and decision supporting. In the CAB framework, informativeness is a cognitive input, as consumers first evaluate whether the presented content is helpful for their understanding of the product before they form internal evaluations. Informative narration reduces uncertainty, improves product understanding, and gives consumers greater confidence to evaluate product characteristics [1]. From the ELM perspective, informative content is a central-route cue, which encourages consumers to evaluate the authenticity and credibility of the communication [16], [26]. When AI narration provides meaningful and relevant information, consumers are more likely to see the message as credible, reliable and trustworthy. Therefore:

H4: Perceived informativeness of AI narration positively influences trustworthiness.

Perceived informativeness is expected to support perceived diagnosticity. While informativeness and diagnosticity are interconnected, they are conceptually separate. Informativeness refers to the relevance, adequacy, and depth of the information presented, whereas perceived diagnosticity refers to the usefulness of that information for assessing options and making decisions [12], [13]. In AI-narrated e-commerce videos, informative narration aids consumers in recognizing essential product characteristics, evaluating alternatives, minimizing uncertainty, and assessing product appropriateness more efficiently. By enhancing the interpretability and usability of product-related information, AI narration increases consumers' perception of its diagnostic value. Therefore:

H5: Perceived informativeness of AI narration positively influences perceived diagnosticity.

Perceived informativeness can also directly influence consumers' behavioral intentions beyond its effect on trustworthiness and diagnosticity. In online purchasing situations, the lack of actual inspection of the product means that buyers often rely on available information. With relevant, complete, and actionable information from AI narration, consumers may be better able to evaluate the product and feel more confident in their decision-making. Such cognitive evaluation can directly enable behavioral responses consistent with the CAB model, if the information is sufficiently useful and action-oriented. ELM suggests that persuasive effects can be directly enhanced by message content that is both compelling and relevant through central-route processing (J. Kitchen et al., 2014). Therefore:

H6: Perceived informativeness of AI narration positively influences consumer behavioral intention.

c. Effects of Trustworthiness and Perceived Diagnosticity

Trustworthiness refers to consumers' perception of AI narration as credible, reliable, and dependable in providing product information. Within the CAB paradigm, trustworthiness signifies an internal evaluative condition that aids consumers in mitigating uncertainty and perceived risk prior to developing behavioral responses. This mechanism is crucial in AI-mediated e-commerce videos, because consumers have limited ability to directly verify the seller, product, or information source. When AI narration is regarded as credible, consumers are more likely to accept the message, depend on the information presented, and develop stronger behavioral intention [9], [27], [28]. Therefore:

H7: Trustworthiness positively influences consumer behavioral intention.

Perceived diagnosticity refers to the extent to which information helps consumers evaluate the quality, performance and suitability of the product for decision-making. Within the CAB-based structure adopted in this study, perceived diagnosticity represents an evaluative mechanism that translates cognitive information processing into behavioral responses. From the ELM perspective, AI narration is an important informational signal that consumers use to determine the relevance, usefulness and sufficiency of the message for product assessment. When information is perceived to be highly diagnostic, consumers can more effectively evaluate alternatives, reduce choice uncertainty, and make confident judgments. Such increased choice confidence increases the likelihood that consumers will transform their evaluations into behavioral intentions [12], [13], [23]. Therefore:

H8: Perceived diagnosticity positively influences consumer behavioral intention.

d. Mediating Roles of Trustworthiness and Perceived Diagnosticity

Trustworthiness is expected to mediate the relationships between AI narration attributes and consumer behavioral intention. From the CAB perspective, the quality and informativeness of AI narration serve as cognitive inputs that influence consumers' appraisal of product information delivered through AI narration. High-quality narration, characterized by clarity, fluency, coherence of pacing, and natural delivery, can be an indicator of competence and professionalism in AI-mediated communication. At the same time, informative narration contains relevant, adequate and decision-facilitating content, which leads consumers to perceive the message as meaningful and reliable. Under the central route of the ELM, consumers are likely to evaluate these narration cues systematically, especially when they rely on e-commerce videos to compensate for the absence of direct product inspection. When AI narration is perceived as credible, reliable, and dependable, consumers' uncertainty and skepticism are reduced, making them more willing to rely on the narrated information and develop favorable behavioral intentions [5], [9], [16]. Therefore:

H9: Trustworthiness mediates the relationship between perceived AI narration quality and consumer behavioral intention.

H10: Trustworthiness mediates the relationship between perceived informativeness of AI narration and consumer behavioral intention.

Perceived diagnosticity is also expected to mediate the effects of AI narration quality and informativeness on consumer behavioral intention. While trustworthiness explains whether consumers believe the narration is credible, perceived diagnosticity explains whether the narrated information is useful for product evaluation and decision-making. High-quality narration enhances processing fluency, reduces interpretive ambiguity, and makes product explanations easier to follow, thereby increasing diagnosticity. Informative narration adds to diagnosticity by offering relevant product attributes, cues for use, comparison points, and decision-oriented content. These qualities are essential in AI-narrated e-commerce videos since consumers have to judge products without being able to touch them. When narration helps consumers understand product quality, compare alternatives, and judge product suitability, they are more likely to feel confident in their evaluation and translate that confidence into behavioral intention [12], [13], [23]. Therefore:

H11: Perceived diagnosticity mediates the relationship between perceived AI narration quality and consumer behavioral intention.

H12: Perceived diagnosticity mediates the relationship between perceived informativeness of AI narration and consumer behavioral intention.

Figure 1 presents the proposed research model, in which AI narration quality and informativeness influence consumer behavioral intention both directly and indirectly through trustworthiness and perceived diagnosticity.

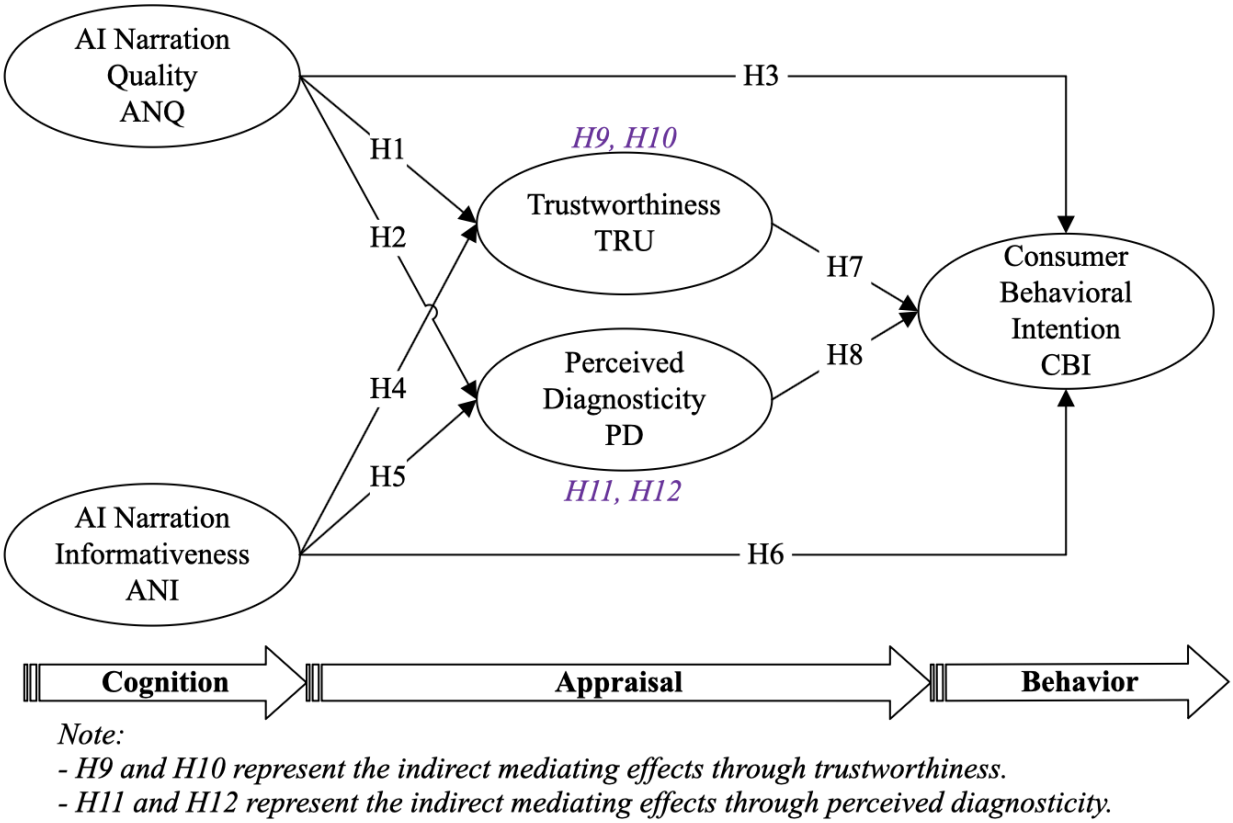


Figure 1: Conceptual Model

Source: Authors' own work

3 METHODOLOGY

This research utilized a quantitative, cross-sectional survey methodology to examine the relationships among perceived AI narration quality, perceived AI narration informativeness, trustworthiness, perceived diagnosticity, and consumer behavioral intention. A quantitative methodology was suitable due to the model's inclusion of several latent constructs and predicted correlations based on the Cognition–Affect–Behavior framework and the Elaboration Likelihood Model. The cross-sectional methodology facilitated the examination of consumers' impressions of AI-narrated e-commerce videos at a single point in time and allowed for the statistical testing of the postulated structural relationships [29].

The target population consisted of Vietnamese consumers aged 18 and above in Ho Chi Minh City who had experienced AI-narrated e-commerce videos (product videos, livestreams, or short-form promotional content) in the past six months. The screening criterion was designed to ensure that participants had relevant and recent experience with AI-mediated communication and could provide informed responses based on actual experience. For the purpose of this study, AI narration was operationally defined as an AI-generated or AI-synthesized voice used to present product-related information within an e-commerce video. It referred specifically to the narrated voice component rather than to the entire video being AI-generated. It also excluded interactive exchanges with AI chatbots or voice assistants, as the focal communication format was predominantly one-way and non-conversational. Since there is no full sampling frame and AI narration in digital commerce is a new field, we used a convenience sample. This non-probability sampling strategy is suitable for exploring new consumer phenomena and elusive user groups [30], but it may constrain the generalizability of the findings.

Data were collected through an online questionnaire administered via Google Forms. To reach consumers familiar with e-commerce videos and digital AI environments, the survey link was distributed via social media and relevant online communities. Data were collected from January to April 2026. Initially, 458 responses were received. After eligibility, completeness, and quality of response screening, 400 valid

responses were retained for final data analysis. This sample size was considered adequate for PLS-SEM because it exceeded the minimum required by the ten-times rule and was sufficient to estimate a model with multiple latent constructs and direct and indirect relationships [31].

The questionnaire consisted of three main sections. The first section included a screening question to confirm respondents' prior exposure to AI narration in e-commerce videos. The second section collected demographic information, including gender, age, occupation, income, and frequency of interacting with AI-narrated e-commerce videos. The third section measured the main constructs of the study, namely AI narration quality, AI narration informativeness, trustworthiness, perceived diagnosticity, and consumer behavioral intention. The study measured five constructs using 26 items adapted from established scales and contextualized for AI-narrated e-commerce videos. Perceived AI narration quality was measured using five items adapted from [32], [33], and [34]. Perceived AI narration informativeness comprised six items adapted from [35], [36], and [37]. Trustworthiness was assessed using five items adapted from [38], [39], [40], and [41]. Perceived diagnosticity was measured using four items adapted from [32], [33], and [34]. Consumer behavioral intention was assessed using six items adapted from [42], [43], and [25]. All items were measured using a seven-point Likert scale ranging from 1, "strongly disagree," to 7, "strongly agree." The complete measurement items and their item-specific sources are presented in Appendix A. The questionnaire was translated into Vietnamese using the back-translation method as recommended by [44] to ensure linguistic and conceptual equivalence. The translation was reviewed by academic specialists for clarity, phrasing, and contextual appropriateness. A pilot test was subsequently conducted with 30 participants to test item clarity and initial reliability. Preliminary results confirmed that the instrument was suitable for the main survey.

Data analysis was performed using SmartPLS with partial least squares structural equation modeling (PLS-SEM). PLS-SEM was selected because it is suitable for predictive research, models with multiple latent constructs, and the analysis of direct and indirect effects [31]. Analysis was conducted using a dual approach. The measurement model was assessed using outer loadings, Cronbach's alpha, composite reliability, average variance extracted, the Fornell–Larcker criterion, and the heterotrait–monotrait ratio to evaluate indicator reliability, internal consistency, convergent validity, and discriminant validity. The structural model was evaluated using variance inflation factors, path coefficients, coefficients of determination, effect sizes, predictive relevance, and the standardized root mean square residual. In addition, PLSpredict was employed to assess out-of-sample predictive performance by examining Q^2_{predict} values and comparing PLS-SEM prediction errors, measured using RMSE and MAE, with those of a linear model benchmark. Bootstrapping with 5,000 resamples was used to test the significance of indirect and direct effects. Bootstrapped indirect effects and confidence intervals were used to test the mediation effects through trustworthiness and perceived diagnosticity. Given the cross-sectional and self-reported nature of the data, common method bias was assessed using Harman's single-factor test. All 26 measurement items were entered into an unrotated principal component analysis, with one factor extracted.

4 RESULTS

4.1 Demographic Characteristics

The sample consisted of 400 respondents from Ho Chi Minh City who had experience with AI-narrated e-commerce videos in the past 6 months. This sample provides a pertinent context for exploring consumer responses to AI narration, as short-form videos and AI-generated digital content are gaining popularity among Vietnamese consumers [6]. The gender distribution was relatively balanced, with females representing 51.2% and males 46.8%. The sample was predominantly young, with 50.2% between the ages of 18 and 24, and 25.0% between the ages of 25 and 34. The sample was mainly composed of students (51.7%), followed by office workers (26.0%) and business/self-employed respondents (20.0%). The majority of respondents are from lower to middle income groups, with 70.3% of them reporting monthly income below 10,000,000 VND. Online shopping is also prevalent, as 39.0% of the respondents shop often and 31.0% shop very often, demonstrating a dynamic e-commerce user demographic consistent with the study's context.

Table 1: Descriptive Analysis (n = 400)

Criteria	Category	Frequency	%
Gender	Female	205	51.2%
	Male	187	46.8%
	Other	8	2.0%
Age	18–24	201	50.2%
	25–34	100	25.0%
	35–44	67	16.8%
	Over 44	32	8.0%
Occupation	Student	207	51.7%
	Office worker	104	26.0%
	Business / Self-employed	80	20.0%
	Others	9	2.3%
Income	Under 5,000,000 VND	143	35.8%
	5-10,000,000 VND	138	34.5%
	10–20,000,000 VND	84	21.0%
	Over 20,000,000 VND	35	8.8%
Frequency of interacting with AI-narrated e-commerce videos	Very often	124	31.0%
	Often	156	39.0%
	Sometimes	92	23.0%
	Rarely	28	7.0%

Source: Authors' survey data

4.2 Common Method Bias Assessment

Since the data were collected from the same respondents using a cross-sectional self-report questionnaire, Harman's single-factor test was conducted to assess common method bias. All 26 measurement items were entered into an unrotated principal component analysis, with one factor extracted. The first factor explained 33.634% of the total variance, which was below the commonly applied threshold of 50%. Therefore, no single factor accounted for the majority of the variance, suggesting that common method bias was unlikely to pose a serious threat to the study findings. Detailed results are provided in Appendix D.

Table 2: Common Method Bias Assessment

Assessment method	Number of items	Variance explained by the first factor	Threshold	Interpretation
Harman's single-factor test	26	33.634%	< 50%	No dominant single factor; common method bias was unlikely to pose a serious threat

Note: All measurement items were entered into an unrotated principal component analysis, with one factor extracted.
Source: Authors' calculation using SPSS.

4.3 Reliability Assessment

Following recommended PLS-SEM procedures, internal consistency reliability was assessed using Cronbach's alpha and composite reliability. As shown in Table 3 the final measurement model comprised 26 indicators across five constructs. Cronbach's alpha values ranged from 0.820 to 0.855, while composite reliability values ranged from 0.875 to 0.892. All values exceeded the recommended threshold of 0.70, indicating satisfactory internal consistency reliability for all constructs [31].

Table 3: Reliability Assessment

Construct	Items	Cronbach's α	Composite Reliability
ANI	6	0.848	0.887
ANQ	5	0.831	0.881
CBI	6	0.855	0.892
PD	4	0.820	0.881

Construct	Items	Cronbach's α	Composite Reliability
TRU	5	0.821	0.875

Note: ANI = AI Narration Informativeness; ANQ = AI Narration Quality; CBI = Consumer Behavioral Intention; PD = Perceived Diagnosticity; TRU = Trustworthiness.

Source: Authors' calculation using SmartPLS 4 software

4.4 Convergent Validity: AVE and Outer Loadings

Following recommended PLS-SEM procedures, convergent validity was assessed using standardized outer loadings and average variance extracted (AVE). All 26 item-level outer loadings exceeded the recommended threshold of 0.70, ranging from 0.718 to 0.853. In addition, all AVE values were above the threshold of 0.50, ranging from 0.567 to 0.650. These results confirm satisfactory indicator reliability and convergent validity. Table 4 summarizes the loading range and AVE for each construct, while the complete item-level outer loadings are reported in Appendix B.

Table 4: Convergent Validity (outer loadings and AVE)

Construct	Items	Loading range	AVE
ANI	6	0.726-0.811	0.567
ANQ	5	0.722-0.822	0.598
CBI	6	0.718-0.853	0.581
PD	4	0.785-0.833	0.650
TRU	5	0.723-0.790	0.583

Source: Authors' calculation using SmartPLS 4 software

4.5 Discriminant Validity Assessment

Discriminant validity was assessed using both the Fornell–Larcker criterion and the heterotrait–monotrait ratio (HTMT). The Fornell–Larcker criterion provides a conventional assessment by comparing the square root of each construct's average variance extracted with its correlations with other constructs [45]. As presented in Table 5, all diagonal values exceeded the corresponding inter-construct correlations. The square roots of the AVE ranged from 0.753 to 0.806, and each value was greater than the highest correlation involving the respective construct. These results provide initial evidence of satisfactory discriminant validity.

Table 5: Discriminant Validity Assessment Using the Fornell–Larcker Criterion

Construct	ANI	ANQ	CBI	PD	TRU
ANI	**0.753**				
ANQ	0.106	**0.773**			
CBI	0.503	0.537	**0.762**		
PD	0.402	0.432	0.608	**0.806**	
TRU	0.398	0.456	0.563	0.527	**0.764**

Source: Authors' calculation using SmartPLS 4 software.

Discriminant validity was examined using the HTMT criterion, which provides a rigorous assessment of construct distinctiveness in PLS-SEM [46]. As presented in Table 6, all HTMT values are below the conservative threshold of 0.85. The highest value is found between perceived diagnosticity and consumer behavioral intention (HTMT = 0.723), followed by trustworthiness and consumer behavioral intention (HTMT = 0.664). Since all values remain below the recommended cut-off, discriminant validity is established, indicating that the constructs are empirically distinct and suitable for structural model assessment.

Table 6: Discriminant Validity Assessment Using HTMT

Construct	ANI	ANQ	CBI	PD	TRU

ANI					
ANQ	0.125				
CBI	0.577	0.639			
PD	0.476	0.518	0.723		
TRU	0.466	0.547	0.664	0.637	

Source: Authors' calculation using SmartPLS 4 software

4.6 Hypothesis Testing and Structural Model Results

Structural relationships were estimated using PLS-SEM with 5,000 bootstrap resamples [31]. As shown in Table 7, all direct structural paths are positive and statistically significant at $p < 0.001$. The results indicate that perceived AI narration quality significantly influences trustworthiness ($\beta = 0.419$, $t = 6.879$), perceived diagnosticity ($\beta = 0.394$, $t = 9.025$), and consumer behavioral intention ($\beta = 0.318$, $t = 6.283$), supporting H1, H2, and H3. Similarly, perceived informativeness of AI narration significantly affects trustworthiness ($\beta = 0.353$, $t = 6.285$), perceived diagnosticity ($\beta = 0.360$, $t = 7.298$), and consumer behavioral intention ($\beta = 0.299$, $t = 6.788$), supporting H4, H5, and H6. At the evaluative stage, trustworthiness has a positive effect on consumer behavioral intention ($\beta = 0.158$, $t = 3.691$), while perceived diagnosticity exerts a stronger effect on consumer behavioral intention ($\beta = 0.268$, $t = 5.956$), supporting H7 and H8. These findings suggest that both AI narration attributes and evaluative mechanisms contribute to behavioral intention, with perceived diagnosticity showing a stronger behavioral effect than trustworthiness.

Table 7: Hypothesis Testing Results

Hypothesis	Structural path	β	t-value	p-value	f^2	Effect size	Result
H1	ANQ → TRU	0.419	6.879	0.000	0.185	Moderate	Supported
H2	ANQ → PD	0.394	9.025	0.000	0.224	Moderate	Supported
H3	ANQ → CBI	0.318	6.283	0.000	0.171	Moderate	Supported
H4	ANI → TRU	0.353	6.285	0.000	0.185	Moderate	Supported
H5	ANI → PD	0.360	7.298	0.000	0.187	Moderate	Supported
H6	ANI → CBI	0.299	6.788	0.000	0.161	Moderate	Supported
H7	TRU → CBI	0.158	3.691	0.000	0.035	Small	Supported
H8	PD → CBI	0.268	5.956	0.000	0.104	Small	Supported

Source: Authors' calculation using SmartPLS 4 software

Effect sizes were also analyzed to assess the practical importance of the structural relationships in addition to statistical significance [47]. The results in Table 7 indicate that the effects of AI narration quality and informativeness on trustworthiness, perceived diagnosticity, and consumer behavioral intention are generally moderate, with f^2 values ranging from 0.161 to 0.224. Trustworthiness and perceived diagnosticity have a relatively small impact on consumer behavioral intention. These results show that AI narration attributes have stronger practical relevance than downstream evaluative mechanisms, although both appraisal mechanisms remain statistically significant.

Figure 2 shows the PLS-SEM structural model with standardized path coefficients, outer loadings and the explained variance for the endogenous constructs. The figure demonstrates how consumer behavioral intention is positively influenced by AI narration quality and informativeness through trustworthiness and perceived diagnosticity.

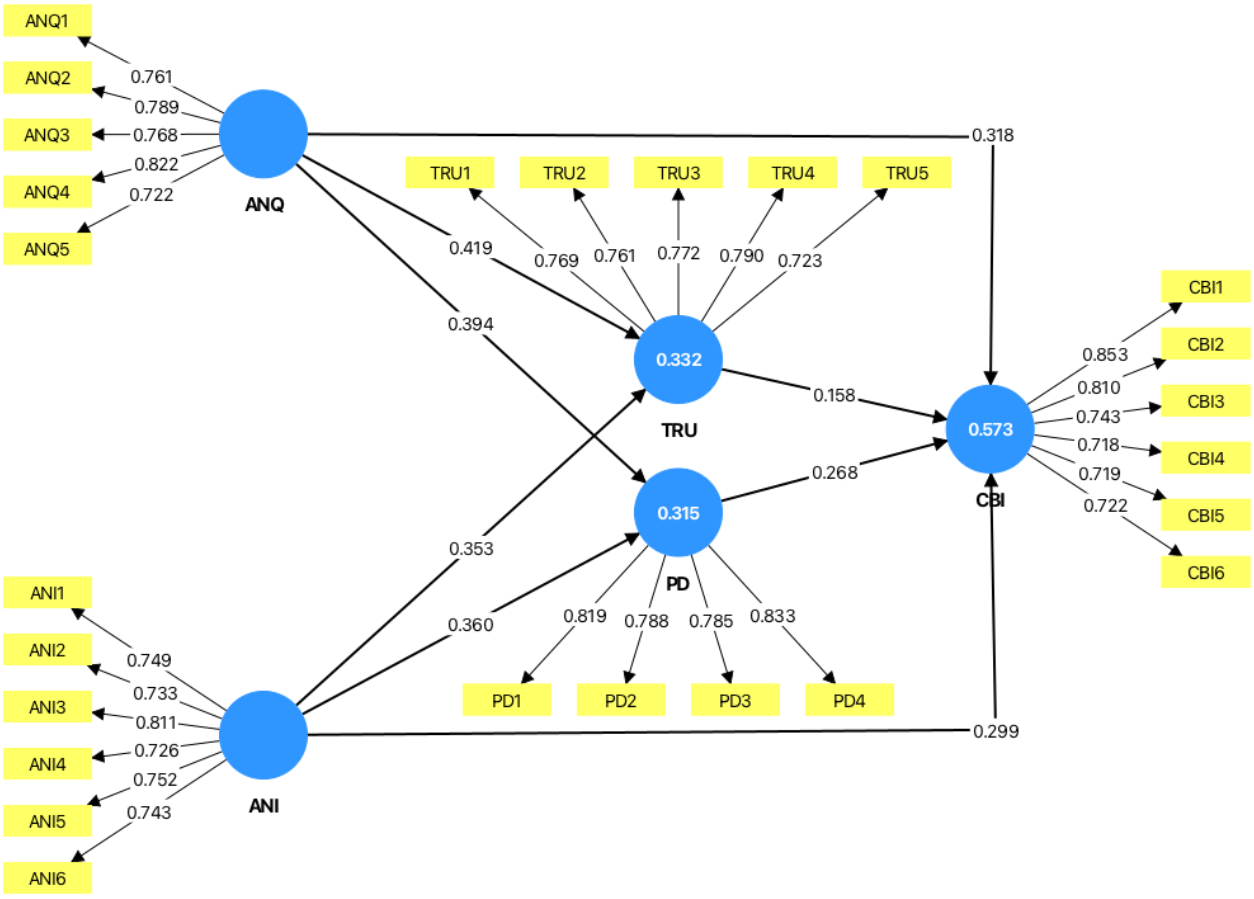


Figure 2: PLS-SEM Structural Model Results

Source: Authors' creation using SmartPLS 4 software

Mediation analysis was then conducted by testing specific indirect effects. As shown in Table 8, all four specific indirect effects are positive and statistically significant, supporting H9 to H12. Trustworthiness was a significant mediator for the relationship between AI narration quality and consumer behavioral intention ($\beta = 0.066$, $t = 3.142$, $p = 0.002$), thus supporting H9. H10 is supported, in which trustworthiness mediates the relation between AI narration informativeness and consumer behavioral intention ($\beta = 0.056$, $t = 2.719$, $p = 0.007$). Perceived diagnosticity significantly mediates the relationship between AI narration quality and consumer behavioral intention ($\beta = 0.106$, $t = 4.966$, $p < 0.001$), which supports H11. Finally, perceived diagnosticity mediates the relationship between AI narration informativeness and consumer behavioral intention ($\beta = 0.096$, $t = 4.870$, $p < 0.001$), thus supporting H12. The significant direct and indirect effects suggest partial mediation. The indirect effects via perceived diagnosticity are stronger than those via trustworthiness, indicating that decision usefulness is a more important path than credibility in translating AI narration attributes into consumer behavioral intention.

Table 8: Indirect Effects through Trustworthiness and Perceived Diagnosticity

Hypothesis	Specific indirect path	β	STDEV	t-value	p-value	Result
H9	ANQ → TRU → CBI	0.066	0.021	3.142	0.002	Supported
H10	ANI → TRU → CBI	0.056	0.020	2.719	0.007	Supported
H11	ANQ → PD → CBI	0.106	0.021	4.966	0.000	Supported
H12	ANI → PD → CBI	0.096	0.020	4.870	0.000	Supported

Source: Authors' calculation using SmartPLS 4 software

4.7 Model Quality and Predictive Assessment

Table 9 summarizes the model's explanatory power, predictive relevance, collinearity, and approximate model fit. The R^2 values were 0.573 for consumer behavioral intention, 0.315 for perceived diagnosticity, and 0.332 for trustworthiness. Thus, the model explained 57.3% of the variance in consumer behavioral intention and approximately one-third of the variance in the two appraisal constructs, with the strongest

explanatory power observed for consumer behavioral intention. The Stone–Geisser Q^2 values were above zero for all endogenous constructs (CBI = 0.326; PD = 0.200; TRU = 0.187), indicating satisfactory predictive relevance [48], [49]. Inner VIF values ranged from 1.011 to 1.645, suggesting no critical collinearity concerns [31]. The SRMR value of 0.064 indicated acceptable approximate model fit, although PLS-SEM model assessment should primarily emphasize explanatory and predictive criteria [31].

Table 9: Model Fit and Predictive Indicators

Criterion	CBI	PD	TRU	Interpretation
R^2	0.573	0.315	0.332	CBI exhibited the strongest explanatory power
Stone–Geisser Q^2	0.326	0.200	0.187	All values exceeded zero, indicating predictive relevance
Inner VIF range	1.300–1.645	1.011–1.011	1.011–1.011	No critical collinearity concerns
SRMR	0.064	-	-	Acceptable approximate model fit

Source: Authors' calculation using SmartPLS 4 software.

Table 10. PLSpredict Assessment

Construct	Construct-level Q^2_{predict}	Indicator-level Q^2_{predict} range	PLS-SEM RMSE lower than LM	PLS-SEM MAE lower than LM
CBI	0.471	0.229–0.360	5 of 6 indicators	6 of 6 indicators
PD	0.298	0.170–0.210	3 of 4 indicators	3 of 4 indicators
TRU	0.309	0.141–0.216	5 of 5 indicators	5 of 5 indicators
Overall	-	0.141–0.360	**13 of 15 indicators**	**14 of 15 indicators**

Note: *PLSpredict was assessed for the endogenous constructs. LM = linear model benchmark; RMSE = root mean squared error; MAE = mean absolute error.*

Source: Authors' calculation using SmartPLS 4 software

Beyond the predictive relevance indicated by the Stone–Geisser Q^2 values, the model's out-of-sample predictive performance was assessed using PLSpredict. As shown in Table 10, all 15 indicators of the endogenous constructs achieved positive Q^2_{predict} values, ranging from 0.141 to 0.360. The construct-level Q^2_{predict} values were also positive for consumer behavioral intention (0.471), perceived diagnosticity (0.298), and trustworthiness (0.309). Compared with the linear model benchmark, PLS-SEM produced lower RMSE values for 13 of the 15 indicators and lower MAE values for 14 indicators. The RMSE exceptions were CBI4 and PD1, while PD1 was the only indicator for which the PLS-SEM MAE exceeded the linear model benchmark. Overall, this pattern indicates that the model demonstrates medium out-of-sample predictive power. Complete indicator-level results are reported in Appendix C.

5 DISCUSSION

The findings support the proposed cognition–evaluation–behavior framework in AI-narrated e-commerce videos. Consumers assess AI narration not only as an auditory or technological feature but also in terms of its clarity and informativeness in communicating product information before forming judgments about its trustworthiness and diagnosticity. The findings provide empirical support for the applicability of the CAB framework in AI-mediated commerce, where narration-related cognitions are associated with behavioral intention both directly and indirectly through evaluative appraisals. Perceived diagnosticity has a stronger effect on behavioral intention than trustworthiness, indicating that consumers are more likely to act when AI narration helps them understand, compare, and evaluate products than when it is perceived as merely believable [12], [13].

The support for all proposed hypotheses can be understood from the coherent information-processing logic of the model. AI narration quality and informativeness represent closely connected but distinct aspects of the consumer experience: the former concerns how information is delivered, whereas the latter concerns the relevance, adequacy, and usefulness of the content itself. In an e-commerce setting where consumers cannot physically inspect products, both delivery quality and informational substance can simultaneously shape credibility, decision usefulness, and behavioral intention. Moreover, the significant direct and indirect

effects indicate partial rather than complete mediation, suggesting that narration attributes can influence behavior immediately while also operating through evaluative mechanisms. Nevertheless, the supported relationships were not uniform in magnitude. The effects of narration quality and informativeness were generally stronger than the downstream effects of trustworthiness and perceived diagnosticity, indicating that statistical significance did not imply equal practical importance across all paths.

At the cognitive input stage, AI narration quality is an important antecedent. Product information delivered through AI narration is more understandable and less cognitively demanding when narrated concisely, articulately, and cohesively. This pattern is broadly consistent with previous research showing that fluent and effective voice-based AI communication can strengthen consumers' confidence and responses to digital content [3], [4], [9]. It also complements evidence from product-presentation videos and online information research showing that information becomes more influential when it helps consumers evaluate product quality and suitability [12], [13], [23]. AI narration informativeness significantly enhances perceived credibility and diagnosticity, indicating that consumers value relevant and adequate information. However, the findings also show that the substance of the information alone is insufficient. For product information to be effective, it needs to be presented clearly and accessibly. This finding is consistent with ELM's central-route processing logic, according to which information quality and message relevance become more persuasive when consumers systematically evaluate the message [15], [16].

Trustworthiness and perceived diagnosticity play distinct but complementary roles in the evaluation phase. Trustworthiness reduces uncertainty by making AI narration appear credible, reliable, and dependable [27], [28]. This finding is consistent with previous AI research that identifies trust as an important condition for consumers' acceptance of voice-based and AI-generated communication [7], [9], [27]. However, the present results suggest that trustworthiness may be necessary without being the most proximal determinant of behavioral intention. In contrast, perceived diagnosticity is more action-oriented because it refers to whether consumers can use the information to evaluate product quality, compare alternatives, and make informed choices [12], [23]. Conceptually, trustworthiness answers whether consumers believe the narration, whereas perceived diagnosticity answers whether they can use it to make a product decision. The latter judgment is positioned closer to behavioral intention because it converts narrated information into an actionable product evaluation. This distinction is important in e-commerce because buyers are often exposed to information overload and cannot physically inspect products. Accordingly, the stronger influence of perceived diagnosticity is consistent with earlier research showing that product-presentation and online-review information is more persuasive when it directly supports product assessment and choice [12], [13], [23]. AI narration is therefore more meaningful when it clarifies the decision-making process rather than merely creating an impression of credibility.

The stronger role of perceived diagnosticity may be particularly salient in the predominantly young and digitally experienced sample examined in this study. Half of the respondents were aged 18–24, 51.7% were students, and 70.0% reported interacting with AI-narrated e-commerce videos often or very often. This profile includes a substantial segment of Gen Z-age consumers who are likely to be relatively familiar with short-form videos and AI-generated digital content in Vietnam [6].

Repeated exposure may normalize the presence of synthetic voices, making the mere credibility of AI narration less differentiating. Once a minimum level of trust is established, these consumers may respond more strongly to whether the narration saves cognitive effort, highlights relevant product attributes, facilitates comparison, and supports an immediate decision. In the urban Vietnamese e-commerce context represented by Ho Chi Minh City, diagnosticity may therefore carry greater behavioral relevance because it helps consumers manage abundant product information and compensate for the inability to inspect products directly. Nevertheless, age group and national context were not modeled as moderators; this interpretation should therefore be viewed as contextually grounded rather than as definitive evidence of a uniquely Vietnamese or Gen Z-specific causal effect.

Although the constructs are theoretically related, the results do not suggest that they are conceptually interchangeable. AI narration quality captures the effectiveness of information delivery, whereas AI narration informativeness captures the value and adequacy of the information provided. Similarly, trustworthiness concerns whether the narration is believable and dependable, while perceived diagnosticity concerns whether the information is useful for evaluating products and making decisions. The Fornell–

Larcker results showed that the square root of the AVE for each construct exceeded its correlations with other constructs, while all HTMT values remained below 0.85. The highest HTMT value was 0.723 between perceived diagnosticity and behavioral intention, which remained below the conservative threshold. These findings reduce concerns that the universal support for the hypotheses was driven primarily by conceptual redundancy among the constructs.

This mechanism is also explained by the mediation results. The magnitude of the indirect effects suggests that trustworthiness and perceived diagnosticity partially mediate the effects of AI narration attributes on behavioral intention. The diagnosticity paths are stronger than the trustworthiness paths, suggesting that decision usefulness is more important than credibility alone in AI-narrated e-commerce videos. This interpretation is supported consistently across the structural results. Perceived diagnosticity had a stronger direct relationship with behavioral intention than trustworthiness ($\beta = 0.268$ versus $\beta = 0.157$) and a larger effect size ($f^2 = 0.104$ versus $f^2 = 0.035$). Likewise, the indirect effects through perceived diagnosticity ($\beta = 0.106$ and $\beta = 0.096$) exceeded the corresponding indirect effects through trustworthiness ($\beta = 0.066$ and $\beta = 0.056$). This repeated pattern across both direct and mediated pathways indicates that diagnosticity functions as the more behaviorally proximal appraisal mechanism. However, both downstream effect sizes remained relatively small, meaning that diagnosticity was stronger than trustworthiness in relative terms rather than an overwhelmingly dominant determinant of behavior. The coexistence of significant direct and indirect effects is theoretically plausible because consumers may respond immediately to clear and informative narration while also forming credibility- and utility-based evaluations that further strengthen their behavioral intentions. This result is consistent with the application of CAB as an organizing framework and shows that, in the present context, narration-related cognitions are associated with behavioral intention through both direct and mediated pathways. The quality and informativeness of AI narration were therefore associated with behavioral intention both directly and indirectly through appraisal-based mechanisms. AI narration should consequently be viewed as an information catalyst and a decision-support tool.

Common method bias was also considered because all constructs were measured through a cross-sectional self-report questionnaire completed by the same respondents. Harman's single-factor test showed that the first factor explained 33.634% of the total variance, below the 50% threshold, suggesting that no single factor dominated the responses. This result, together with satisfactory discriminant validity, indicates that the support for all hypotheses was unlikely to be solely attributable to common method bias. However, Harman's test cannot completely rule out shared-method variance, and the findings should therefore be interpreted with appropriate caution.

More specifically, the findings suggest that credibility enables consumers to accept AI-narrated information, whereas diagnosticity determines whether that information can be translated into product evaluation and behavioral intention, particularly among young consumers who frequently encounter AI-mediated video content. Managers should not treat AI narration merely as a natural-sounding or promotional feature. It should enable consumers to analyze product information, consider alternatives, and make informed decisions. Hence, companies should strive for clear, comparable, product-specific descriptions and actionable cues in AI-narrated e-commerce videos.

6 CONCLUSIONS & RECOMMENDATIONS

This study explored the mediating roles of trustworthiness and perceived diagnosticity in the influence of AI narration quality and informativeness on consumer behavioral intention in e-commerce videos. The results show that both narration attributes significantly affect behavioral intention directly and indirectly. Perceived diagnosticity is a more powerful mechanism than trustworthiness, suggesting that consumers are more responsive to AI narration when it helps product evaluation and decision-making. The value of AI narration lies not only in perceived credibility but also in its ability to help consumers interpret, compare, and decide.

The study makes three theoretical contributions. First, it contextualizes the CAB framework and ELM within AI-narrated e-commerce videos. CAB organizes AI narration quality and informativeness as cognitive inputs, trustworthiness and perceived diagnosticity as evaluative appraisals, and behavioral intention as the outcome [17], [18], while ELM explains why clear, relevant, and useful narration can

encourage systematic message processing [14], [21]. Second, the study distinguishes trustworthiness from perceived diagnosticity as related but conceptually distinct appraisal mechanisms. Trustworthiness reflects whether consumers perceive AI narration as credible and dependable, whereas perceived diagnosticity reflects whether the narrated information helps them evaluate products and make decisions. Third, the findings show that AI narration quality and informativeness are associated with behavioral intention through both direct and partially mediated pathways. This pattern provides contextual empirical support for applying and integrating established theoretical perspectives in AI-narrated e-commerce videos without claiming to extend CAB or ELM.

From a managerial perspective, AI narration should be positioned as a decision-support tool, not just a promotional tool. Brands should develop AI narration scripts that explain product characteristics clearly, highlight specific applications and enable comparative evaluation [8]. Generic advertising statements should be minimized because they may improve visibility but do not improve the quality of decision-making. At the same time, the delivery of narration remains important. Clear, well-articulated, and natural vocal delivery can decrease cognitive load and increase perceived competence [6], [7]. But good presentation must not disguise poor product knowledge. Effective AI narration requires both natural voice delivery and substantively valuable content.

This study has several limitations. First, it draws on cross-sectional self-report data, which limits causal inference. Although Harman's single-factor test did not indicate a serious common method bias problem, shared-method variance cannot be completely ruled out. Second, the sample was predominantly young and student-based and may reflect the active user base of short-form e-commerce videos, but this composition may limit generalizability to older and higher-income consumers. Third, the study examined behavioral intention rather than actual buying behavior. Fourth, the study focuses on trustworthiness and perceived diagnosticity and does not consider other AI-specific perceptions and psychological responses. Future research could examine perceived AI authenticity and AI transparency as antecedents of trustworthiness, as consumers may respond differently depending on whether the synthetic nature and information sources of the narration are clearly disclosed. AI anthropomorphism could also be investigated as a factor shaping perceived naturalness, social presence, and trust in AI narration. In addition, AI skepticism and AI anxiety may act as boundary conditions that weaken consumers' responses to narration quality and informativeness. Other mechanisms, including perceived risk and perceived personalization, may further explain how AI narration affects consumer evaluation and behavior. Future research should also use experimental or longitudinal designs, compare AI narration with human narration or text-based communication, and include behavioral data, such as clickstream or purchase records, to improve causal and predictive validity.

AI narration is most effective when it enables consumers to make informed decisions. Credibility matters, but decision utility is the key factor affecting consumers' behavioral intention in AI-narrated e-commerce videos.

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