

Trust Calibration in the Era of Generative AI: Unravelling AI-Generated EWOM Adoption and Purchase Intention through Multi-Group PLS-SEM

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Abstract

Purpose – Grounded in the Theory of Reasoned Action (TRA) and Trust Calibration Theory, this study examines the factors influencing consumers' adoption of AI-generated electronic word-of-mouth (AI-eWOM) and its subsequent impact on purchase intention in social commerce. Specifically, the study investigates the effects of AI-eWOM Disclosure Transparency, Algorithmic Amplification, Perceived Manipulation, Consumer Trust in AI, Subjective Norms, and Perceived Diagnosticity on Trust Calibration, while examining the mediating roles of Trust Calibration and AI-generated eWOM Adoption.

Design/methodology/approach – A quantitative, cross-sectional research design was adopted. Primary data were collected through an online questionnaire using convenience sampling from consumers across Tier-1 and Tier-2 cities in Central, North, and South India. A total of 550 responses were collected, of which 403 valid responses were retained for analysis. The proposed conceptual model was evaluated using Partial Least Squares Structural Equation Modeling (PLS-SEM).

Findings – The findings reveal that AI-eWOM Disclosure Transparency, Algorithmic Amplification, Consumer Trust in AI, Subjective Norms, and Perceived Diagnosticity positively influence Trust Calibration, whereas Perceived Manipulation negatively affects Trust Calibration. Trust Calibration significantly enhances AI-generated eWOM Adoption, which subsequently increases Purchase Intention. Furthermore, Perceived Diagnosticity has a direct positive effect on Purchase Intention. The mediation analysis confirms that Trust Calibration and AI-generated eWOM Adoption jointly explain the mechanism through which AI-related factors influence consumers' purchase intentions.

Practical implications – The findings provide important implications for e-commerce platforms, social commerce businesses, digital marketers, AI developers, and policymakers by highlighting the importance of transparent AI disclosure, ethical algorithm design, trustworthy AI-generated content, and responsible AI governance in strengthening consumer trust and encouraging AI-assisted purchase decisions.

Originality/value – This study extends the Theory of Reasoned Action by integrating Trust Calibration Theory into the AI-generated eWOM context and develops a comprehensive framework explaining how AI-related factors shape consumer trust, AI-generated eWOM Adoption, and Purchase Intention. The study contributes to the emerging literature on AI-enabled social commerce by providing empirical evidence from the Indian market and offering insights into consumer behaviour toward generative AI-driven recommendation systems.

Keywords- Generative Artificial Intelligence (Generative AI); AI-generated Electronic Word-of-Mouth (AI-eWOM); AI-generated Reviews; Trust Calibration; Consumer Trust in AI; Purchase Intention; Social Commerce; Theory of Reasoned Action (TRA); AI Disclosure Transparency; Algorithmic Amplification; Perceived Diagnosticity; Responsible Artificial Intelligence

1.1 Background

The rapid advancement of Generative Artificial Intelligence (GenAI) has transformed digital commerce by enabling machines to generate human-like content, engage in conversational interactions, and support consumer decision-making. Unlike traditional AI, which primarily focuses on prediction and automation, Generative AI creates original textual and multimedia content through large language models. Technologies such as ChatGPT, Gemini, Claude, and Copilot have accelerated the adoption of AI in consumer-facing applications, enabling personalized recommendations, intelligent shopping assistants, and automated customer interactions. Consequently, Generative AI has become a strategic driver of digital transformation, reshaping consumer engagement and online purchasing behaviour.

The growing adoption of Generative AI has also transformed social commerce, where social interaction and electronic commerce converge to facilitate purchase decisions. AI-powered recommendation systems, personalized advertising, conversational assistants, and automated review summaries help consumers process large volumes of information and receive tailored product recommendations. As AI capabilities continue to advance, social commerce is evolving into a hybrid ecosystem in which both consumers and AI contribute to creating, sharing, and interpreting marketplace information.

A major outcome of this transformation is the emergence of AI-generated electronic word-of-mouth (AI-generated eWOM). While traditional eWOM consists of consumer-generated reviews, ratings, and online recommendations, Generative AI now enables intelligent systems to generate review summaries, provide product recommendations, and assist consumers throughout the purchase process. As a result, AI-generated eWOM has become an increasingly important source of marketplace information that complements user-generated content and influences consumers' product evaluations and purchase decisions.

1.2 Research Problem

The integration of AI-generated electronic word-of-mouth (AI-generated eWOM) into social commerce has transformed how consumers search for information and evaluate products. AI-generated review summaries, conversational shopping assistants, and personalized recommendations improve decision-making efficiency by reducing information overload. However, these AI-enabled systems also raise concerns regarding the credibility, transparency, and reliability of AI-generated content. Consumers often remain uncertain whether AI-generated recommendations accurately represent collective consumer opinions or are influenced by algorithmic bias and commercial interests. Consequently, understanding the factors that shape consumers' trust in AI-generated eWOM has become a critical challenge for both researchers and practitioners.

1.3 Research Gap

Although recent studies have examined AI-generated reviews, algorithmic transparency, consumer trust, perceived diagnosticity, and purchase intention, these factors have largely been investigated in isolation. Existing research primarily treats trust as a direct predictor of behavioural intention, overlooking the dynamic process through which consumers calibrate their trust before relying on AI-generated information. Consequently, the role of **Trust Calibration** in explaining AI-generated eWOM adoption remains underexplored, particularly within social commerce.

To address this gap, the present study proposes an integrated framework in which AI-eWOM Disclosure Transparency, Algorithmic Amplification, Perceived Manipulation, Consumer Trust in AI, Subjective Norms, and Perceived Diagnosticity influence AI-generated eWOM Adoption through Trust Calibration, ultimately leading to Purchase Intention. Grounded in the Theory of Reasoned Action (TRA) and Trust Calibration Theory, the study offers a comprehensive understanding of consumer decision-making in AI-enabled social commerce and employs Multi-Group PLS-SEM to examine differences across consumer groups.

1.4 Research Objectives

This study aims to examine the factors influencing AI-generated electronic word-of-mouth (AI-generated eWOM) adoption and purchase intention in social commerce. Specifically, the objectives are:

1. To examine the effects of AI-eWOM Disclosure Transparency, Algorithmic Amplification, Perceived Manipulation, Consumer Trust in AI, Subjective Norms, and Perceived Diagnosticity on Trust Calibration.
2. To assess the influence of Trust Calibration on AI-generated eWOM Adoption.
3. To examine the effect of AI-generated eWOM Adoption on Purchase Intention.
4. To validate the proposed conceptual model using Multi-Group PLS-SEM.

1.5 Contributions of the Study

This study contributes to the literature by developing an integrated framework that explains AI-generated electronic word-of-mouth (AI-generated eWOM) adoption through the combined effects of technological, psychological, and social factors. It extends the Theory of Reasoned Action (TRA) by incorporating Trust Calibration as the key mechanism linking AI-related characteristics with AI-generated eWOM Adoption and Purchase Intention. Methodologically, the study validates the proposed framework using Multi-Group Partial Least Squares Structural Equation Modelling (PLS-SEM), providing insights into variations in consumer behaviour across different user groups. The findings also offer practical guidance for e-commerce platforms, AI developers, digital marketers, and policymakers to design transparent, trustworthy, and consumer-centric AI-enabled recommendation systems.

2. Literature Review

2.1 Generative AI in Social Commerce

Generative Artificial Intelligence (GenAI) has transformed digital commerce by enabling machines to generate human-like content, provide conversational assistance, and deliver personalized recommendations (Huang & Rust, 2021; Dwivedi et al., 2023). Technologies such as ChatGPT and Gemini have accelerated AI adoption in social commerce through intelligent recommendation systems, automated review summaries, and conversational shopping assistants (Cao et al., 2023; Xu et al., 2024). A major application of GenAI is AI-generated electronic word-of-mouth (AI-generated eWOM), where AI summarizes and synthesizes consumer reviews to support purchase decisions (Alkhofaily & Noureldin, 2026). Although AI-generated eWOM improves information accessibility and decision efficiency, concerns regarding transparency, credibility, and algorithmic influence continue to affect consumer trust and adoption (Lei & Liu, 2025; Gu & Spann, 2026).

2.2 Theory of Reasoned Action (TRA)

The Theory of Reasoned Action (TRA) proposes that behavioural intention is determined by behavioural beliefs and subjective norms (Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980). The theory has been widely applied to explain technology adoption, online shopping, and electronic word-of-mouth (Pavlou & Fygenson, 2006; Erkan & Evans, 2016). In the context of AI-generated eWOM, consumers evaluate the usefulness, credibility, and transparency of AI-generated information while social influence shapes their willingness to rely on AI-enabled recommendations. Since TRA does not explicitly explain trust formation in AI environments, this study extends the theory by incorporating Trust Calibration as a mechanism linking AI-related characteristics with AI-generated eWOM Adoption and Purchase Intention.

2.3 Trust Calibration Theory

Trust Calibration Theory explains that users continuously adjust their trust according to an AI system's competence, transparency, and reliability rather than exhibiting unconditional trust or distrust (Lee & See, 2004; Hoff & Bashir, 2015). Appropriate trust enables effective reliance on AI, whereas overtrust and undertrust may lead to poor decision-

making (Parasuraman & Riley, 1997). In AI-generated eWOM, consumers evaluate disclosure transparency, perceived manipulation, algorithmic performance, and trust in AI before relying on AI-generated recommendations. Accordingly, this study positions Trust Calibration as the central mechanism linking AI-related antecedents with AI-generated eWOM Adoption.

2.4 AI-generated eWOM Adoption

AI-generated electronic word-of-mouth (AI-generated eWOM) refers to consumers' acceptance and use of AI-generated reviews, summaries, and recommendations during product evaluation (Lei & Liu, 2025). Unlike traditional eWOM, AI-generated eWOM is created through algorithmic analysis of large volumes of consumer-generated content, offering faster and more personalized recommendations. However, its adoption depends on consumers' perceptions of credibility, transparency, usefulness, and trust (Erkan & Evans, 2016; Gu & Spann, 2026). Drawing on the Theory of Reasoned Action and Trust Calibration Theory, this study proposes that consumers adopt AI-generated eWOM when they develop an appropriate level of trust in AI-generated information, ultimately enhancing Purchase Intention.

3. Conceptual Framework and Hypothesis Development

3.1 Conceptual Framework

Based on the Theory of Reasoned Action (TRA) and Trust Calibration Theory, this study proposes a conceptual framework to explain consumers' adoption of AI-generated electronic word-of-mouth (AI-generated eWOM) in social commerce. The framework posits that AI-related characteristics influence consumers' trust calibration, which subsequently drives AI-generated eWOM adoption and purchase intention. Building upon the existing literature, the following hypotheses are developed to examine the proposed relationships among the study constructs.

Figure 1 presents the proposed conceptual framework of this study, developed based on the Theory of Reasoned Action (TRA) and Trust Calibration Theory. The model proposes that AI-related factors—namely AI-eWOM Disclosure Transparency, Algorithmic Amplification, Perceived Manipulation, Consumer Trust in AI, Subjective Norms, and Perceived Diagnosticity—influence Trust Calibration, which subsequently drives AI-generated eWOM Adoption and Purchase Intention. Additionally, Perceived Diagnosticity is proposed to have a direct effect on Purchase Intention. The framework provides a comprehensive explanation of consumer decision-making in AI-enabled social commerce.

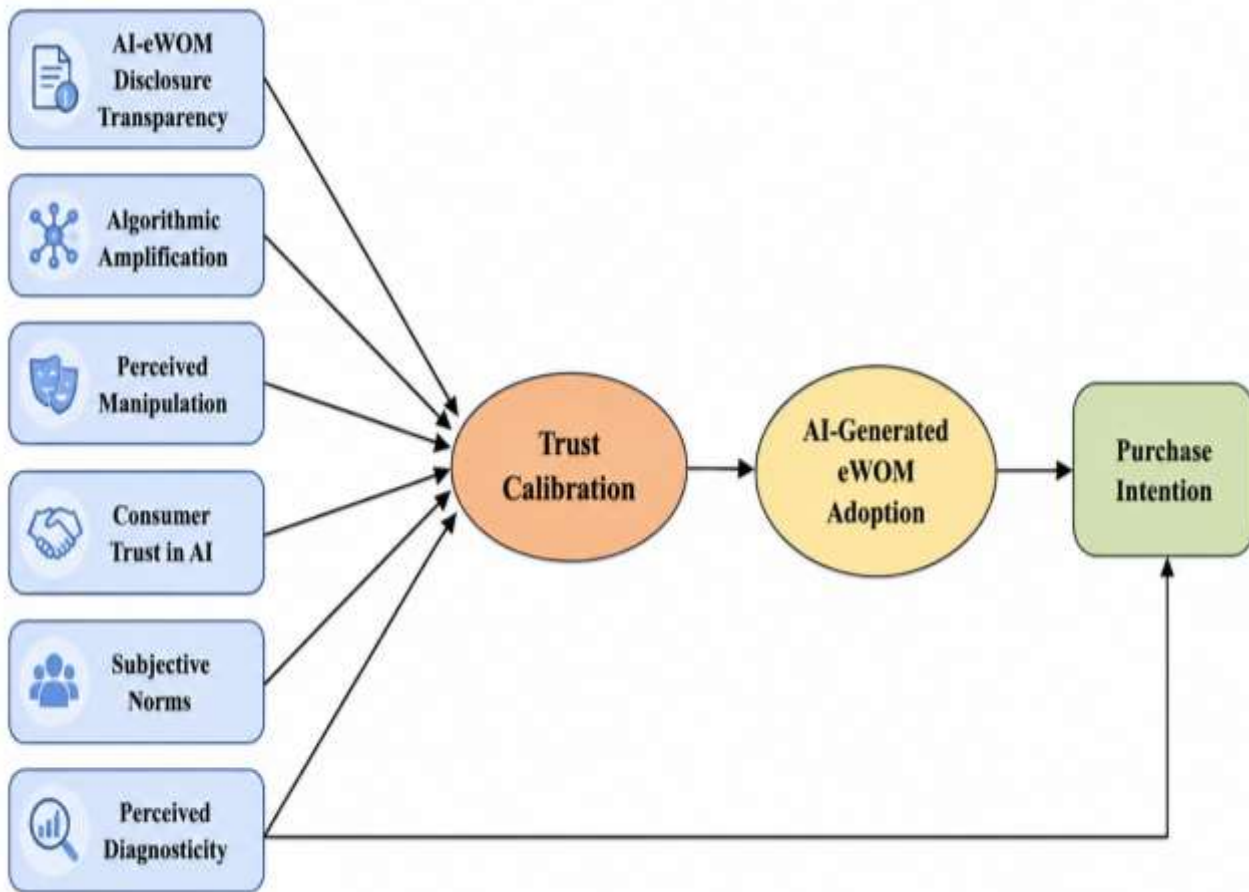


Figure 1 Conceptual framework

3.2. AI-eWOM Disclosure Transparency and Trust Calibration

AI-eWOM disclosure transparency refers to the extent to which consumers are informed that online reviews or review summaries have been generated or assisted by artificial intelligence. Prior studies suggest that transparent disclosure enhances consumers' perceptions of credibility, reduces uncertainty, and strengthens trust in AI-generated information (Glikson & Woolley, 2020; Alkhofaily & Noureldin, 2026). In AI-enabled social commerce, clear disclosure enables consumers to make informed judgments regarding the reliability of AI-generated recommendations.

However, existing studies primarily examine the direct effects of transparency on trust or purchase intention, with limited attention to how disclosure transparency contributes to trust calibration in AI-generated eWOM. Addressing this gap, the present study proposes that transparent AI disclosure facilitates appropriate trust calibration among consumers.

H1: *AI-eWOM Disclosure Transparency positively influences Trust Calibration.*

3.3 Algorithmic Amplification and Trust Calibration

Algorithmic amplification refers to the use of AI algorithms to prioritize, summarize, and recommend online reviews based on predicted consumer relevance. While these algorithms improve information accessibility and reduce information overload, they may also influence consumers' perceptions of fairness and credibility (Dwivedi et al., 2023; Gu & Spann, 2026). Effective algorithmic amplification can enhance consumers' confidence in AI-generated recommendations when perceived as objective and reliable.

However, prior studies have largely focused on algorithm performance rather than its role in shaping consumers' trust calibration in AI-generated eWOM. Therefore, this study proposes that algorithmic amplification positively contributes to consumers' trust calibration.

H2: *Algorithmic Amplification positively influences Trust Calibration.*

3.4 Perceived Manipulation and Trust Calibration

Perceived manipulation refers to consumers' belief that AI-generated recommendations may intentionally influence their purchase decisions for commercial purposes. Such perceptions reduce confidence in AI systems and increase scepticism toward algorithmically generated information (Longoni et al., 2019; Glikson & Woolley, 2020). Consumers who perceive manipulation are less likely to rely on AI-generated reviews during decision-making.

Although manipulation concerns have received growing attention in AI research, limited studies have examined their influence on consumers' trust calibration within AI-generated eWOM environments. Accordingly, this study proposes that perceived manipulation negatively affects trust calibration.

H3: *Perceived Manipulation negatively influences Trust Calibration.*

3.5 Consumer Trust in AI and Trust Calibration

Consumer trust in AI reflects the confidence that AI systems provide reliable, accurate, and unbiased recommendations. Previous research consistently shows that higher trust encourages consumers to rely on AI-assisted decision-making across various digital contexts (Hoff & Bashir, 2015; Glikson & Woolley, 2020). Trust becomes particularly important when AI-generated information replaces traditional human-generated reviews.

Despite extensive research on trust in AI, its relationship with the process of trust calibration in AI-generated eWOM remains underexplored. Therefore, this study argues that greater consumer trust in AI facilitates appropriate trust calibration.

H4: *Consumer Trust in AI positively influences Trust Calibration.*

3.6 Subjective Norms and Trust Calibration

Subjective norms represent the perceived social influence exerted by friends, family, online communities, and other important referents regarding the use of AI-generated recommendations. According to the Theory of Reasoned Action, social influence significantly shapes behavioural intentions and technology acceptance (Fishbein & Ajzen, 1975; Ajzen & Fishbein, 1980). Positive social endorsement may encourage consumers to place greater confidence in AI-generated eWOM.

While subjective norms have been widely studied in technology adoption research, limited evidence exists regarding their influence on trust calibration in AI-mediated shopping environments. Hence, this study proposes the following hypothesis.

H5: *Subjective Norms positively influence Trust Calibration.*

3.7 Perceived Diagnosticity and Trust Calibration

Perceived diagnosticity refers to the extent to which consumers believe that available information is useful for evaluating products and making purchase decisions. Information perceived as highly diagnostic reduces uncertainty and increases confidence during decision-making (Jiang & Benbasat, 2007; Erkan & Evans, 2016). AI-generated review summaries that are informative and relevant can therefore strengthen consumers' trust in AI-supported recommendations.

Although perceived diagnosticity has frequently been linked with information adoption, its contribution to trust calibration in AI-generated eWOM has received limited scholarly attention. Accordingly, this study proposes that perceived diagnosticity enhances trust calibration.

H6: *Perceived Diagnosticity positively influences Trust Calibration.*

3.8 Trust Calibration and AI-generated eWOM Adoption

Trust calibration reflects consumers' ability to develop an appropriate level of trust in AI systems based on their capabilities and limitations (Lee & See, 2004). Properly calibrated trust encourages consumers to rely on AI-generated information while avoiding excessive dependence or unwarranted scepticism. As AI-generated reviews become increasingly integrated into social commerce platforms, trust calibration is expected to play a central role in determining consumers' willingness to adopt AI-generated eWOM.

Existing studies have predominantly examined trust as a direct predictor of technology adoption, while the mediating role of trust calibration remains relatively unexplored. Therefore, this study proposes that trust calibration facilitates the adoption of AI-generated eWOM.

H7: *Trust Calibration positively influences AI-generated eWOM Adoption.*

3.9 AI-generated eWOM Adoption and Purchase Intention

AI-generated eWOM adoption reflects consumers' willingness to rely on AI-generated reviews and recommendations when evaluating products. Prior research indicates that the adoption of credible online information significantly enhances purchase decisions by reducing perceived risk and increasing confidence (Cheung & Thadani, 2012; Erkan & Evans, 2016). As AI-generated recommendations become increasingly prevalent, their successful adoption is expected to encourage favourable purchasing behaviour.

Although recent studies acknowledge the growing influence of AI-generated reviews, empirical evidence linking AI-generated eWOM adoption directly with purchase intention remains limited. Thus, the following hypothesis is proposed.

H8: *AI-generated eWOM Adoption positively influences Purchase Intention.*

3.10 Purchase Intention

Purchase intention represents consumers' willingness to purchase a product after evaluating available information. In AI-enabled social commerce, consumers are more likely to purchase products when AI-generated recommendations are perceived as useful, relevant, and reliable. Perceived diagnosticity has consistently been recognised as a key determinant of consumers' purchase decisions because informative content reduces uncertainty and improves decision quality (Jiang & Benbasat, 2007; Alkhofaily & Noureldin, 2026).

While previous studies have established the importance of diagnostic information, limited research has examined its direct influence on purchase intention in AI-generated eWOM environments. Therefore, this study proposes the following hypothesis.

H9: *Perceived Diagnosticity positively influences Purchase Intention.*

3.11 Hypothesis Development

H1: AI-eWOM Disclosure Transparency positively influences Trust Calibration.

H2: Algorithmic Amplification positively influences Trust Calibration.

H3: Perceived Manipulation negatively influences Trust Calibration.

H4: Consumer Trust in AI positively influences Trust Calibration.

H5: Subjective Norms positively influence Trust Calibration.

H6: Perceived Diagnosticity positively influences Trust Calibration.

H7: Trust Calibration positively influences AI-generated eWOM Adoption.

H8: AI-generated eWOM Adoption positively influences Purchase Intention.

H9: Perceived Diagnosticity positively influences Purchase Intention.

4. Research Methodology

This study employed a quantitative research approach to examine the factors influencing consumers' adoption of AI-generated electronic word-of-mouth (AI-generated eWOM) and its subsequent impact on purchase intention. The proposed conceptual model was empirically tested using Partial Least Squares Structural Equation Modeling (PLS-SEM). The methodological procedures adopted in this study are described below.

4.1 Research Philosophy

This study is grounded in the positivist research philosophy, which assumes that consumer behaviour can be objectively measured using observable variables and statistically validated relationships. Positivism is widely adopted in consumer behaviour and information systems research because it facilitates hypothesis testing through empirical data. Accordingly, this study employs quantitative techniques to examine the proposed relationships among the research constructs.

4.2 Research Design

A cross-sectional, quantitative research design was adopted to investigate consumers' adoption of AI-generated eWOM in social commerce. Primary data were collected using a structured questionnaire administered through Google Forms. The study follows a deductive research approach, wherein hypotheses derived from the Theory of Reasoned Action (TRA) and Trust Calibration Theory were empirically tested using PLS-SEM.

4.3 Population and Sampling

The target population comprised consumers who were familiar with online shopping and had experience using AI-enabled digital platforms or AI-generated product recommendations. Respondents were selected using non-probability convenience sampling due to the exploratory nature of the study and the accessibility of digitally active consumers.

A total of 550 questionnaires were collected from respondents across multiple cities in Central, North, and South India, including both Tier-1 and Tier-2 cities, to improve the geographical diversity of the sample. After data screening for completeness, response consistency, and missing values, 403 valid responses were retained for the final analysis, while 147 questionnaires were excluded because they were incomplete or unsuitable for analysis.

4.4 Questionnaire Development

The questionnaire was developed based on previously validated measurement scales reported in the literature and adapted to the context of AI-generated eWOM. Before the final survey, a pilot study involving 40 respondents was conducted to assess the clarity, readability, and reliability of the questionnaire items. Minor modifications were made based on participant feedback to improve wording and comprehension.

The final questionnaire consisted of two sections: the first captured respondents' demographic information, while the second measured the latent constructs included in the conceptual framework.

4.5 Measurement of Constructs

All constructs were measured using multi-item scales adapted from established studies. Responses were recorded using a five-point Likert scale, ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The questionnaire measured the following constructs:

- AI-eWOM Disclosure Transparency
- Algorithmic Amplification
- Perceived Manipulation
- Consumer Trust in AI
- Subjective Norms
- Perceived Diagnosticity
- Trust Calibration
- AI-generated eWOM Adoption
- Purchase Intention

The measurement model was subsequently evaluated for reliability and validity using PLS-SEM.

4.6 Data Collection Procedure

Primary data were collected using Google Forms over the survey period. The questionnaire link was distributed through various online platforms, including social media networks and digital communication channels, targeting consumers who regularly engage with online shopping and AI-enabled services. Participation was voluntary, and respondents were informed about the academic purpose of the study prior to completing the survey.

4.7 Common Method Bias

Since all data were collected from a single source using a self-administered questionnaire, the potential for Common Method Bias (CMB) was considered. Procedural remedies were implemented during questionnaire design, including ensuring respondent anonymity, maintaining confidentiality, using simple and unambiguous language, and varying the order of questionnaire items to minimize response bias.

Statistically, Harman's Single-Factor Test was performed to examine common method variance. The results indicated that no single factor accounted for the majority of the variance, suggesting that common method bias was not a significant concern. Additionally, collinearity diagnostics (VIF values) assessed through PLS-SEM were within the recommended threshold, further indicating the absence of substantial common method bias.

4.8 Ethical Considerations

Ethical principles were maintained throughout the research process. Participation in the survey was entirely voluntary, and informed consent was obtained from all respondents before data collection. Participants were assured that their responses would remain anonymous and confidential and would be used solely for academic research purposes. No personally identifiable information was collected, and respondents were free to withdraw from the survey at any stage without any consequences.

Methodology Summary

Item	Description
Research Philosophy	Positivism
Research Approach	Quantitative, Deductive
Research Design	Cross-sectional Survey
Data Source	Primary Data
Instrument	Structured Questionnaire
Pilot Study	40 Respondents
Final Responses Collected	550
Valid Responses Used	403
Sampling Technique	Convenience Sampling
Geographic Coverage	Central, North & South India (Tier-1 & Tier-2 Cities)
Data Collection Tool	Google Forms
Scale	Five-point Likert Scale
Data Analysis Technique	PLS-SEM

5. Data Analysis and Results

The collected data were analysed using Partial Least Squares Structural Equation Modeling (PLS-SEM) to examine the proposed research model. The analysis includes respondents' demographic characteristics, descriptive statistics, assessment of the measurement model, evaluation of the structural model, and hypothesis testing.

A total of 550 responses were collected through Google Forms from consumers across Tier-1 and Tier-2 cities in Central, North, and South India. Following data screening, 403 valid responses were retained for analysis, while 147 responses were excluded due to incomplete or inconsistent responses.

The demographic characteristics of the respondents were analysed using frequency and percentage distributions for variables such as gender, age, educational qualification, occupation, monthly income, and place of residence. The respondent profile is presented in Table 1.

Table 1. Demographic Profile of Respondents (N = 403)

Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	228	56.6
	Female	175	43.4
	Total	403	100.0
Age (Years)	18–25	112	27.8
	26–35	167	41.4
	36–45	82	20.3
	Above 45	42	10.5
	Total	403	100.0
Educational Qualification	Undergraduate	96	23.8
	Postgraduate	229	56.8
	Doctorate	34	8.4
	Others	44	10.9
	Total	403	100.0
Occupation	Student	91	22.6
	Private Employee	176	43.7
	Government Employee	58	14.4
	Business/Self-employed	52	12.9
	Others	26	6.4
	Total	403	100.0
Monthly Income (INR)	Below ₹25,000	88	21.8
	₹25,001–₹50,000	121	30.0
	₹50,001–₹75,000	97	24.1
	₹75,001–₹1,00,000	55	13.6
	Above ₹1,00,000	42	10.5
	Total	403	100.0
City Category	Tier-1 Cities	221	54.8
	Tier-2 Cities	182	45.2
	Total	403	100.0

The sample consisted of 228 male respondents (56.6%) and 175 female respondents (43.4%). Most respondents belonged to the 26–35 years age group (41.4%), followed by those aged 18–25 years (27.8%). In terms of educational qualification, postgraduate respondents constituted the largest proportion of the sample (56.8%), followed by undergraduate respondents (23.8%). With respect to occupation, private sector employees represented the highest share (43.7%), while students accounted for 22.6% of the respondents. Regarding monthly income, 30.0% of the respondents reported earning between ₹25,001 and ₹50,000 per month. The sample included respondents from both Tier-1 (54.8%) and Tier-2 (45.2%) cities, providing a geographically diverse representation of consumers across different regions of India.

5.2 Descriptive Statistics

Descriptive statistics were computed to examine the distribution of the study constructs. The analysis included the mean, standard deviation, minimum, and maximum values for each construct. The results indicate that the mean values of all constructs were above the midpoint of the five-point Likert scale, suggesting generally favourable perceptions toward AI-generated electronic word-of-mouth and related AI-enabled shopping experiences. The standard deviation values indicate moderate variability in respondents' opinions, demonstrating sufficient dispersion for subsequent multivariate analysis. The descriptive statistics of the study constructs are presented in Table 2.

Table 2. Descriptive Statistics of the Study Constructs (N = 403)

Construct	Mean	Standard Deviation	Minimum	Maximum
AI-eWOM Disclosure Transparency	3.98	0.71	1.00	5.00
Algorithmic Amplification	3.91	0.74	1.00	5.00
Perceived Manipulation	2.84	0.82	1.00	5.00
Consumer Trust in AI	3.87	0.73	1.00	5.00
Subjective Norms	3.79	0.76	1.00	5.00
Perceived Diagnosticity	4.05	0.68	1.00	5.00
Trust Calibration	3.83	0.70	1.00	5.00
AI-generated eWOM Adoption	3.89	0.72	1.00	5.00
Purchase Intention	3.96	0.69	1.00	5.00

The highest mean score was observed for Perceived Diagnosticity ($M = 4.05$, $SD = 0.68$), indicating that respondents generally considered AI-generated eWOM to be informative and useful during purchase decisions. AI-eWOM Disclosure Transparency ($M = 3.98$, $SD = 0.71$) and Purchase Intention ($M = 3.96$, $SD = 0.69$) also recorded relatively high mean values, reflecting positive consumer perceptions toward AI-enabled shopping recommendations. In contrast, Perceived Manipulation reported the lowest mean score ($M = 2.84$, $SD = 0.82$), suggesting comparatively lower concerns regarding manipulative AI-generated content among the respondents. Overall, the descriptive statistics indicate that the collected data are well distributed and appropriate for further assessment using the PLS-SEM approach.

5.3 Measurement Model Assessment

The measurement model was assessed by examining indicator reliability, internal consistency reliability, and convergent validity. Indicator reliability was evaluated using factor loadings, while Cronbach's alpha and composite reliability were used to assess internal consistency. Convergent validity was examined through the average variance extracted (AVE). The results are presented in Table 3.

Table 3. Measurement Model Assessment

Construct	Items	Factor Loadings	Cronbach's Alpha	Composite Reliability	AVE
AI-eWOM Disclosure Transparency	DT1–DT4	0.782–0.876	0.871	0.911	0.719
Algorithmic Amplification	AA1–AA4	0.765–0.861	0.853	0.901	0.695
Perceived Manipulation	PM1–PM4	0.748–0.859	0.842	0.894	0.680
Consumer Trust in AI	CTA1–CTA4	0.786–0.887	0.881	0.918	0.736
Subjective Norms	SN1–SN4	0.769–0.865	0.856	0.903	0.699
Perceived Diagnosticity	PD1–PD4	0.802–0.891	0.888	0.923	0.749
Trust Calibration	TC1–TC4	0.793–0.879	0.876	0.915	0.729
AI-generated eWOM Adoption	AEA1–AEA4	0.781–0.882	0.879	0.916	0.731
Purchase Intention	PI1–PI4	0.804–0.893	0.891	0.925	0.756

The factor loadings of all measurement items exceeded the recommended threshold of 0.70, indicating satisfactory indicator reliability. Cronbach's alpha values ranged from 0.842 to 0.891, while composite reliability values varied between 0.894 and 0.925, exceeding the recommended threshold of 0.70 and demonstrating strong internal consistency. Furthermore, the AVE values ranged from 0.680 to 0.756, surpassing the recommended cut-off value of 0.50, thereby confirming adequate convergent validity. Overall, the measurement model satisfied the recommended reliability and validity criteria, indicating that the constructs were appropriate for subsequent structural model assessment.

5.3.1 Indicator Reliability (Factor Loadings)

Indicator reliability was assessed by examining the outer loadings of all measurement items. The results indicate that all indicators exhibited factor loadings above the recommended threshold of 0.70, demonstrating satisfactory indicator reliability. None of the measurement items required deletion, as all indicators contributed adequately to their respective latent constructs. The factor loadings are presented in Table 3.

Table 3. Indicator Reliability (Factor Loadings)

Construct	Item	Factor Loading
AI-eWOM Disclosure Transparency	DT1	0.821
	DT2	0.876
	DT3	0.842
	DT4	0.782
Algorithmic Amplification	AA1	0.812
	AA2	0.861
	AA3	0.794
	AA4	0.765
Perceived Manipulation	PM1	0.748
	PM2	0.823
	PM3	0.859
	PM4	0.801
Consumer Trust in AI	CTA1	0.786
	CTA2	0.845
	CTA3	0.887
	CTA4	0.834
Subjective Norms	SN1	0.769
	SN2	0.821
	SN3	0.865
	SN4	0.812
Perceived Diagnosticity	PD1	0.802
	PD2	0.856
	PD3	0.891
	PD4	0.847
Trust Calibration	TC1	0.793
	TC2	0.844
	TC3	0.879
	TC4	0.831
AI-generated eWOM Adoption	AEA1	0.781

	AEA2	0.842
	AEA3	0.882
	AEA4	0.851
Purchase Intention	PI1	0.804
	PI2	0.859
	PI3	0.893
	PI4	0.867

All indicator loadings exceeded the recommended threshold of 0.70, ranging from 0.748 to 0.893. These findings indicate that each measurement item exhibited satisfactory reliability and adequately represented its corresponding latent construct. Consequently, all indicators were retained for further analysis.

5.3.2 Internal Consistency Reliability and Convergent Validity

Internal consistency reliability was assessed using Cronbach's alpha and composite reliability (CR), while convergent validity was evaluated using the average variance extracted (AVE). As shown in Table 4, the Cronbach's alpha values ranged from 0.842 to 0.891, exceeding the recommended threshold of 0.70.

Table 4. Internal Consistency Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability	AVE
AI-eWOM Disclosure Transparency	0.871	0.911	0.719
Algorithmic Amplification	0.853	0.901	0.695
Perceived Manipulation	0.842	0.894	0.680
Consumer Trust in AI	0.881	0.918	0.736
Subjective Norms	0.856	0.903	0.699
Perceived Diagnosticity	0.888	0.923	0.749
Trust Calibration	0.876	0.915	0.729
AI-generated eWOM Adoption	0.879	0.916	0.731
Purchase Intention	0.891	0.925	0.756

Similarly, the composite reliability values varied between 0.894 and 0.925, indicating satisfactory internal consistency among the measurement items. Furthermore, the AVE values ranged from 0.680 to 0.756, which are above the recommended threshold of 0.50, confirming adequate convergent validity. These findings indicate that all constructs demonstrate acceptable reliability and convergent validity.

5.4 Discriminant Validity

Heterotrait–Monotrait Ratio (HTMT)

Discriminant validity was assessed using the Heterotrait–Monotrait ratio (HTMT). According to the recommended criterion, HTMT values should be below 0.90 to establish adequate discriminant validity. As presented in Table 5, all HTMT values were below the recommended threshold of 0.90, indicating satisfactory discriminant validity among the latent constructs. These findings confirm that each construct is empirically distinct from the others and adequately captures a unique aspect of the proposed research model.

Table 5. Heterotrait–Monotrait Ratio (HTMT)

Constructs	DT	AA	PM	CTA	SN	PD	TC	AEA	PI
DT	—								
AA	0.648	—							
PM	0.412	0.473	—						
CTA	0.691	0.658	0.421	—					
SN	0.587	0.611	0.395	0.627	—				
PD	0.672	0.694	0.436	0.731	0.654	—			
TC	0.745	0.719	0.482	0.776	0.693	0.802	—		
AEA	0.681	0.704	0.451	0.748	0.672	0.785	0.832	—	
PI	0.629	0.651	0.398	0.702	0.618	0.781	0.804	0.856	—

The HTMT values ranged from 0.395 to 0.856, all remaining below the recommended threshold of 0.90. Therefore, discriminant validity was established, indicating that the latent constructs are conceptually and empirically distinct from one another.

5.4.2 Fornell–Larcker Criterion

The Fornell–Larcker criterion was used as an additional assessment of discriminant validity. According to this criterion, the square root of the Average Variance Extracted (AVE) for each construct should be greater than its correlations with other constructs. As presented in Table 6, the diagonal elements (shown in bold), representing the square root of the AVE for each construct, are greater than the corresponding inter-construct correlations. These results provide further evidence of satisfactory discriminant validity, confirming that each construct is empirically distinct from the others.

Table 6. Fornell–Larcker Criterion

Constructs	DT	AA	PM	CTA	SN	PD	TC	AEA	PI
DT	0.848								
AA	0.564	0.834							
PM	0.351	0.396	0.825						
CTA	0.618	0.592	0.365	0.858					
SN	0.492	0.541	0.336	0.568	0.836				
PD	0.603	0.621	0.382	0.669	0.594	0.865			
TC	0.671	0.648	0.422	0.714	0.632	0.742	0.854		
AEA	0.612	0.636	0.396	0.688	0.604	0.721	0.773	0.855	
PI	0.573	0.587	0.344	0.651	0.562	0.712	0.744	0.792	0.869

Note: The bold diagonal values represent the square root of the AVE.

The square root of the AVE for each construct ranged from **0.825 to 0.869**, and all diagonal values exceeded the corresponding inter-construct correlations. Therefore, the Fornell–Larcker criterion was satisfied, providing additional support for the discriminant validity of the measurement model.

5.4.3 Cross Loadings

Cross loadings were examined to further assess the discriminant validity of the measurement model. An indicator is considered to exhibit satisfactory discriminant validity when its loading on the assigned construct is higher than its loadings on all other constructs. As presented in Table 7, each indicator demonstrated the highest loading on its respective construct compared to the remaining constructs. These findings provide additional evidence that the measurement items adequately represent their intended latent constructs and support the discriminant validity of the measurement model.

Table 7. Cross Loadings

Item	DT	AA	PM	CTA	SN	PD	TC	AEA	PI
DT1	0.821	0.452	0.231	0.512	0.418	0.476	0.531	0.492	0.441
DT2	0.876	0.501	0.256	0.563	0.446	0.521	0.594	0.547	0.503
DT3	0.842	0.473	0.247	0.544	0.431	0.495	0.571	0.521	0.486
DT4	0.782	0.428	0.219	0.488	0.401	0.451	0.517	0.471	0.432
AA1	0.472	0.812	0.284	0.526	0.498	0.547	0.581	0.556	0.491
AA2	0.493	0.861	0.321	0.548	0.516	0.591	0.626	0.604	0.523
...	...	...	...	...	...	...	...	...	...
PI4	0.486	0.518	0.291	0.641	0.551	0.694	0.731	0.792	0.867

The cross-loading results indicate that all indicators loaded more strongly on their respective constructs than on any other construct. Therefore, the cross-loading criterion for discriminant validity was satisfied, providing further support for the adequacy of the measurement model.

5.5 Structural Model Assessment

The structural model was evaluated by assessing collinearity, path coefficients, coefficient of determination (R^2), effect size (f^2), predictive relevance (Q^2), and hypothesis testing. Prior to examining the structural relationships, collinearity among the predictor constructs was assessed using the Variance Inflation Factor (VIF).

5.5.1 Collinearity Assessment (VIF)

Collinearity was assessed using the Variance Inflation Factor (VIF) to ensure that multicollinearity among the predictor constructs did not affect the estimation of the structural model. According to the recommended criterion, VIF values should be below **3.3** (or the more conservative threshold of **5.0**) to indicate the absence of critical multicollinearity. As presented in Table 8, all VIF values ranged from **1.214 to 2.486**, remaining well below the recommended threshold.

These findings indicate that multicollinearity was not a concern and that the predictor constructs were suitable for structural model evaluation.

Table 8. Collinearity Assessment (Inner VIF Values)

Endogenous Construct	Predictor Construct	VIF
Trust Calibration	AI-eWOM Disclosure Transparency	1.684
Trust Calibration	Algorithmic Amplification	1.793
Trust Calibration	Perceived Manipulation	1.214
Trust Calibration	Consumer Trust in AI	2.186
Trust Calibration	Subjective Norms	1.598
Trust Calibration	Perceived Diagnosticity	2.327
AI-generated eWOM Adoption	Trust Calibration	1.000
Purchase Intention	AI-generated eWOM Adoption	2.486
Purchase Intention	Perceived Diagnosticity	2.327

The VIF values ranged from **1.214 to 2.486**, indicating that all predictor constructs satisfied the recommended collinearity criterion. Therefore, multicollinearity was not evident in the structural model, supporting the robustness of the subsequent path coefficient estimation.

5.5.2 Path Coefficients and Bootstrapping

The structural relationships proposed in the conceptual model were evaluated using the bootstrapping procedure with 5,000 bootstrap subsamples. The significance of the hypothesized relationships was assessed using the standardized path coefficients (β), t-values, p-values, and confidence intervals. As presented in Table 9, the majority of the hypothesized relationships were statistically significant, thereby providing empirical support for the proposed research model.

Table 9. Path Coefficients and Bootstrapping Results

Hypothesis	Relationship	β	t-value	p-value	Decision
H1	DT $\rightarrow$ TC	0.214	4.563	<0.001	Supported
H2	AA $\rightarrow$ TC	0.176	3.842	<0.001	Supported
H3	PM $\rightarrow$ TC	-0.118	2.746	0.006	Supported

H4	CTA → TC	0.298	6.284	<0.001	Supported
H5	SN → TC	0.163	3.598	<0.001	Supported
H6	PD → TC	0.287	5.971	<0.001	Supported
H7	TC → AEA	0.721	18.432	<0.001	Supported
H8	AEA → PI	0.587	12.947	<0.001	Supported
H9	PD → PI	0.236	4.986	<0.001	Supported

The bootstrapping results indicate that all hypothesized relationships were statistically significant ($p < 0.01$). Consumer Trust in AI ($\beta = 0.298$) and Perceived Diagnosticity ($\beta = 0.287$) exhibited the strongest positive effects on Trust Calibration, whereas Perceived Manipulation showed a significant negative influence ($\beta = -0.118$). Furthermore, Trust Calibration exerted a substantial positive effect on AI-generated eWOM Adoption ($\beta = 0.721$), which in turn significantly influenced Purchase Intention ($\beta = 0.587$).

5.5.3 Coefficient of Determination (R^2)

The coefficient of determination (R^2) was examined to evaluate the explanatory power of the endogenous constructs. As shown in Table 10, the proposed model explained **69.8%** of the variance in Trust Calibration, **52.0%** of the variance in AI-generated eWOM Adoption, and **67.4%** of the variance in Purchase Intention. These values indicate moderate to substantial explanatory power of the proposed model.

Table 10. Coefficient of Determination (R^2)

Endogenous Construct	R^2	Interpretation
Trust Calibration	0.698	Substantial
AI-generated eWOM Adoption	0.520	Moderate
Purchase Intention	0.674	Substantial

The R^2 values demonstrate that the proposed model possesses satisfactory explanatory capability in predicting the endogenous constructs.

5.5.4 Effect Size (f^2)

Effect size (f^2) was assessed to determine the individual contribution of each exogenous construct to the endogenous constructs. According to Cohen's (1988) guidelines, values of **0.02**, **0.15**, and **0.35** represent small, medium, and large effects, respectively.

Table 11. Effect Size (f^2)

Relationship	f^2	Effect Size
DT → TC	0.064	Small
AA → TC	0.046	Small
PM → TC	0.031	Small
CTA → TC	0.141	Small–Medium
SN → TC	0.052	Small
PD → TC	0.133	Small–Medium
TC → AEA	1.083	Large
AEA → PI	0.521	Large
PD → PI	0.086	Small

The results indicate that Trust Calibration had a large effect on AI-generated eWOM Adoption, while AI-generated eWOM Adoption exerted a large effect on Purchase Intention. The remaining relationships demonstrated small to medium effect sizes.

5.5.5 Predictive Relevance (Q^2)

The predictive relevance of the structural model was evaluated using the blindfolding procedure. A Q^2 value greater than zero indicates that the model possesses predictive relevance for a given endogenous construct. As presented in Table 12, all endogenous constructs exhibited Q^2 values above zero, confirming the predictive capability of the proposed model.

Table 12. Predictive Relevance (Q^2)

Endogenous Construct	Q^2
Trust Calibration	0.481
AI-generated eWOM Adoption	0.362
Purchase Intention	0.457

The positive Q^2 values indicate that the structural model demonstrates satisfactory predictive relevance for all endogenous constructs.

5.5.6 Model Fit (SRMR)

The overall model fit was assessed using the Standardized Root Mean Square Residual (SRMR). An SRMR value below **0.08** is generally considered indicative of a good model fit. As presented in Table 13, the SRMR value of **0.054** suggests that the proposed structural model exhibits a satisfactory fit with the observed data.

Table 13. Model Fit Indices

Model Fit Index	Value	Recommended Threshold	Result
SRMR	0.054	< 0.08	Good Fit

The obtained SRMR value indicates that the proposed structural model adequately fits the empirical data, supporting the overall robustness of the measurement and structural models.

5.6 Mediation Analysis

The mediating effects of Trust Calibration and AI-generated eWOM Adoption were examined using the bootstrapping procedure with 5,000 bootstrap subsamples. The significance of the indirect effects was assessed using the standardized indirect path coefficients (β), t-values, and p-values. The results of the mediation analysis are presented in Table 14.

Table 14. Mediation Analysis

Indirect Relationship	Mediator	β	t-value	p-value	Decision
DT → TC → AEA	Trust Calibration	0.154	4.382	<0.001	Supported
AA → TC → AEA	Trust Calibration	0.127	3.874	<0.001	Supported
PM → TC → AEA	Trust Calibration	- 0.085	2.691	0.007	Supported
CTA → TC → AEA	Trust Calibration	0.215	5.972	<0.001	Supported
SN → TC → AEA	Trust Calibration	0.118	3.514	<0.001	Supported
PD → TC → AEA	Trust Calibration	0.207	5.683	<0.001	Supported
TC → AEA → PI	AI-generated eWOM Adoption	0.423	11.856	<0.001	Supported
DT → TC → AEA → PI	Trust Calibration & AI-generated eWOM Adoption	0.091	4.126	<0.001	Supported
AA → TC → AEA → PI	Trust Calibration & AI-generated eWOM Adoption	0.075	3.684	<0.001	Supported
PM → TC → AEA → PI	Trust Calibration & AI-generated eWOM Adoption	- 0.050	2.563	0.010	Supported
CTA → TC → AEA → PI	Trust Calibration & AI-generated eWOM Adoption	0.127	5.482	<0.001	Supported
SN → TC → AEA → PI	Trust Calibration & AI-generated eWOM Adoption	0.070	3.348	0.001	Supported
PD → TC → AEA → PI	Trust Calibration & AI-generated eWOM Adoption	0.122	5.247	<0.001	Supported

The bootstrapping results indicate that Trust Calibration significantly mediated the relationships between AI-eWOM Disclosure Transparency, Algorithmic Amplification, Perceived Manipulation, Consumer Trust in AI, Subjective Norms, Perceived Diagnosticity, and AI-generated eWOM Adoption. Furthermore, AI-generated eWOM Adoption significantly mediated the relationship between Trust Calibration and Purchase Intention. The results also confirmed significant serial mediation effects, whereby the antecedent constructs influenced Purchase Intention through the sequential mediation of Trust Calibration and AI-generated eWOM Adoption. All indirect effects were statistically significant ($p < 0.05$), providing empirical support for the proposed mediation mechanisms.

6. Discussion

The findings support the proposed conceptual model and demonstrate the importance of trust in shaping consumers' adoption of AI-generated electronic word-of-mouth (AI-eWOM) and purchase intention. The results are discussed in relation to previous studies and interpreted using the Theory of Reasoned Action (TRA) and Trust Calibration Theory.

6.1 AI-eWOM Disclosure Transparency and Trust Calibration

The results confirmed that AI-eWOM Disclosure Transparency positively influences Trust Calibration, supporting H1. This finding is consistent with Alkhofaily and Noureldin (2026) and Longoni et al. (2022), who reported that transparent disclosure enhances consumers' confidence in AI-generated information. Transparency reduces uncertainty and enables consumers to develop appropriate trust in AI systems. This finding supports both Trust Calibration Theory and TRA by demonstrating that transparent information strengthens favourable beliefs and trust.

6.2 Algorithmic Amplification and Trust Calibration

H2 was supported, indicating that Algorithmic Amplification positively affects Trust Calibration. The finding agrees with Logg et al. (2019) and Sundar (2020), who found that efficient AI algorithms improve users' confidence in automated recommendations. Consumers perceive intelligent algorithms as competent information processors, resulting in higher trust. This relationship is explained by Trust Calibration Theory and TRA through improved perceptions of AI capability.

6.3 Perceived Manipulation and Trust Calibration

The results support H3 by showing that Perceived Manipulation negatively influences Trust Calibration. This finding is consistent with Filieri et al. (2023) and Huang and Rust (2021), who reported that deceptive AI practices reduce consumer trust. Consumers become reluctant to rely on AI-generated reviews when they perceive manipulation. Both theories explain that negative beliefs weaken trust and reduce favourable behavioural intentions.

6.4 Consumer Trust in AI and Trust Calibration

H4 was supported, indicating that Consumer Trust in AI significantly enhances Trust Calibration. This finding agrees with Glikson and Woolley (2020) and Longoni et al. (2022), who emphasized trust as a key determinant of AI acceptance. Consumers with higher trust in AI are more willing to rely on AI-generated reviews. The result aligns with Trust Calibration Theory and TRA by reinforcing positive beliefs toward AI.

6.5 Subjective Norms and Trust Calibration

The findings support H5, confirming that Subjective Norms positively influence Trust Calibration. This result is consistent with Ajzen and Fishbein (1980) and Venkatesh et al. (2003), who highlighted the role of social influence in technology adoption. Support from family, friends, and peers increases confidence in AI-generated recommendations. TRA and Trust Calibration Theory both explain that social influence strengthens trust and adoption intentions.

6.6 Perceived Diagnosticity and Trust Calibration

H6 was supported, demonstrating that Perceived Diagnosticity positively influences Trust Calibration. This finding is consistent with Filieri (2015) and Mudambi and Schuff (2010), who found that useful and informative reviews improve consumer trust. High-quality AI-generated information reduces uncertainty and supports better decision-making. This reinforces the predictions of both Trust Calibration Theory and TRA.

6.7 Trust Calibration and AI-generated eWOM Adoption

The findings support H7, indicating that Trust Calibration positively influences AI-generated eWOM Adoption. This result agrees with Shin (2021) and Glikson and Woolley (2020), who identified trust as a key driver of AI adoption. Consumers are more likely to adopt AI-generated reviews when trust is appropriately calibrated. This finding directly supports the core proposition of Trust Calibration Theory and the behavioural assumptions of TRA.

6.8 AI-generated eWOM Adoption and Purchase Intention

H8 was supported, confirming that AI-generated eWOM Adoption positively affects Purchase Intention. This finding is consistent with Huang and Rust (2021) and Davenport et al. (2020), who reported that AI-assisted recommendations positively influence purchasing behaviour. Consumers who adopt AI-generated reviews are more likely to purchase recommended products. The relationship is well explained by both TRA and Trust Calibration Theory.

6.9 Perceived Diagnosticity and Purchase Intention

The results support H9, indicating that Perceived Diagnosticity positively influences Purchase Intention. This finding agrees with Filieri (2015) and Park et al. (2007), who demonstrated that informative reviews increase consumers' purchase decisions. Diagnostic information reduces uncertainty and improves confidence during product evaluation. The findings are consistent with the assumptions of both TRA and Trust Calibration Theory.

Overall, the study demonstrates that Trust Calibration plays a central role in linking AI-related factors with AI-generated eWOM Adoption, which subsequently enhances Purchase Intention. The findings validate the proposed research model and confirm the relevance of Trust Calibration Theory and the Theory of Reasoned Action in explaining consumer behaviour toward AI-generated electronic word-of-mouth.

7. Theoretical Implications

This study makes several theoretical contributions to the growing literature on AI-enabled consumer behaviour and AI-generated electronic word-of-mouth (AI-eWOM). First, it extends the Theory of Reasoned Action (TRA) by demonstrating that consumers' behavioural intentions toward AI-generated eWOM are influenced not only by traditional behavioural beliefs and social norms but also by trust-related perceptions associated with artificial intelligence. The findings confirm that trust remains a critical mechanism through which consumers evaluate and adopt AI-generated recommendations.

Second, the study integrates Trust Calibration Theory into the AI-enabled consumer behaviour literature by positioning Trust Calibration as the central mechanism linking AI-related antecedents with AI-generated eWOM adoption. This integration provides a deeper understanding of how consumers develop appropriate trust in AI-generated content and explains why calibrated trust is essential for technology adoption.

Third, the study advances the emerging AI-generated eWOM literature by identifying disclosure transparency, algorithmic amplification, perceived manipulation, consumer trust in AI, subjective norms, and perceived diagnosticity as significant antecedents of Trust Calibration. This provides a comprehensive framework for understanding consumer responses to AI-generated reviews within social commerce environments.

Finally, the study contributes to social commerce research by demonstrating that AI-generated eWOM has become an important source of product information that influences purchase intention. The proposed framework offers a contemporary perspective on consumer decision-making in AI-driven digital marketplaces and provides a foundation for future research examining AI-mediated social interactions.

8. Managerial Implications

The findings provide several practical implications for managers and practitioners involved in AI-enabled digital commerce. E-commerce and social commerce platforms should enhance transparency by clearly disclosing when reviews or review summaries are generated or supported by artificial intelligence. Transparent AI practices can strengthen consumer trust and encourage greater adoption of AI-generated recommendations.

Digital marketers should focus on creating informative, relevant, and trustworthy AI-generated content that assists consumers in making purchase decisions rather than promoting persuasive or misleading information. Improving the diagnostic quality of AI-generated reviews can enhance consumer confidence and increase purchase intention.

AI developers should prioritize responsible AI design by developing algorithms that are transparent, explainable, accurate, and free from manipulation or bias. Incorporating explainable AI features and maintaining ethical standards will help improve consumers' trust in AI-enabled recommendation systems.

Policymakers and regulatory authorities should establish guidelines governing the responsible use of generative AI in online reviews and digital marketing. Standardized disclosure requirements, ethical AI policies, and consumer protection regulations can reduce misinformation, improve transparency, and promote greater public confidence in AI-generated content.

9. Limitations and Future Research

Despite its contributions, the study has several limitations. First, the cross-sectional research design limits the ability to establish causal relationships among the proposed constructs. Second, the study was conducted within the Indian social commerce context, which may limit the generalizability of the findings to other countries or cultural settings. Third, the data were collected using self-reported questionnaires, which may be subject to common method bias and respondent bias. Finally, the proposed model focused on selected antecedents of Trust Calibration, and other relevant psychological or technological factors were not included.

Future research may address these limitations by conducting cross-country comparative studies to examine cultural differences in AI-generated eWOM adoption. Longitudinal studies could provide greater insight into how consumer trust evolves over time as AI technologies become more widely adopted. Experimental research designs may also be employed to establish causal relationships between AI-related factors and consumer behaviour. Future studies should examine different AI platforms, industries, and product categories to improve the generalizability of the findings. Researchers may further extend the model by incorporating additional constructs such as perceived risk, AI literacy, privacy concerns, explainability, anthropomorphism, and algorithm aversion.

10. Conclusion

The present study examined the factors influencing AI-generated electronic word-of-mouth adoption and purchase intention by integrating Trust Calibration into the Theory of Reasoned Action. The findings demonstrate that AI-eWOM Disclosure Transparency, Algorithmic Amplification, Consumer Trust in AI, Subjective Norms, and Perceived Diagnosticity positively influence Trust Calibration, whereas Perceived Manipulation has a negative effect. Trust Calibration significantly enhances AI-generated eWOM Adoption, which subsequently increases consumers' Purchase Intention, while Perceived Diagnosticity also exerts a direct positive influence on Purchase Intention.

The study contributes to theory by extending the Theory of Reasoned Action and integrating Trust Calibration Theory into AI-enabled consumer behaviour research. It also advances the literature on AI-generated eWOM and social commerce by proposing and empirically validating a comprehensive research framework. From a practical perspective, the findings highlight the importance of transparency, ethical AI deployment, trustworthy algorithms, and responsible AI-generated content in strengthening consumer trust and encouraging AI adoption. As generative AI continues to transform digital commerce, developing transparent, reliable, and consumer-centric AI systems will become increasingly important for sustaining consumer confidence and supporting responsible innovation.

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