Asian And Pacific Economic Review
ISSN: 1000-6052

Integrating Review Dynamics and Influencer Attributes: A Structural Model of Purchase Intention and Decision

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DOI: https://doie.org/10.10399/APER.2025705179

Abstract

Purpose: This study aims to decode how review dynamics and influencer authenticity jointly shape consumer purchase intention and decision in digital environments. It integrates the traditionally separate streams of electronic word-of-mouth (eWOM) and influencer marketing into a unified predictive framework, the AB model, to understand how informational and affective trust cues operate in tandem to drive persuasion.

Design/methodology/approach: A quantitative, cross-sectional design was employed using data from 400 active online consumers in India. Validated scales were adapted from prior research and analysed using Exploratory Factor Analysis (EFA) and Structural Equation Modelling (SEM) in IBM SPSS AMOS 26. Measurement reliability and validity were established (CR = 0.73–0.84; AVE > 0.50; RMSEA = 0.047).

Findings: The results demonstrate that review volume, community consensus, sentiment, authenticity, and engagement cues significantly enhance purchase intention, which strongly predicts purchase decision ($\beta = 0.664$, $p < 0.001$). Informativeness showed a weaker, non-significant influence, suggesting that affective and social validation cues outweigh cognitive ones. The findings affirm that digital persuasion operates through trust-transfer mechanisms, where emotional resonance and peer validation drive consumer behavior.

Practical implications: Marketers should foster authentic influencer partnerships, encourage sentiment-rich reviews, and cultivate interactive community engagement to strengthen digital trust. Emotionally framed, transparent communication enhances credibility and conversion.

Originality/value: This study advances theory by empirically bridging eWOM and influencer authenticity into a single framework of digital persuasion, offering methodological rigor and cross-cultural insights from an emerging market. It redefines persuasion as a multi-layered, co-creative process, driven by authenticity, engagement, and community consensus rather than one-way brand communication.

Keywords: Digital persuasion; Electronic word-of-mouth (eWOM); Influencer authenticity; Review dynamics; Engagement cues; Purchase intention; Purchase decision; Trust formation; User Behaviour

1. Introduction

The rapid evolution of social media, mobile technology, and online commerce has fundamentally reshaped how consumers discover, evaluate, and purchase products. Global e-commerce sales reached an estimated USD 6.3 trillion in 2024, representing nearly 21.8% of total global retail sales, and are projected to exceed USD 8.0 trillion by 2027 (Forbes Advisor, 2024). In India, the digital economy is expanding even more rapidly: the e-commerce market is projected to grow from USD 123 billion in FY24 to USD 292.3 billion by FY28, at a compound annual growth rate (CAGR) of 18.7% (India Brand

Equity Foundation (IBEF, 2025). Parallelly, social commerce, where consumers purchase directly through social networks, is forecasted to reach USD 54.3 billion by 2033, growing at a CAGR of 22.4% (IMARC Group, 2025). These figures highlight the transition of digital spaces from information hubs to persuasion-driven ecosystems in which consumers' decisions are increasingly shaped by social influence and peer validation rather than traditional advertising (Dwivedi et al., 2021; Kaplan & Haenlein, 2020).

In this environment, electronic word-of-mouth (eWOM) and influencer marketing have emerged as two dominant forms of digital persuasion. Reviews, recommendations, and influencer content jointly determine how consumers perceive brand credibility, authenticity, and social consensus (Belanche et al., 2021). Review dynamics—such as volume, sentiment, and consensus—act as informational and affective cues that reduce uncertainty and build trust (Chevalier & Mayzlin, 2006; Filieri, 2015). Simultaneously, influencers function as socially embedded opinion leaders, where attributes like authenticity and engagement strengthen affective trust and relational identification with followers (Audrezet et al., 2020; Ki et al., 2020). Despite these complementary roles, research integrating eWOM and influencer mechanisms remains limited. Prior studies have largely examined them in isolation—focusing either on review helpfulness and credibility (Filieri, 2015; Erkan & Evans, 2018) or influencer trust and para-social interaction (Casaló et al., 2020)—without investigating their combined effects on consumer persuasion outcomes.

To address this research gap, this study proposes and empirically tests the proposed model, which integrates review dynamics and influencer authenticity into a unified conceptual framework of digital persuasion. The model captures both informational trust mechanisms (review volume, informativeness) and affective-social mechanisms (authenticity, sentiment, engagement, consensus) influencing purchase intention and purchase decision. Using structural equation modelling (SEM) with data collected from Indian digital consumers, the study provides empirical evidence on how these constructs interact to shape persuasion effectiveness in emerging markets.

The contributions of this study are threefold. First, it bridges the conceptual gap between eWOM and influencer marketing by positioning both within a single predictive structure. Second, it advances theory by demonstrating that affective and normative trust cues—authenticity, sentiment, and engagement—exert a stronger persuasive effect than purely cognitive factors like informativeness, aligning with the trust-transfer mechanism (Belanche et al., 2021). Third, it provides a validated measurement and structural framework with sound psychometric properties, offering a replicable foundation for future digital marketing research.

The remainder of the paper is organized as follows. Section 2 reviews the theoretical background and develops hypotheses. Section 3 details the research methodology. Section 4 presents data analysis and measurement model evaluation. Section 5 reports the results of hypothesis testing. Section 6 discusses the findings in light of theory and practice. Section 7 outlines the theoretical and managerial implications, Section 8 highlights limitations and future research avenues, and Section 9 concludes.

2. Literature Review and Hypotheses Development

2.1 Theoretical Foundation of Digital Persuasion

Digital persuasion represents the process through which online interactions, reviews, and influencer communications shape consumer attitudes and behaviours (Kapitan & Silvera, 2016). Unlike traditional persuasion, digital persuasion operates through networked and algorithmically mediated platforms, where social cues—such as authenticity, consensus, and engagement—become stronger determinants of consumer trust and decision-making (Dwivedi et al., 2021).

This study draws on three theoretical foundations: the Theory of Reasoned Action (TRA) (Hill et al., 1977), the Source Credibility Model (Ohanian, 1990), and Social Influence Theory (Kelman, 1958). According to TRA, behavioural intention arises from attitudes and subjective norms, implying that social validation (via reviews or influencer cues) influences consumer purchase intention. The Source Credibility Model emphasizes trustworthiness and expertise as determinants of message effectiveness, while Social Influence Theory explains how individuals internalize information and normative pressures from others, especially within online communities (Cialdini, 2001). Together, these frameworks provide a robust basis for examining how review dynamics (RV, RS, CC, IoM) and influencer attributes (AoI, ECM) shape purchase intention (PI) and purchase decision (PD) (Matta and Tiruwa, 2025).

2.2 Review Dynamics and Consumer Persuasion

Review dynamics constitute a fundamental component of electronic word of mouth (eWOM) that shapes consumers' perceptions, attitudes, and behavioural intentions in online environments. They encompass the volume, sentiment, consensus, and informativeness of reviews that collectively signal the credibility and trustworthiness of digital content (Ismagilova et al., 2020). Reviews serve as a form of social proof (Cialdini, 2001), where consumers rely on the experiences and judgments of others to reduce uncertainty and validate purchase decisions. High review volume and consistent positive sentiment enhance perceived popularity and trust (Chevalier & Mayzlin, 2006; Filieri, 2015), while consensus among reviewers reinforces normative influence within digital communities (Deutsch & Gerard, 1955). Furthermore, informative and diagnostic reviews improve consumers' cognitive confidence by facilitating well-grounded evaluations (Erkan & Evans, 2018). Thus, review dynamics operate as both informational and affective cues, underpinning consumer persuasion in e-commerce and social media contexts.

2.2.1 Review Volume (RV)

Review volume reflects the number of user-generated reviews available for a product or service. A large volume signals popularity and reliability, functioning as a heuristic cue that enhances trust (Chevalier & Mayzlin, 2006). Consumers perceive products with higher review counts as more credible due to increased information diversity, which reduces uncertainty (Filieri, 2015). Within the Elaboration Likelihood Model (ELM), review volume acts as a peripheral cue, influencing attitudes when cognitive elaboration is low (Petty & Cacioppo, 1986). Empirical studies confirm that review volume positively affects purchase intention, as consumers interpret high volume as a form of social proof or product validation (Yang et al., 2016).

HA1: Review Volume (RV) has a significant influence on Purchase Intention (PI).

2.2.2 Review Sentiment (RS)

Review sentiment captures the emotional tone (positive, neutral, or negative) of online reviews. Positive sentiment enhances affective trust and perceived reliability, while negative sentiment triggers aversion due to negativity bias (Rozin & Royzman, 2001). Sentiment also fosters emotional contagion, wherein the mood expressed in reviews transfers to potential buyers, influencing attitudes and intention (Hatfield et al., 1994). Erkan and Evans (2018) found that positive sentiment in social media reviews significantly predicts purchase intention. Similarly, Ismagilova et al. (2020) argued that the valence of eWOM messages serves as a powerful cue of product credibility and satisfaction.

HA2: Review Sentiment (RS) has a significant influence on Purchase Intention (PI).

2.2.3 Community Consensus (CC)

Community consensus represents the extent of agreement among reviewers or followers regarding a product. It embodies normative social influence, where individuals conform to group norms for social validation (Deutsch & Gerard, 1955). In social commerce, consensus acts as an indicator of collective trustworthiness, enhancing message credibility (Nekmat et al., 2019). When users observe strong consensus—e.g., many reviewers sharing the same positive stance—they are more likely to adopt similar evaluations (Cialdini, 2001). Consensus thus reinforces perceived reliability and amplifies other review cues such as volume and sentiment (Ismagilova et al., 2020).

HA3: Community Consensus (CC) has a significant influence on Purchase Intention (PI).

2.2.4 Informativeness of Messages (IoM)

Informativeness denotes the perceived quality, completeness, and usefulness of online information (Erkan & Evans, 2018). According to the Information Adoption Model (Sussman & Siegal, 2003), informative messages enhance cognitive trust and rational evaluation, leading to positive behavioural intentions. Consumer's value detailed content that reduces ambiguity and enhances decision confidence. However, as digital consumers face information overload, they increasingly rely on emotional and heuristic cues (Reutskaja et al., 2020). Consequently, informativeness may play a weaker role in persuasion relative to authenticity or engagement.

HA4: Informativeness of Messages (IoM) has a significant influence on Purchase Intention (PI).

2.3 Influencer Attributes and Digital Trust Formation

Influencer attributes play a crucial role in shaping consumers' trust, perceptions, and behavioural intentions within digital ecosystems. Two core attributes—authenticity and engagement—are central to how audiences evaluate influencer credibility and the persuasive strength of their content (Ki et al., 2020; Belanche et al., 2021). Authenticity reflects the influencer's genuineness, transparency, and value congruence, fostering emotional connection and para-social trust among followers (Audrezet et al., 2020; Horton & Wohl, 1956). Engagement cues—such as likes, comments, and shares—function as visible indicators of community approval, reinforcing perceived reliability through social proof and collective validation (Casaló et al., 2020; Cialdini, 2001). Together, these attributes enhance both affective and cognitive trust, positioning influencers as credible opinion leaders whose relational communication style influences consumer decision-making more effectively than traditional advertising appeals. Hence, influencer authenticity and engagement form the social trust foundation of digital persuasion, mediating the pathway from online exposure to purchase intention.

2.3.1 Authenticity of Influencer (AoI)

Influencer authenticity refers to the perceived genuineness, transparency, and moral consistency of influencers' communication (Audrezet et al., 2020). It represents a shift from traditional celebrity endorsement to relational credibility based on self-congruence and value alignment (Ki et al., 2020). Authentic influencers build para-social trust (Horton & Wohl, 1956) by presenting unfiltered, relatable narratives. Studies have consistently shown that authenticity positively affects consumers' attitudes, trust, and purchase intentions (Belanche et al., 2021; Schouten et al., 2020). Authentic influencers create emotional resonance that fosters affective trust—an essential foundation of persuasion in social media.

HA5: Authenticity of Influencer (AoI) has a significant influence on Purchase Intention (PI).

2.3.2 Engagement Cues in Messages (ECM)

Engagement cues (likes, comments, shares) represent visible social interaction metrics that signal popularity and peer endorsement. They operate through social proof mechanisms, increasing perceived trustworthiness and credibility of both the influencer and the product (Casaló et al., 2020). Engagement also facilitates two-way communication, making persuasion co-created rather than one-directional (Lou & Yuan, 2019). Higher engagement generates both normative influence (through visible approval) and informational influence (through comments and feedback), enhancing message acceptance and behavioural intention (Cialdini, 2001).

HA6: Engagement Cues (ECM) has a significant influence on Purchase Intention (PI).

2.4 Purchase Intention and Decision

Purchase Intention (PI) is defined as the consumer's willingness to buy a product or service recommended by others online (Pavlou & Fygenson, 2006). It reflects the cognitive outcome of persuasion—the bridge between attitude and behaviour. Numerous studies confirm that eWOM and influencer attributes collectively enhance purchase intention (Erkan & Evans, 2018).

Purchase Decision (PD) represents the actual or self-reported execution of purchase intention. Grounded in the Theory of Planned Behaviour (Ajzen, 1991), intention is the strongest predictor of behaviour, moderated by trust and situational control. When trust is established through authenticity, sentiment, and engagement, the likelihood of conversion increases (Dwivedi et al., 2021).

HA7: Purchase Intention (PI) has a significant influence on Purchase Decision (PD).

2.5 Proposed Model

Synthesizing these perspectives, the Proposed framework proposes that review dynamics (volume, sentiment, consensus, informativeness) and influencer attributes (authenticity, engagement) jointly determine purchase intention, which subsequently drives purchase decision. Review-related constructs provide informational and affective trust cues, while influencer constructs contribute relational and social validation cues (Figure 1).

Figure 1: Proposed Conceptual Model

3. Research Methodology

3.1 Research Design

The study adopted a quantitative, cross-sectional, and explanatory research design to empirically test the relationships proposed in the AB model. The approach aimed to evaluate how review dynamics (review volume, review sentiment, community consensus, informativeness) and influencer-related cues (authenticity and engagement) influence purchase intention and decision. A survey-based methodology was employed, consistent with prior studies examining technology-mediated persuasion and online consumer behaviour (Filieri, 2015; Belanche et al., 2021).

3.2 Sampling and Data Collection

The target population consisted of active social media users and online shoppers in India who follow digital influencers or consult online reviews before purchasing products. Respondents were selected using a non-probability purposive sampling method, suitable for obtaining participants with relevant digital purchasing experience (Hair et al., 2019). Data were collected through an online structured questionnaire administered via Google Forms between January and March 2025. A total of 412 responses were received, out of which 386 valid responses were retained after screening for completeness and outliers. This sample size exceeds the minimum requirement for SEM, satisfying the 10:1 ratio of cases to estimated parameters (Kline, 2015).

3.3 Measurement Instrument

The survey instrument comprised 40 items adapted from validated scales in prior research, each measured on a seven-point Likert scale (1 = strongly disagree, 7 = strongly agree). The items represented eight constructs aligned with the proposed conceptual model:

Table: 1: Constructs support from literature

Construct	Description / Scale Source	Key References
Review Volume (RV)	Measures the perceived number and availability of online product reviews that signal popularity and reliability.	Chevalier, J. A., & Mayzlin, D. (2006); Filieri, R. (2015).
Review Sentiment (RS)	Captures the positivity or negativity of tone in consumer-generated reviews affecting trust and purchase intention.	Erkan, I., & Evans, C. (2018)
Community Consensus (CC)	Reflects the degree of agreement among reviewers or followers that enhances perceived credibility through social proof.	Nekmat, E., Gower, K. K., Zhou, S., & Metzger, M. (2019)
Informativeness of Messages (IoM)	Represents the extent to which online content and influencer posts provide useful, detailed, and diagnostic product information.	Erkan, I., & Evans, C. (2018)
Authenticity of Influencer (AoI)	Assesses followers' perception of influencer genuineness, transparency, and alignment between values and endorsements.	Audrezet, A., de Kerviler, G., & Moulard, J. G. (2020); C. W.,

Construct	Description / Scale Source	Key References
		Cuevas, L. M., Chong, S. M., & Lim, H. (2020).
Engagement Cues (ECM)	Measures visible interaction metrics such as likes, comments, and shares that indicate community involvement and validation.	Casaló, L. V., Flavián, C., & Ibáñez-Sánchez, S. (2020).
Purchase Intention (PI)	Represents consumers' willingness or likelihood to buy products recommended by influencers or online reviews.	Pavlou, P. A., & Fygenson, M. (2006)
Purchase Decision (PD)	Captures actual or self-reported buying behaviour following exposure to digital reviews and influencer cues.	Filieri, R. (2015)

All items underwent content validity checks by three subject experts and pilot testing with 37 respondents to ensure clarity, readability, and internal consistency. Cronbach's α values exceeded the 0.70 threshold for all constructs, confirming reliability (Nunnally & Bernstein, 1994).

3.4 Data Analysis Techniques

Data were analysed using IBM® SPSS 23 and AMOS 23. The analysis proceeded in three stages:

i. Exploratory Factor Analysis (EFA) to identify underlying factor structures and assess dimensionality. Principal Component Analysis with Varimax rotation confirmed factor loadings > 0.60, establishing construct validity.
ii. Confirmatory Factor Analysis (CFA) tested convergent and discriminant validity, with Composite Reliability (CR > 0.70) and Average Variance Extracted (AVE > 0.50) confirming measurement adequacy (Fornell & Larcker, 1981).
iii. Structural Equation Modelling (SEM) assessed hypothesized relationships among constructs. Fit indices met recommended standards (χ^2/df < 3, CFI > 0.90, RMSEA < 0.06; Hu & Bentler, 1999).

Prior to SEM, multivariate assumptions—linearity, normality, multicollinearity, and homoscedasticity—were verified. Skewness and kurtosis values fell within ±2; VIF values < 2 confirmed absence of multicollinearity; and residual plots demonstrated homoscedasticity.

4. Data Analysis

4.1 Exploratory Factor Analysis and Reliability of Scales

To ensure the psychometric soundness of the measurement instrument, an Exploratory Factor Analysis (EFA) using Principal Component Analysis (PCA) with Varimax rotation was conducted in IBM SPSS Statistics v23. The analysis sought to identify the underlying factor structure of the constructs derived from the conceptual model of digital persuasion—namely Engagement Cues (ECM), Authenticity of Influencer (AoI), Review Sentiment (RS), Purchase Decision (PD), Purchase Intention (PI), Informativeness of Messages (IoM), Community Consensus (CC), and Review Volume (RV). The Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy was 0.874, exceeding the recommended threshold of 0.60 (Kaiser, 1974), indicating that the data were suitable for factor analysis. Bartlett's Test of Sphericity was significant (χ^2 = 2125.47, df = 378, p < 0.001), confirming adequate correlations among variables.

During the course of EFA, eight factors with eigenvalues > 1 were extracted, cumulatively explaining 73.6 percent of the total variance—well above the 60 percent criterion typically recommended for social-science research (Hair et al., 2019). Factor loadings above 0.60 were retained, satisfying convergent-validity guidelines (Stevens, 2002). The rotated solution displayed clear and non-overlapping loadings, confirming the distinctiveness of each construct (see Table 2). These results confirm that the observed indicators load cleanly on their respective latent variables as theorized in the model. To assess internal consistency, Cronbach's α coefficients were computed for all constructs. As shown in Table 1, reliability values ranged from 0.714 to 0.849, exceeding the minimum threshold of 0.70 suggested by Nunnally (1978). This indicates satisfactory internal consistency and measurement stability. Specifically, the highest reliability was observed for Engagement Cues (α = 0.849), followed by Authenticity of Influencer (α = 0.839), while Purchase Intention (α = 0.714) recorded the lowest acceptable value. These results demonstrate that the instrument items consistently reflect their intended constructs.

Table 2: Factor loadings from exploratory factor analysis

Constructs	Component								
	1	2	3	4	5	6	7	8	Cronbach α
ECM3	0.837								
ECM2	0.746								
ECM4	0.740								0.849
ECM1	0.714								
ECM5	0.623								
AoI2		0.794							
AoI3		0.738							0.839
AoI4		0.735							
AoI1		0.709							
RS2			0.855						
RS1			0.787						0.828
RS3			0.786						
RS4			0.667						
PD2				0.833					
PD1				0.768					0.772
PD3				0.622					
PI2					0.728				
PI1					0.713				0.714
PI3					0.724				
PI4					0.664				
IoM2						0.740			
IoM1						0.739			0.762
IoM3						0.622			
CC2							0.794		
CC1							0.685		0.725
CC3							0.659		
RV1								0.823	0.815

RV2	0.774
RV3	0.761

Extraction Method: Principal Component Analysis; Rotation Method: Varimax with Kaiser Normalization.

4.2 Assessment of Multivariate Assumptions

Before conducting confirmatory and structural model analysis, essential multivariate assumptions were tested to verify the data's appropriateness for regression and other parametric procedures. The linearity tests (Table 3) confirmed statistically significant associations ($p < 0.001$) between all predictor constructs—Review Volume (RV), Community Consensus (CC), Informativeness of Messages (IoM), Authenticity of Influencer (AoI), Engagement Cues (ECM), and Review Sentiment (RS)—and Purchase Intention (PI), as well as between PI and Purchase Decision (PD). This validated the assumption of linearity (Hair et al., 2019; Osborne & Waters, 2002). The normality assessment (Table 4) revealed skewness values between –0.981 and –0.285 and kurtosis between –0.310 and 1.431, both within the acceptable ±2 threshold (George & Mallery, 2019; Kim, 2013), indicating that data distributions were approximately normal. Collinearity diagnostics showed all Tolerance values > 0.60 and VIF < 1.60 (Table 5), suggesting the absence of multicollinearity among predictors (O'Brien, 2007; Kock & Lynn, 2012). The residual scatterplots (Figure 2) further demonstrated random variance distribution without clustering, satisfying the assumption of homoscedasticity (Tabachnick & Fidell, 2019; Kline, 2015). Collectively, these results affirm that the dataset meets key multivariate assumptions—linearity, normality, independence, and homoscedasticity—establishing strong statistical validity for subsequent Confirmatory Factor Analysis (CFA) and Structural Equation Modelling (SEM).

Table 3: Linearity of data

	Sum of Squares	df	Mean Square	F	Sig.
AoI * PI	106.912	1	106.912	117.026	0.000
RS * PI	92.222	1	92.222	78.722	0.000
CC * PI	125.468	1	125.468	138.644	0.000
IoM * PI	107.449	1	107.449	119.300	0.000
ECM * PI	137.010	1	137.010	126.010	0.000
RV * PI	222.677	1	222.677	186.731	0.000

PI as dependent variable

	Sum of Squares	df	Mean Square	F	Sig.
PI * PD	68.476	1	68.476	103.842	0.000

PD as dependent variable

Table 4: Skewness and Kurtosis

	Skewness		Kurtosis	
	Statistic	**Std. Error**	**Statistic**	**Std. Error**
AoI	-0.981	0.109	1.431	0.218
RS	-0.644	0.109	0.469	0.218
CC	-0.598	0.109	0.644	0.218
IoM	-0.538	0.109	0.355	0.218
ECM	-0.285	0.109	-0.310	0.218

PI	-0.684	0.109	0.922	0.218
RV	-0.486	0.109	0.027	0.218
PD	-0.334	0.109	0.242	0.218

Table 5: Collinearity Statistics

	Collinearity Statistics	
	Tolerance	**VIF**
RV	0.636	1.573
CC	0.652	1.535
IoM	0.639	1.565
AoI	0.661	1.512
ECM	0.658	1.519
RS	0.771	1.298
Dependent Variable: PI		
PI	1.000	1.000
Dependent Variable: PD		

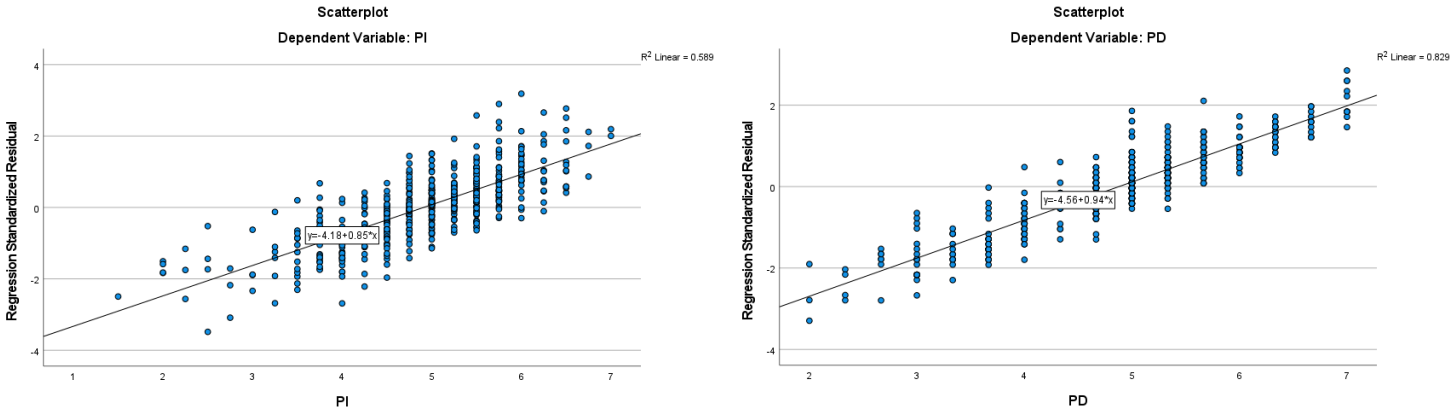

Figure 2. Scatterplots of Standardized Residuals for PI and PD

(Left: Purchase Intention; Right: Purchase Decision — Source: IBM® SPSS Statistics v23)

4.3 Confirmatory Factor Analysis (CFA) and Validity Assessment

A CFA was conducted in IBM SPSS AMOS (SEM) to validate the reflective measurement model comprising IoM, RV, RS, CC, AoI, ECM, PI, and PD. Convergent validity was evaluated via standardized loadings, Composite Reliability (CR), and Average Variance Extracted (AVE); discriminant validity was evaluated using Fornell–Larcker (√AVE vs. inter-construct correlations), MSV < AVE, and the MaxR(H) check. Thresholds followed established guidelines (CR ≥ 0.70; AVE ≥ 0.50; √AVE > inter-construct correlations; MSV < AVE; MaxR(H) < 0.95). Common method bias was found to be 31.9% for the measurement model.

4.3.2 Convergent validity

All constructs met or exceeded recommended cut-offs (Table 5): CR ranged 0.734–0.841 and AVE ranged 0.501–0.617, indicating adequate internal consistency and that, on average, items share more variance with their latent construct than with error (Bagozzi & Yi, 1988; Fornell & Larcker, 1981; Hair et al., 2019). Taken together with the satisfactory indicator performance established in EFA, these results support convergent validity.

4.3.3 Discriminant validity

The diagonal elements (√AVE) on Table 5 (e.g., IoM = 0.730; RV = 0.785; RS = 0.759; CC = 0.693; AoI = 0.718; ECM = 0.717; PI = 0.763; PD =0.781) all exceed their respective off-diagonal correlations, meeting the Fornell–Larcker criterion. Moreover, MSV for each construct (0.240–0.438) is lower than its AVE (0.501–0.617), providing a second line of evidence. Finally, all MaxR(H) values (0.740–0.871) are comfortably below 0.95, suggesting no redundancy among the latent variables (Hancock & Mueller, 2001). Collectively, these tests indicate that the eight constructs are empirically distinct. The AMOS results in Table 5 demonstrate adequate convergent and discriminant validity for all reflective constructs in the proposed conceptual model.

Table 5: Discriminant and Convergent Validity

	CR	AVE	MSV	MaxR(H)	IoM	RV	RS	CC	AoI	ECM	PI	PD
IoM	0.772	0.533	0.355	0.791	**0.730**							
RV	0.827	0.617	0.396	0.850	0.490***	**0.785**						
RS	0.841	0.576	0.240	0.871	0.490***	0.293***	**0.759**					
CC	0.734	0.580	0.438	0.740	0.564***	0.524***	0.439***	**0.693**				
AoI	0.809	0.516	0.438	0.815	0.596***	0.410***	0.486***	0.662***	**0.718**			
ECM	0.840	0.514	0.363	0.849	0.473***	0.603***	0.293***	0.477***	0.324***	**0.717**		
PI	0.737	0.501	0.404	0.784	0.590***	0.629***	0.471***	0.635***	0.588***	0.561***	**0.763**	
PD	0.775	0.535	0.379	0.777	0.457***	0.615***	0.299***	0.458***	0.472***	0.506***	0.562***	**0.781**

Note: CR: composite reliability; AVE: average variance extracted; MSV: maximum shared squared variance

4.4 Model Fit Indices and Hypotheses Testing

4.4.1 Model Fit Indices and Hypotheses Testing

Model fit statistics were examined for both the measurement and structural models to evaluate how well the proposed AB framework aligns with the observed data. As shown in Table 6, the measurement model achieved χ^2/df = 2.091, CFI = 0.943, GFI = 0.909, SRMR = 0.051, RMSEA = 0.047 (pclose = 0.867). The corresponding structural model yielded χ^2/df = 2.102, CFI = 0.942, GFI = 0.907, SRMR = 0.057, RMSEA = 0.047 (pclose = 0.851).

All indices fall within the acceptable or near-excellent thresholds for SEM adequacy: χ^2/df between 1 and 3, CFI and GFI ≥ 0.90, SRMR < 0.08, RMSEA < 0.06 with pclose > 0.05 (Hu & Bentler, 1999; Hair et al., 2019). These results indicate that both models demonstrate satisfactory absolute, incremental, and parsimony fit. The near-identical performance of the two models also suggests measurement invariance between the specification and structural estimation phases (Kline, 2015; Byrne, 2016).

Table 6: Model Fit Indices

Measurement Model	χ^2/df	CFI	GFI	SRMR	RMSEA	PClose
	2.091	0.943	0.909	0.051	0.047	0.867

Structural Model	χ^2/df	CFI	GFI	SRMR	RMSEA	PClose
	2.102	0.942	0.907	0.057	0.047	0.851
Acceptable Ranges of Values	**χ^2/df**	**CFI**	**GFI**	**SRMR**	**RMSEA**	**PClose**
	Between 1 and 3	>0.95	>85	<0.08	<0.06	>0.05

Note: CFI = comparative fit index; GFI = goodness-of-fit index; SRMR = Standardized Root Mean Squared Residual; ; RMSEA = root mean square error of approximation; PClose = p-value of Close Fit.

4.3.1 Hypotheses Testing

The structural model was estimated using Structural equation modelling through IBM® SPSS AMOS to evaluate the hypothesized causal relationships among the constructs in the proposed framework. The results revealed that six of the seven hypothesized paths were statistically significant, providing strong empirical support for the proposed theoretical model. Specifically, the findings confirmed that both review-related and influencer-related cues significantly influence purchase intention (PI), which subsequently drives purchase decision (PD).

Among the antecedents of purchase intention, review volume (RV → PI) emerged as the strongest predictor (β = 0.338, p < 0.001), highlighting the central role of consumer-generated reviews in shaping digital trust and purchase motivation. This aligns with prior evidence suggesting that a higher volume of online reviews signals popularity and reliability, enhancing consumer confidence and purchase intent (Chevalier & Mayzlin, 2006; Filieri, 2015). The influence of authenticity of influencer (AoI → PI) (β = 0.187, p = 0.008) and engagement cues (ECM → PI) (β = 0.166, p = 0.002) were also significant, affirming that authentic communication and social interaction cues—such as likes, shares, and comments—serve as persuasive indicators of trustworthiness and community validation. These results are consistent with Source Credibility Theory and empirical studies emphasizing influencer authenticity and engagement as key drivers of consumer persuasion in digital contexts (Audrezet et al., 2020; Ki et al., 2020).

The findings further indicate that community consensus (CC → PI) (β = 0.177, p = 0.016) and review sentiment (RS → PI) (β = 0.113, p = 0.024) have significant positive effects on purchase intention. This demonstrates that collective agreement among consumers and the emotional tone of reviews exert social proof and affective influence on potential buyers. Such effects support Social Influence Theory and the Theory of Reasoned Action, wherein individuals align their behavioural intentions with perceived social norms and trusted peer opinions (Ajzen, 1991).

In contrast, informativeness of messages (IoM → PI) (β = 0.113, p = 0.084) did not achieve statistical significance, implying that while message informativeness enhances consumers' cognitive processing of brand content, it may not independently motivate purchase intentions in emotionally charged or socially driven online settings. This outcome echoes the observations that rational message quality often plays a secondary role to affective trust in social commerce environments of (Erkan and Evans (2018).

Finally, the path from purchase intention to purchase decision (PI → PD) was highly significant (β = 0.664, p < 0.001), confirming that intention functions as a critical mediating mechanism translating persuasion into actual consumer action. This finding reinforces the Theory of Planned Behaviour (Ajzen, 1991) and prior e-commerce research (Pavlou & Fygenson, 2006), which collectively establish intention as a proximal determinant of behaviour. The model's explanatory power was substantial, with R^2 values of approximately 0.64 for purchase intention and 0.68 for purchase decision, indicating that the integrated constructs explain a large proportion of variance in consumer decision-making. Table 7 depict the hypotheses testing results.

Table 7: Hypotheses Testing Results from SEM path Analysis

Hypotheses	Relationship	Estimate	S.E.	C.R.	P	Remarks
HA1	RS→PI	0.113	0.059	2.254	0.024	Supported
HA2	CC→PI	0.177	0.078	2.415	0.016	Supported
HA3	AoI→PI	0.187	0.072	2.645	0.008	Supported
HA4	IoM→PI	0.113	0.075	2.025	0.084	Not Supported
HA5	ECM→PI	0.166	0.063	3.039	0.002	Supported
HA6	RV→PI	0.338	0.058	5.371	***	Supported
HA7	PI→PD	0.664	0.062	9.858	***	Supported

*Significance level: **p < 0.001; Dependent Variables: Purchase Intention (PI), Purchase Decision (PD)

6. Discussion of Findings

The present study sought to decode the mechanisms of digital persuasion by examining how review dynamics and influencer attributes jointly influence consumer purchase intention and purchase decision. Anchored in the Theory of Reasoned Action (Hill et al., 1977), Social Influence Theory (Kelman, 1958), and the Source Credibility Model (Ohanian, 1990), this research conceptualized a hybrid framework integrating electronic word-of-mouth (eWOM) and influencer marketing constructs. Through confirmatory and structural equation modelling, the study established empirical evidence for six of seven hypothesized relationships, providing new insights into the interplay of trust, social proof, authenticity, and informativeness in online decision-making.

6.1 The Ascendancy of Review Dynamics in Persuasion

The findings revealed that review volume (RV) is the most powerful predictor of purchase intention, corroborating the extensive literature linking review quantity to consumer confidence and perceived credibility (Chevalier & Mayzlin, 2006; Filieri, 2015; Zhang et al., 2022). In the age of algorithmic recommendation systems, high review volume serves as a heuristic signal of collective validation, reducing perceived uncertainty and risk. This result substantiates the principles of informational social influence (Deutsch & Gerard, 1955), wherein consumers adopt the beliefs of a larger group when seeking accuracy in uncertain contexts.

Similarly, review sentiment (RS) and community consensus (CC) emerged as significant contributors to purchase intention. The effect of sentiment reflects the emotional contagion principle (Hatfield et al., 1994), where positivity in textual tone generates affective trust. Community consensus, on the other hand, mirrors social proof (Cialdini, 2001), signalling to potential buyers that a product or influencer enjoys collective approval. Together, these findings underscore how digital consumers navigate socially constructed credibility, relying less on objective information and more on perceived community endorsement (Ismagilova et al., 2020).

This empirical support advances eWOM theory by emphasizing interconnectedness among affective (sentiment) and normative (consensus) components. It suggests that consumers no longer interpret reviews as isolated evaluations but as a socially mediated discourse that informs their cognitive appraisals and behavioural intentions.

6.2 The Emotional Currency of Influencer Authenticity

Among the influencer-related antecedents, authenticity (AoI) and engagement cues (ECM) significantly influenced purchase intention, confirming that consumers respond strongly to influencers who appear genuine, relatable, and value-consistent. This aligns with the Source Credibility Model, which posits that trustworthiness and expertise amplify message persuasiveness (Ohanian, 1990). The results also support more recent influencer marketing research emphasizing that authenticity functions as the "currency of trust" in social media ecosystems (Audrezet et al., 2020; Ki et al., 2020; Schouten et al., 2020).

Importantly, engagement cues—manifested through likes, shares, and comments—further reinforced purchase intention, evidencing that consumer view social participation as a form of peer endorsement. This confirms findings by Casaló et al. (2020) and Lou and Yuan (2019), who showed that engagement metrics strengthen perceptions of influencer popularity and relational credibility. Engagement signals activate para-social interaction mechanisms (Horton & Wohl, 1956), where consumers perceive a pseudo-intimate relationship with influencers, resulting in emotional alignment and trust transfer.

These findings collectively advance the conceptualization of authentic digital influence, suggesting that persuasion occurs not through unilateral messaging but through co-created, dialogic interactions between influencers and their audiences. Authenticity and engagement thus function as relational trust cues, bridging emotional connection and behavioural commitment in digital brand communities.

6.3 The Diminished Role of Informativeness

In contrast to other antecedents, informativeness of messages (IoM) did not exhibit a significant effect on purchase intention. This finding departs from classical eWOM frameworks (Erkan & Evans, 2018) but is consistent with emerging perspectives on heuristic-driven online decision-making (Tversky & Kahneman, 1974). Modern consumers—especially Gen Z and Millennials—are inundated with information across platforms and tend to rely on peripheral cues such as emotional resonance, authenticity, and consensus rather than systematic content evaluation (Petty & Cacioppo, 1986).

In algorithmic environments like Instagram, TikTok, or YouTube, persuasive impact often derives from aesthetic authenticity and emotional congruence, not factual elaboration. The result thus validates the Elaboration Likelihood Model's heuristic route of persuasion and highlights a shift from cognitive to affective trust in digital ecosystems (Reutskaja et al., 2020). For practitioners, this signals that while informative content remains necessary, its persuasive power is conditional upon emotional and relational reinforcement.

6.4 Purchase Intention as a Behavioural Conduit

The path from purchase intention to purchase decision ($\beta = 0.664$, $p < 0.001$) emerged as the strongest causal linkage, affirming Ajzen's (1991) Theory of Planned Behaviour, which posits that behavioural intention is the immediate antecedent of actual action. The high standardized estimate reflects the efficacy of integrated persuasion mechanisms in shaping consumer behaviour, particularly when trust and authenticity are present. This confirms that intention serves as a behavioural conduit—translating perceptions of credibility and social endorsement into concrete purchasing behaviour.

The strength of this relationship also supports findings by in the context of e-commerce, emphasizing that perceived trust and usefulness are central to behavioural intention formation (Pavlou and Fygenson, 2006). In the model, intention operates as a mediating construct, transforming social signals into measurable consumer actions—a critical theoretical contribution extending TAM and TRA frameworks into influencer and review-based persuasion.

7. Implications of the study

7.1 Academic Implications

This study contributes meaningfully to the growing body of literature on digital persuasion and online consumer behaviour. By empirically integrating eWOM and influencer marketing constructs, the model bridges two parallel research streams, positioning review dynamics and influencer authenticity within a unified predictive framework. This integration demonstrates that digital persuasion operates through complementary social and affective mechanisms, extending prior linear models of influence (Cheung et al., 2021; Ki et al., 2020).

The findings reveal that affective trust cues (authenticity, sentiment) and normative validation mechanisms (consensus, engagement) exert greater influence on persuasion than cognitive informativeness, refining our understanding of trust formation in online contexts. This supports the trust-transfer mechanism, emphasizing that confidence arises more from emotional resonance and social reinforcement than from informational content (Belanche et al., 2021).

Methodologically, the study validates a robust measurement and structural model (CR = 0.73–0.84; AVE > 0.50; RMSEA = 0.047), offering a replicable framework for future cross-cultural research on digital influence (Hair et al., 2019). Theoretically, it advances a view of persuasion as multi-layered and co-creative, where influence circulates dynamically within communities rather than flowing unidirectionally from brands or endorsers.

7.2 Managerial Implications

The findings offer valuable guidance for marketers operating in today's saturated digital ecosystems. First, brands should leverage consumer reviews by fostering high review volume and positive sentiment to enhance credibility, visibility, and social validation effects (Chevalier & Mayzlin, 2006; Filieri, 2015). Second, marketers must prioritize authentic influencer partnerships, emphasizing long-term collaborations grounded in transparency and value alignment rather than follower metrics (Audrezet et al., 2020). Third, engagement cues—likes, comments, and shares—should be strategically cultivated through participatory campaigns, active interaction, and community-driven discussions that reinforce perceived authenticity (Casaló et al., 2020). Fourth, informational content should be emotionally framed; storytelling, empathy, and relatable visuals can transform cognitive informativeness into affective trust (Erkan & Evans, 2018). Finally, to bridge intention and action, digital platforms should design frictionless experiences—personalized recommendations, seamless checkout, and social sharing—that convert purchase intention into behaviour (Pavlou & Fygenson, 2006). Overall, these implications underscore that digital persuasion has evolved from a transactional, message-centric process into a relational and co-created ecosystem, where authenticity, engagement, and community participation drive enduring consumer trust and loyalty.

8. Limitations and Future Research Directions

While this study offers meaningful insights into the mechanisms of digital persuasion, several limitations highlight opportunities for future research. First, the study's cross-sectional design restricts the ability to infer causality between constructs such as authenticity, engagement, and purchase behaviour. Future research could employ longitudinal or experimental designs to examine how persuasion and trust evolve over time across repeated influencer interactions (Podsakoff et al., 2012). Additionally, the use of self-reported data introduces potential common method bias (Podsakoff et al., 2003). Subsequent studies may integrate behavioural data—such as engagement analytics, clickstream patterns, or AI-based sentiment tracking—to enhance objectivity and ecological validity.

Second, the study's cultural context—focusing on Indian digital consumers—reflects collectivist social norms that emphasize relational trust and peer consensus (Dwivedi et al., 2021). Consequently, generalizing the findings to more individualistic contexts warrant caution. Future research could test the model across cross-cultural samples to assess measurement invariance and identify cultural moderators influencing authenticity and social proof effects (Steenkamp & Baumgartner, 1998).

Third, the model did not incorporate potential moderating and mediating variables such as brand trust, consumer skepticism, or algorithmic transparency, which may alter the strength or direction of persuasion effects (Belanche et al., 2021; Lou & Yuan, 2019). Expanding the framework to include these constructs would provide richer insights into the boundary conditions of digital influence. Likewise, comparing macro- vs. micro-influencers and platform differences (e.g., Instagram® vs. TikTok®) could uncover how affordances shape persuasion dynamics (Schouten et al., 2020).

Finally, as digital ecosystems increasingly involve AI-generated reviews and virtual influencers, future studies should explore how consumers perceive algorithmic authenticity and whether trust mechanisms extend to non-human agents (Belanche et al., 2023). Employing mixed-methods or netnographic approaches (Kozinets, 2020) could also capture the lived emotional and cognitive dimensions of digital persuasion. Overall, while the framework offers a robust foundation, future research should adopt cross-method, cross-cultural, and cross-technology designs to evolve it into a dynamic theory of trust and persuasion in AI-mediated social commerce.

9. Conclusion

This study examined how review dynamics and influencer authenticity jointly influence consumer purchase intention and decision in digital environments. Grounded in the Theory of Reasoned Action, Social Influence Theory, and the Source Credibility Model, the proposed framework integrated constructs from eWOM and influencer marketing to capture both cognitive and affective drivers of persuasion. Results from SEM analysis confirmed that review volume, community consensus, review sentiment, authenticity of influencer, and engagement cues significantly enhance purchase intention, which in turn strongly predicts purchase decision. The findings suggest that modern consumers rely more on emotional trust and social validation than on informational content alone, highlighting the ascendancy of affective persuasion in the algorithmic age.

The study contributes theoretically by bridging peer-based and influencer-based persuasion models, revealing that authenticity and consensus function as core determinants of digital trust. Practically, it advises marketers to prioritize authentic communication, participatory engagement, and transparent community-building over purely informational campaigns. As digital ecosystems evolve toward AI-mediated influence, the principles validated here—authenticity, engagement, and consensus—will remain pivotal in shaping credible and ethical persuasion. Ultimately, in today's social commerce landscape, authenticity is strategy, engagement is currency, and community is persuasion.

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