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eWOM QUALITY AND TRUST IN SOCIAL COMMERCE: PREDICTING INDIAN MILLENNIALS' PURCHASE INTENTION

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ABSTRACT

Think about the last time a friend’s Instagram post subtly convinced you to buy something. You probably didn’t reach for a product manual or call customer service. Instead, you skimmed through user reviews, noticed how many people had already purchased it, and let that quiet social signal tip the balance. This everyday experience lies at the heart of social commerce—a marketplace where peer influence, user-generated content, and platform design come together to shape what we buy.

While this phenomenon feels intuitive, the precise ways these forces interact—especially in a country as large, diverse, and culturally rich as India—remain only partially understood. This study seeks to deepen that understanding by integrating two well-established theoretical lenses: the Technology Acceptance Model (TAM) and the Elaboration Likelihood Model (ELM). Drawing on survey data from 387 Indian millennial online shoppers, we develop and test a unified model of social commerce adoption using Partial Least Squares Structural Equation Modeling (PLS-SEM).

The results reveal that perceived usefulness ($\beta = 0.38, p < 0.001$), social influence ($\beta = 0.29, p < 0.001$), and consumer trust ($\beta = 0.35, p < 0.001$) significantly drive purchase intention, while perceived risk acts as a notable deterrent ($\beta = -0.24, p < 0.001$). Importantly, we find that the quality of electronic word-of-mouth (eWOM) does not influence purchase intention directly. Instead, it works entirely through building consumer trust ($\beta = 0.41, p < 0.001$), highlighting a full mediation effect.

Together, the model explains 54.6% of the variance in purchase intention and 49.3% in consumer trust. These findings contribute to the literature by offering fresh insights into social commerce dynamics within an emerging market context that has received relatively limited attention. For practitioners, the results provide clear guidance on where to focus platform investments—from strengthening trust-building mechanisms to improving review quality—for maximum impact on buying behavior.

Keywords: *social commerce; eWOM quality; consumer trust; purchase intention; perceived usefulness; social influence; perceived risk; TAM; ELM; PLS-SEM; India*

1. INTRODUCTION

Social commerce did not appear suddenly. It evolved from a growing recognition among platforms, retailers, and consumers that shopping has always been, at its core, a deeply social activity. Long before Instagram Shopping or WhatsApp Business, people turned to friends for recommendations, showed off new purchases, and sought validation from their social circles before making a buying decision. Digital platforms simply scaled this natural behavior and embedded it directly into the shopping interface (Liang & Turban, 2011). The result is an environment where a stranger's thoughtful review, a micro-influencer's unboxing video, or a friend's tagged post can move a consumer from casual interest to checkout within minutes.

The commercial stakes are significant. The global social commerce market was valued at USD 724.6 billion in 2022 and is projected to surpass USD 6.2 trillion by 2030 (Statista, 2023). India stands out as one of the most dynamic contributors to this expansion. With a massive millennial population that has come of age alongside the internet, a rapidly growing digital user base, and deep-rooted cultural norms of seeking peer advice and social validation before purchasing, the Indian context offers a particularly compelling setting for studying social commerce adoption (Dwivedi et al., 2022). Despite this potential, however, rigorous empirical research on the drivers of Indian consumers' social commerce purchase intentions remains limited.

A key challenge lies in theoretical fragmentation. While previous studies have explored important factors such as eWOM, social influence, trust, and perceived risk, they have often examined them in isolation. Few have integrated these elements into a unified framework that captures both the practical evaluation of platforms and the persuasive power of social information (Shu & Scott, 2014; Hajli et al., 2017). Two established theories are especially well-positioned to bridge this gap: the Technology Acceptance Model (TAM) (Davis, 1989), which explains how consumers assess the usefulness and ease of a technology, and the Elaboration Likelihood Model (ELM) (Petty & Cacioppo, 1986), which illuminates how the quality of persuasive cues—such as credible reviews—shapes attitudes. Used together, they provide a richer understanding than either could alone.

One particularly underexplored question is whether eWOM quality influences purchase intention directly or primarily through building trust. If the effect is fully mediated by trust—as we propose—then the pathway from review quality to buying behavior hinges on an important relational step. This distinction carries meaningful implications for both theory and platform design, especially regarding how reviews are encouraged and moderated (Hajli et al., 2017; Ismagilova et al., 2020).

In light of these gaps, this study has four main objectives: (1) to examine the roles of perceived usefulness and perceived ease of use from TAM in shaping social commerce purchase intention; (2) to assess how social influence and eWOM quality affect consumer trust and purchase intention; (3) to test whether consumer trust mediates the relationship between eWOM quality and purchase intention; and (4) to investigate the extent to which perceived risk dampens purchase intention. Through this work, we aim to advance the multi-theoretical understanding of social commerce while contributing much-needed empirical evidence from the Indian market.

The remainder of the paper is structured as follows. Section 2 develops the theoretical background and hypotheses. Section 3 outlines the research design and methodology. Section 4 presents the findings. Sections 5 and 6 discuss theoretical and practical implications, and Section 7 concludes.

2. Theoretical Background and Hypothesis Development

2.1 Social Commerce: What It Is and Why It Matters Theoretically

Social commerce can be best understood as electronic commerce enhanced by social media features—ratings, reviews, referrals, community discussions, and social network integration—that are seamlessly woven into the shopping journey (Liang & Turban, 2011). This goes beyond simply adding social tools. It reflects a fundamental shift in how we view online purchasing: not as a solitary, purely cognitive act, but as a process embedded in social context, community norms, and interpersonal influence (Hajli, 2015; Wang & Zhang, 2012). When consumers read dozens of reviews, check seller verification badges, or notice that several friends have bought the same product, they are participating in social commerce.

This shift has real consequences. Platforms that effectively incorporate social features tend to see higher purchase frequency, larger order values, and greater brand loyalty than traditional e-commerce sites (Cheng et al., 2019; Shu & Scott, 2014). Understanding the psychological mechanisms behind these outcomes is therefore important for both scholars and practitioners.

Various theoretical frameworks have been applied to social commerce, including TAM (Davis, 1989), the Theory of Planned Behaviour (Ajzen, 1991), Social Support Theory (Hajli et al., 2017), and ELM (Petty & Cacioppo, 1986). This study integrates TAM and ELM because they complement each other effectively. TAM addresses the utilitarian question—*Is this platform useful and easy to use?*—while ELM focuses on the persuasive dimension—*How does the quality of social information shape my confidence?* Together, they capture both the functional and social-cognitive aspects of social commerce adoption (Zhang & Benyoucef, 2016; Cheng et al., 2019).

2.2 The Technology Acceptance Model and Social Commerce Adoption

Davis (1989) introduced TAM to explain technology adoption through two core constructs: perceived usefulness (PU), the belief that a system will enhance performance or outcomes, and perceived ease of use (PEOU), the belief that it will require minimal effort. The model has demonstrated strong explanatory power across contexts, including social commerce.

In this setting, PU reflects whether consumers believe platforms like Instagram Shopping help them save time, access better information, or make wiser decisions. PEOU captures how intuitive and effortless the platform feels. Empirical studies consistently support these relationships. Cheng et al. (2019) identified PU as the strongest predictor of purchase intention among Chinese users, while similar patterns appear in South and Southeast Asian mobile commerce research (Islam et al., 2021; Alalwan et al., 2020). These findings lead to the following hypotheses:

H1: Perceived usefulness will have a significant positive effect on social commerce purchase intention. **H2:** Perceived ease of use will have a significant positive effect on perceived usefulness.

2.3 eWOM Quality and the Road to Consumer Trust

When consumers read reviews on social commerce platforms, they are not just gathering product details—they are judging the credibility of strangers' experiences. This is where eWOM quality becomes critical. Electronic word-of-mouth (eWOM) includes any positive or negative consumer statements about products or companies shared online (Hennig-Thurau et al., 2004). On social commerce sites, it appears as reviews, ratings, Q&A sections, and influencer content, and it ranks among the most influential information sources in purchase decisions (Ismagilova et al., 2020).

Not all reviews carry equal weight. High-quality eWOM—informative, accurate, detailed, and credible—triggers what ELM terms *central route processing*: thoughtful, effortful evaluation that leads to stronger and more lasting attitude change (Petty & Cacioppo, 1986). Research shows that review accuracy, completeness, and relevance are powerful drivers of trust (Filieri et al., 2018; Ismagilova et al., 2020). In India, where institutional consumer protections are often perceived as weaker, credible peer reviews may play an even more vital role in building trust (Sharma & Crossler, 2014).

H3: Social influence will have a significant positive effect on social commerce purchase intention.
H4: eWOM quality will have a significant positive effect on consumer trust in social commerce platforms.

2.4 Trust: The Gateway to Purchase

Trust remains one of the most robust constructs in consumer behavior research. In social commerce, it represents a consumer's willingness to rely on a platform and its sellers, based on expectations of competence and good intent (McKnight et al., 2002). It helps bridge the gap between what is seen on a screen and the actual product received.

Trust is especially important in social commerce because transactions often involve unfamiliar sellers on platforms originally built for social interaction rather than commerce. Institutional safeguards are frequently limited, making trust dependent on signals such as review quality, seller reputation, and community engagement (Gefen et al., 2003; Hajli et al., 2017). Studies consistently show a strong link between trust and purchase intention (Pavlou, 2003; Hajli et al., 2017; Lim et al., 2022).

H5: Consumer trust will have a significant positive effect on social commerce purchase intention.
H6: Perceived risk will have a significant negative effect on social commerce purchase intention.
H7: The relationship between eWOM quality and purchase intention will be fully mediated by consumer trust.

2.5 Social Influence: Shopping Is a Collective Act

In India, where consulting family and friends before a significant purchase is both common and culturally expected, social influence emerges as a particularly powerful driver. Defined as the perception that important others endorse a behavior (Ajzen, 1991; Venkatesh et al., 2003), social influence operates through peer recommendations, visible network activity, and influencer modeling.

India's collectivist cultural orientation, combined with high social media usage among millennials and platform features that make peer behavior highly visible, strengthens this effect (Dwivedi et al., 2022; Wang et al., 2022; Cheng et al., 2019).

2.6 Perceived Risk: Why Consumers Hesitate

Even with strong social signals, many consumers hesitate. Concerns about product quality, payment security, delivery, or returns constitute perceived risk—the subjective assessment of potential losses (Bauer, 1960; Peter & Ryan, 1976). Because many social commerce transactions lack robust institutional protections, perceived risk can be particularly salient (Forsythe et al., 2006; Lim et al., 2022). This highlights the need for platforms to address risk directly rather than relying solely on trust-building.

3. Research Methodology

3.1 Research Design

This study employed a quantitative, cross-sectional survey design within a positivist paradigm, which is well-suited for testing hypothesized relationships and drawing generalizable insights (Saunders et al., 2019). Ethical approval was secured from the institutional review board, and all participants provided informed consent. Participation was voluntary and anonymous.

3.2 Sample and Data Collection

The target population consisted of Indian millennials (aged 21–40) who had used at least one social commerce platform (Instagram Shopping, Facebook Marketplace, Pinterest, or WhatsApp Business) and made at least one platform-influenced purchase in the previous six months. This group was selected because millennials lead social commerce adoption in India and best reflect the social and digital behaviors central to the study (IAMAI, 2023).Data were collected via a structured online questionnaire using Qualtrics Audience, supplemented by purposive snowball sampling on social media. From 450 distributed surveys, 401 were returned (89.1% response rate). After screening for completeness and attention checks, 387 valid responses remained. A power analysis confirmed the sample size was sufficient to detect medium effects with high statistical power.Table 1 Respondent Demographic Profile (N = 387) Characteristic	Frequency	Percentage
Gender: Female	217	54.1%
Gender: Male	183	45.9%
Age: 21–25 years	117	28.4%
Age: 26–35 years	178	43.2%
Age: 36–40 years	81	19.7%
Age: 41–45 years	36	8.7%
Education: Undergraduate	86	20.9%
Education: Postgraduate	277	67.3%
Education: Doctoral	49	11.8%
Purchase frequency: Weekly or more	295	71.6%
Purchase frequency: Monthly	117	28.4%

Note. Source: Primary survey data. Percentages may not sum to 100 due to rounding.

3.3 Measurement Instruments

All constructs were measured using established multi-item reflective scales adapted from prior studies in social commerce, information systems, and marketing. Respondents rated each item on a seven-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree).

Perceived Usefulness (four items) and Perceived Ease of Use (three items) were adapted from Davis (1989) and Cheng et al. (2019). Social Influence (four items) drew from Venkatesh et al. (2003), while eWOM Quality (four items) was based on Ismagilova et al. (2020) and Filieri et al. (2018). Consumer Trust (five items) used the Web Trust Scale by McKnight et al. (2002), Purchase Intention (three items) came from Dodds et al. (1991), and Perceived Risk (four items) was adapted from Forsythe et al. (2006) and Sharma and Crossler (2014).

Before launching the full survey, the scales were reviewed by three digital marketing academics and pilot-tested with 25 participants from the target group. Small wording changes were made to better suit the social commerce context—such as shifting generic technology references to platform-specific language—while keeping the core meaning and structure of each construct intact.

3.4 Controlling for Common Method and Non-Response Bias

Several steps were taken during survey design to minimize common method bias (CMB). Predictor and outcome variables were separated into different sections, item order was randomized for half the respondents, and participants were reminded that there were no right or wrong answers (Podsakoff et al., 2003). Statistically, Harman's single-factor test showed that the largest factor explained only 22.7% of the variance—well below the 50% threshold indicating serious concern. A common latent factor analysis also revealed negligible differences in loadings ($\Delta CFI < 0.02$). These checks suggest that common method bias is not a major issue in this dataset.

Non-response bias was evaluated using the wave analysis approach by comparing the first 30% and last 30% of respondents across key demographics (Armstrong & Overton, 1977). No significant differences were found (all $p > 0.05$), indicating that early and late respondents were similar and that non-response bias is unlikely to have meaningfully affected the results.

3.5 Analytical Approach

Data were analyzed using SmartPLS 4.0 (Ringle et al., 2022) following the standard two-stage procedure for partial least squares structural equation modeling (PLS-SEM). First, the measurement model was assessed for reliability and validity. In the second stage, the structural model was evaluated using bias-corrected bootstrapping with 5,000 resamples to generate path coefficients, confidence intervals, R^2 values, effect sizes (f^2), and predictive relevance (Q^2 using blindfolding with omission distance of 7). Mediation was tested following Zhao et al.'s (2010) framework, where an indirect effect is considered significant if its bootstrapped confidence interval does not include zero.

4. RESULTS

4.1 Measurement Model

Table 2 presents the measurement model results. All constructs showed strong reliability, with Cronbach's alpha values ranging from 0.80 to 0.91 and composite reliability (CR) from 0.86 to 0.94. Convergent validity was also satisfactory, with average variance extracted (AVE) values between 0.64 and 0.79, and all item loadings above 0.70 (ranging from 0.70 to 0.94). These results confirm that the scales are reliable and valid.

Table 2 Measurement Model: Reliability and Convergent Validity Statistics

Construct	α	CR	AVE	Factor Loadings
Perceived Usefulness (PU)	0.88	0.91	0.73	0.74–0.91
Perceived Ease of Use (PEOU)	0.84	0.89	0.67	0.71–0.87
Social Influence (SI)	0.82	0.87	0.65	0.70–0.86
eWOM Quality (eQ)	0.86	0.90	0.69	0.72–0.89
Consumer Trust (CT)	0.91	0.94	0.79	0.78–0.94
Purchase Intention (PI)	0.85	0.90	0.75	0.75–0.91
Perceived Risk (PR)	0.80	0.86	0.64	0.70–0.84

Note. α = Cronbach's Alpha; CR = Composite Reliability; AVE = Average Variance Extracted. All individual item loadings significant at $p < 0.001$.

4.2 Discriminant Validity

Table 3 shows the Heterotrait-Monotrait (HTMT) ratios. All values fell between 0.29 and 0.74, below the recommended threshold of 0.85 (Henseler et al., 2015). The highest ratio (0.74 between eWOM Quality and Consumer Trust) aligns with the expected theoretical relationship due to the hypothesized mediation. Overall, discriminant validity is well established.

Table 3 Heterotrait-Monotrait (HTMT) Matrix for Discriminant Validity (N = 387)

Construct	PU	PEOU	SI	eQ	CT	PI	PR
PU	—						
PEOU	0.72	—					
SI	0.54	0.48	—				
eQ	0.61	0.55	0.52	—			
CT	0.67	0.58	0.60	0.74	—		
PI	0.71	0.62	0.58	0.68	0.72	—	
PR	0.33	0.29	0.37	0.41	0.44	0.38	—

Note. HTMT = Heterotrait-Monotrait Ratio. Values < 0.85 confirm discriminant validity (Henseler et al., 2015). PU = Perceived Usefulness; PEOU = Perceived Ease of Use; SI = Social Influence; eQ = eWOM Quality; CT = Consumer Trust; PI = Purchase Intention; PR = Perceived Risk.

4.3 Structural Model and Hypothesis Testing

The structural model demonstrated good fit (SRMR = 0.058) and strong explanatory power, accounting for 54.6% of the variance in purchase intention ($R^2 = 0.546$) and 49.3% in consumer trust ($R^2 = 0.493$). Q^2 values of 0.41 and 0.37 further indicated meaningful predictive relevance.

As shown in Table 4, all hypotheses were supported. Perceived usefulness had a strong positive effect on purchase intention (H1: $\beta = 0.38$, $p < 0.001$). Perceived ease of use significantly influenced perceived usefulness (H2: $\beta = 0.44$, $p < 0.001$). Social influence positively predicted purchase intention (H3: $\beta = 0.29$, $p < 0.001$), reflecting the cultural importance of peer input in India. eWOM quality strongly shaped consumer trust (H4: $\beta = 0.41$, $p < 0.001$), which in turn drove purchase intention (H5: $\beta = 0.35$, $p < 0.001$). Perceived risk negatively affected purchase intention (H6: $\beta = -0.24$, $p < 0.001$). Finally, H7 was supported with full mediation: the indirect effect of eWOM quality on purchase intention via trust was significant (indirect $\beta = 0.17$, 95% CI [0.11, 0.24]), while the direct effect became non-significant.

Table 4 Structural Model Path Coefficients and Hypothesis Testing

Hypothesis & Path	β	t-stat	p-value	95% CI	f²	Result
H1: PU → Purchase Intention	0.38	7.82	< 0.001	[0.29, 0.47]	0.11	Supported
H2: PEOU → PU	0.44	9.17	< 0.001	[0.35, 0.53]	0.14	Supported
H3: SI → Purchase Intention	0.29	5.63	< 0.001	[0.19, 0.39]	0.07	Supported
H4: eQ → Consumer Trust	0.41	8.44	< 0.001	[0.32, 0.51]	0.12	Supported
H5: CT → Purchase Intention	0.35	6.98	< 0.001	[0.26, 0.45]	0.09	Supported
H6: PR → Purchase Intention	−0.24	4.71	< 0.001	[−0.34, −0.14]	0.05	Supported
H7: eQ → PI (via CT) — indirect	0.17	4.88	< 0.001	[0.11, 0.24]	—	Supported

Note. β = standardized path coefficient; t-statistics from bias-corrected bootstrapping (5,000 subsamples); CI = 95% confidence interval; f^2 = effect size. PU = Perceived Usefulness; PEOU = Perceived Ease of Use; SI = Social Influence; eQ = eWOM Quality; CT = Consumer Trust; PI = Purchase Intention; PR = Perceived Risk.

5. DISCUSSION

5.1 What This Study Adds to Theory

This study makes three notable theoretical contributions. First, it successfully integrates TAM and ELM into a single model of social commerce adoption. While these frameworks have been used separately before, their combination here captures both the practical evaluation of platform usefulness and the persuasive role of social information—two distinct but interconnected processes in social commerce.

Second, the full mediation finding is particularly insightful. eWOM quality does not directly drive purchases; instead, it builds trust, which then influences buying behavior. This suggests that many earlier studies may have overstated the direct effect of reviews by not accounting for trust as the key mechanism. The result refines existing social support frameworks (e.g., Hajli et al., 2017) by pinpointing where review quality fits in the process.

Third, the study adds to the limited literature on social commerce in emerging markets like India. The relatively strong role of social influence aligns with collectivist cultural patterns and highlights that drivers of adoption can vary across contexts.

5.2 Implications for Practice

The results offer clear guidance for platforms and brands in India. Review quality emerged as the strongest predictor of trust ($\beta = 0.41$), suggesting that investments in better review systems—such as authenticity checks, helpfulness ratings, and structured templates—should be prioritized as core trust-building tools rather than cosmetic features.

The negative effect of perceived risk ($\beta = -0.24$) highlights the need for visible risk-reduction measures, including clear buyer protections, secure payment badges, and straightforward return policies tailored to local contexts.

Finally, the importance of social influence supports focused influencer strategies, particularly with micro-influencers whose endorsements feel more authentic and community-oriented.

5.3 Limitations and Where to Go From Here

Like all studies, this one has limitations. Its cross-sectional design limits causal inferences and insights into how relationships evolve over time. Longitudinal or experimental studies would be valuable next steps. The focus on Indian millennials also restricts generalizability to other age groups or countries. Future research could examine actual purchase behavior instead of intentions and explore the growing impact of AI-generated content on trust and decision-making.

6. CONCLUSION

At its heart, social commerce succeeds because people tend to trust other people more than brands. The findings of this study reinforce that idea. Indian millennial consumers are more likely to buy when platforms feel useful, when their social circle is involved, when they trust the seller, and when reviews are credible and detailed. Unresolved risks, however, can still hold them back.

The key insight—that review quality influences purchases entirely by building trust—suggests platforms should view high-quality reviews as a long-term trust investment rather than a quick conversion tool. By integrating TAM and ELM, this study offers a more complete picture of why consumers embrace (or hesitate with) social commerce. The model explains a substantial portion of purchase intention and trust, providing both theoretical depth and practical value for this important market.

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