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The Influence of AI-Curated Electronic Word-of-Mouth and Organic Electronic Word-of-Mouth on Purchase Decisions with the Role of Customer Trust Mediation Among Generation Z TikTok Store Users in Surabaya

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ABSTRACT

The rapid development of artificial intelligence (AI) is increasingly shaping the information consumers receive and their decision-making on social commerce platforms. This study compares the effects of AI-curated electronic word-of-mouth (e-WOM), in which consumer-generated information is selected and personalized by algorithms, and organic e-WOM, which is voluntarily shared based on consumer experiences, on purchase decisions among Generation Z TikTok Shop users in Surabaya. It also examines customer trust as a mediating variable, using the Technology Acceptance Model (TAM) as the theoretical foundation. A quantitative survey of 229 respondents was analyzed using PLS-SEM with SmartPLS 4. The results show that AI-curated e-WOM significantly affects customer trust ($\beta = 0.539$; $p < 0.001$) and purchase decisions ($\beta = 0.368$; $p < 0.001$), whereas organic e-WOM significantly affects purchase decisions ($\beta = 0.142$; $p = 0.009$) but not customer trust ($\beta = 0.148$; $p = 0.060$). Customer trust significantly influences purchase decisions ($\beta = 0.462$; $p < 0.001$) and mediates the relationship between AI-curated e-WOM and purchase decisions ($\beta = 0.249$; $p < 0.001$), but not between organic e-WOM and purchase decisions ($\beta = 0.069$; $p = 0.061$). These findings indicate that AI-curated e-WOM builds customer trust while influencing purchases, whereas organic e-WOM directly influences purchase decisions without significantly strengthening trust. The study contributes to digital marketing literature by demonstrating distinct mechanisms through which algorithmically curated and organic e-WOM shape consumer behavior in social commerce.

Contribution to Sustainable Development Goals (SDGs):

SDG 7: Affordable and Clean Energy

SDG 9: Industry, Innovation and Infrastructure

SDG 12: Responsible Consumption and Production

1. INTRODUCTION

1.1. Research Background

Social commerce integrates commercial transactions with social interaction, user-generated content, and platform-mediated recommendations. Its design therefore changes not only where consumers buy but also how they discover, evaluate, and validate

product information [1]. This issue is particularly salient on TikTok Shop, where product discovery is embedded in short-form video, live commerce, comments, and algorithmically personalized feeds.

Electronic word-of-mouth (e-WOM) can reduce information asymmetry and influence consumers' purchase decisions by shaping the perceived usefulness, relevance, and credibility of product information [3]. Recent evidence also indicates that information quality, credibility, and quantity remain relevant to



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online purchase intentions among Generation Z consumers [5]. However, much of the existing e-WOM literature treats digital word of mouth as a relatively homogeneous construct, despite the increasing role of platform algorithms in determining which consumer-generated messages become visible, in what order, and to whom.

This study distinguishes the recommender system from its informational outcome. A recommender system represents the algorithmic infrastructure that predicts, ranks, and personalizes content, whereas AI-curated e-WOM refers to consumer-generated product information that users encounter after being selected, prioritized, or personalized through such algorithmic processes. In contrast, organic e-WOM refers to voluntary, experience-based product information communicated by consumers without algorithmic personalization as the primary mechanism through which the information is presented. Although the visibility of organic e-WOM may still be influenced by platform algorithms, its defining characteristic in this study lies in its consumer-originated and non-personalized informational pathway. This distinction matters because algorithmic relevance and interpersonal authenticity may build consumer trust through different mechanisms.

From a technology-acceptance perspective, the Technology Acceptance Model (TAM) provides an overarching theoretical foundation for understanding the technological context in which AI-supported information is delivered and consumed. TAM proposes that **perceived usefulness and perceived ease of use shape technology acceptance** [8]. However, these core TAM constructs are not operationalized in the present study because the research does not examine technology acceptance as its empirical outcome. Instead, TAM provides the theoretical context for understanding the role of AI-enabled technology, while the empirical relationships are developed from the literature on e-WOM, customer trust, and purchase decision.

1.2. Research Gap and Contribution

Prior studies establish that e-WOM, trust, and platform characteristics affect social-commerce behavior, but three unresolved gaps remain. Theoretically, few studies model algorithmic curation and consumer-originated communication as distinct stimuli operating through the same psychological mechanism. Empirically, evidence is limited on whether trust carries the effects of both information routes among Generation Z users in an emerging-economy city. Practically, platforms and sellers lack clear evidence on whether personalization or peer-authored content should be prioritized when designing trustworthy product discovery.

This study addresses those gaps by Ref. (1) operationally separating AI-curated from organic e-WOM; (2) testing customer trust as a mediator of both routes; and (3) examining a bounded sample of Generation Z TikTok Shop users in Surabaya. Surabaya provides a relevant urban social-commerce setting, while the bounded context avoids claiming national representativeness. The contribution is not a formal test of whether one coefficient is statistically larger than another; rather, it identifies distinct direct and indirect patterns that can inform theory and platform practice

1.3. Research Objective

This study aims to analyze the effect of hydrochloric acid (HCl) concentration variations on the purity of silica extracted from coal fly ash, evaluate the effect of sonication time on the particle size of the resulting silicon, and determine the optimum conditions for the extraction and sonication processes to obtain high-purity silica and nanosilicon with the best characteristics.

1.4. Literature Review and Hypothesis Development

The study uses the Stimulus–Organism–Response (S-O-R) framework as its primary explanatory foundation. AI-curated and organic e-WOM are information stimuli, customer trust represents the internal organism state, and the purchase decision is the behavioral response. The Technology Acceptance Model (TAM) is retained only as a complementary lens for understanding why algorithmically organized information may be experienced as useful or easy to process; its core constructs are neither measured nor tested in the structural model.

1.4.1. Theoretical Foundation: S-O-R and the Supporting Role of TAM

The Stimulus–Organism–Response (S-O-R) framework provides the primary explanatory foundation for this study. Originally proposed by Ref. [6] the S-O-R framework explains how external environmental stimuli influence individuals' internal cognitive or affective states, which subsequently shape behavioral responses. In social commerce, information, technological, and social cues can function as stimuli that influence consumers' internal evaluations, trust, and subsequent behavioral responses [1]. In the present study, AI-curated e-WOM and organic e-WOM are conceptualized as external information stimuli, customer trust represents the consumer's internal evaluative state, and purchase decision represents the resulting behavioral response.

This theoretical mapping provides the basis for examining the mediation mechanism proposed in the study. AI-curated e-WOM may provide information that is selected, prioritized, and personalized according to users' characteristics and behavioral patterns, potentially increasing the perceived relevance and accessibility of product information. In contrast, organic e-WOM provides experience-based information and social validation originating from other consumers. Both forms of e-WOM may influence purchase decisions directly, while their effects may also operate indirectly by shaping consumers' trust in the information, product, seller, or platform.

The Technology Acceptance Model (TAM) is retained as a complementary theoretical lens for contextualizing consumers' interaction with AI-enabled recommendation technology. TAM proposes that perceived usefulness and perceived ease of use are fundamental determinants of technology acceptance [8]. In the present study, TAM is not employed as the empirical explanatory model because perceived usefulness and perceived ease of use are not included as research constructs or operationalized in the measurement instrument. Accordingly, the structural model estimates no TAM pathways. Instead, TAM provides contextual support for understanding why consumers may be receptive to information organized and delivered through algorithmically supported recommendation systems.

Taken together, S-O-R explains the empirical stimulus–trust–purchase mechanism tested in this study, whereas TAM provides complementary theoretical context for consumers' interaction

with AI-enabled information delivery. This distinction ensures that the theoretical claims remain aligned with the constructs actually measured and the relationships empirically tested in the research model.

1.4.2. *AI Curated E-WOM Electronic (Word of Mouth)*

AI-curated e-WOM is defined here as consumer-generated product information that a platform's AI recommender system selects, ranks, and personalizes for a particular user. The AI does not author the e-WOM; it controls exposure to existing reviews, videos, comments, or other consumer content. This operational boundary distinguishes the construct from an AI-generated recommendation and from the recommender system itself.

Algorithmic curation can increase perceived relevance by matching content to behavioral traces, prior interactions, and inferred preferences. This may reduce search costs and cognitive overload, but it can also create concerns about opacity, manipulation, and bias. Research on AI acceptance shows that trust is central to users' willingness to rely on AI-enabled technologies, while explainability and transparency help users evaluate whether reliance is warranted [10].

In human-AI interaction, perceived competence alone is insufficient: users also evaluate whether outputs are understandable, controllable, and aligned with their goals [11]. Accordingly, AI-curated e-WOM may encourage purchase when the selected information appears relevant and credible, and may build trust when personalization is accompanied by consistent and transparent platform behavior.

On TikTok Shop, the recommender system can prioritize product videos, reviews, and comments based on search history and interaction patterns. When users perceive this curated information as useful and congruent with their needs, it can simplify product evaluation and increase confidence in a purchase. Thus, AI-curated e-WOM is expected to influence both the behavioral response and the trust mechanism.

1.4.3. *Organic E-Wom Electronic (Word of Mouth)*

Organic e-WOM refers to voluntary, consumer-authored communication based on product or service experience rather than seller-authored or sponsored promotion. It includes reviews, comments, and user videos perceived as spontaneous and experience based. Unlike algorithmic curation, its persuasive value is primarily associated with source credibility, diagnosticity, and social proof. The term does not imply that platform distribution is entirely free from algorithms. E-WOM research shows that information quality, credibility, usefulness, and the receiver's need for information shape information adoption and purchase intention [3].

Evidence among Generation Z similarly indicates that credible and useful social-media e-WOM supports online purchase intention [5]. Organic e-WOM may therefore reduce uncertainty by providing concrete accounts of product performance and use. On TikTok Shop, users encounter experience-based product videos and comments from other consumers. Positive and diagnostic content can affect a purchase directly through social proof; however, anonymous sources, commercial incentives, information overload, and suspected manipulation may weaken its capacity to build trust. These competing mechanisms make empirical testing necessary.

1.4.4. *Customer Trust*

Customer trust is the consumer's willingness to rely on a seller, platform, or information source based on perceived competence, integrity, and benevolence. Trust is especially important in digital transactions because consumers cannot inspect products or sellers directly and must tolerate uncertainty about information accuracy, fulfilment, and data use [13].

In social commerce, trust can be directed toward multiple objects: the platform, seller, recommender system, or consumer-generated information. This construct captures customers' overall confidence that the information and transaction environment is dependable. AI-curated e-WOM may build that confidence through consistent relevance, whereas organic e-WOM may build it through authentic peer experience.

Algorithmic trust should not be treated as automatic acceptance. Explainability, transparency, feedback, and user control help consumers calibrate reliance on AI recommendations [10]. If curation appears intrusive or commercially manipulative, personalization may reduce rather than increase trust. This conditional logic is important when interpreting a positive average effect.

Within the S-O-R framework, trust is the organism state that translates external information cues into a response. It can reduce perceived risk and increase confidence that acting on a recommendation will produce an acceptable outcome. Accordingly, trust is expected to influence purchase decisions and may mediate the effects of both e-WOM routes.

The two routes nonetheless differ conceptually. Trust in AI-curated e-WOM depends on perceived algorithmic competence and responsible curation, whereas trust in organic e-WOM depends more heavily on source authenticity and message credibility. Comparing their indirect effects can reveal whether the same psychological mechanism operates across both forms of information exposure.

1.4.5. *Purchase Decision*

A purchase decision is the consumer's selection of a product and commitment to buy after evaluating available alternatives and information [19]. In social commerce, product attributes interact with information quality, recommender-system cues, social influence, and trust. Consequently, a purchase decision may follow a deliberative trust-building process or a more immediate response to relevant information and social proof. For Generation Z TikTok Shop users, product discovery, evaluation, and purchase can occur within the same content stream. Recent studies report that e-WOM, perceived value, ease of use, and trust are associated with purchase decisions in TikTok Shop contexts [15]. These findings support including both information stimuli and trust, while the present study advances the comparison between algorithmically curated and organic e-WOM.

2.6 Hypothesis Development

AI-curated e-WOM may strengthen customer trust because algorithmic selection can increase the relevance and accessibility of consumer-generated information. Prior research indicates that users' trust in AI-supported systems is influenced by perceived competence, transparency, and the relevance of algorithmic outputs [10]. In social-commerce environments, personalized information may therefore reduce information-search costs and

uncertainty, increasing confidence in the information encountered. Accordingly, this study proposes:

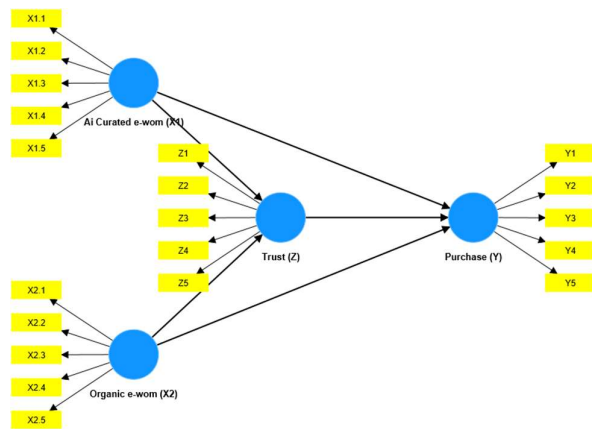


Figure 1. Conceptual Framework Model

Source: SmartPLS Output 4 (2026)

Based on this model, seven research hypotheses are formulated as follows:

H1: AI-curated e-WOM positively and significantly influences Purchase Decisions.

H2: Organic e-WOM positively and significantly influences the Purchase Decision.

H3: AI-curated e-WOM has a positive and significant influence on Customer Trust.

H4: Organic e-WOM positively and significantly affects Customer Trust.

H5: Customer Trust positively and significantly influences the Purchase Decision.

H6: Customer Trust mediates the relationship between AI-curated e-WOM and Purchase Decisions.

H7: Customer Trust mediates the relationship between organic e-WOM and Purchase Decision.

2. METHODOLOGY

2.1. Research Design

A cross-sectional quantitative survey examined the relationships among AI-curated e-WOM, organic e-WOM, customer trust, and

purchase decisions. The design tests associations within a theoretically specified model; because the data are cross-sectional and nonexperimental, the study interprets causal language cautiously.

The model was estimated with partial least squares structural equation modeling (PLS-SEM) in SmartPLS 4. PLS-SEM was selected because the study emphasizes prediction, includes latent reflective constructs, and tests indirect effects [18]. We assessed statistical significance using nonparametric bootstrapping.

2.2. Population and Sample

This study's population consists of Generation Z consumers who use TikTok Shop in Surabaya, Indonesia. Generation Z was chosen because this demographic is one of the most active user groups in social commerce, characterized by high digital literacy and frequent exposure to AI-based recommendation systems.

This study uses purposeful sampling techniques. Respondents are required to meet the following criteria: belong to Generation Z, have used TikTok Shop, have previously received AI-based product recommendations or product-related information on TikTok Shop, and have purchased or are considering buying products through TikTok Shop. We collected the data through a self-administered online questionnaire distributed via Google Forms for approximately one month (May 2026). We obtained 229 valid responses for the final analysis after excluding incomplete questionnaires. In terms of gender, the sample includes men and women aged 17 to 27 years.

The sample size is considered adequate for PLS-SEM analysis. According to Ref. [18], PLS-SEM is suitable for studies with relatively small to medium sample sizes and complex research models. In addition, the study meets the rule 10 times, which recommends that the minimum sample size should be at least ten times the number of the largest structural pathways directed to any endogenous construction. Since the maximum number of arrows pointing to a single construct in the proposed model is three, the recommended minimum sample size is 30 respondents. Therefore, the final sample of 229 respondents significantly exceeded the recommended minimum and provided sufficient statistical strength for hypothesis testing.

2.3. Instrument Measurement and Development

All constructs were measured using five-point Likert-type scales ranging from 1 (strongly disagree) to 5 (strongly agree). The instrument was adapted from established e-WOM, algorithmic trust, online trust, and consumer-decision literature and contextualized for TikTok Shop. Each reflective construct comprised five indicators, as evidenced by the reported measurement model.

Table 1. Constructs and measurement domains

Construct(five items each)	Operational domain	Indicator	Question	Indicative source
AI-curated e-WOM	Relevance, personalization, usefulness, and perceived credibility of algorithmically selected consumer information	Content relevance	The product content that appears on TikTok Shop is often in line with my interests	[10]
		Automatic recommendations	I often see products without looking for them	
		Personalization	The content that appears feels tailored to me	
		Algorithmic Exposure	Products often appear repeatedly on the homepage	
		Ease of understanding the product	Content helps me understand the product	
Organic e-WOM	Consumer-authored reviews, experience-based content, credibility, and information usefulness	Active search	I search for product information independently	[3]
		Read reviews	I read the comments before buying	
		Evaluation of information	I compared several reviews	
		Credibility	I trust my own search results more	
		Review-based decisions	Reviews influenced my decision	
Customer trust	Perceived competence, integrity, dependability, and transaction assurance	Trust of information	I trust the product information I see	[13]
		Reliability	Reliable product information	
		Confidence	I am confident in the products shown	
		A sense of security	I feel safe to buy	
		Trust recommendations	I believe the product recommendations	
Purchase decision	Product evaluation, choice, and commitment to purchase	Interest	I am interested in buying a product	[19]
		Info-based decisions	Information influenced my decisions	
		Purchase by recommendation	I bought because of the recommendation	
		Confidence in results	I am confident in my decision	
		Purchase intent	I intend to buy a product	

Source: SmartPLS Output 4 (2026)

Table 1: The final questionnaire should document the original item source, adaptation and translation procedure, expert review, pilot test, and complete item wording. These details are necessary for replication and content-validity assessment.

3. RESULT

3.1. Measurement Model Analysis Results (External Model)

The measurement model was evaluated to assess the validity and reliability of the research construct before testing the structural relationships between latent variables. Following the recommendations of [18], the evaluation consisted of convergent validity, discriminant validity, Mean Variance Extracted (AVE), Composite Reliability (CR), and Cronbach's Alpha. The following results, as shown in Figure 2, are from my Smart PLS research.

3.1.1. Indicator Reliability and Convergent Validity

Convergent validity is evaluated using the indicator's external loading value. According to Ref. [18], the indicator is considered valid when its loading value exceeds 0.70. As shown in Table 2, all measurement indicators have external loadings above the recommended threshold, indicating that each indicator represents its corresponding latent construct. Therefore, all indicators are retained for further analysis.

Table 2. Outer Loadings, Cronbach's Alpha, Composite Reliability, and AVE

Variable	Indicators	Loading	CA	CR	AVE
Ai Curated e-wom (X1)	X1.1	0.837	0.905	0.909	0.727
	X1.2	0.896			
	X1.3	0.899			
	X1.4	0.769			
	X1.5	0.857			
Organic e-wom (X2)	X2.1	0.887	0.916	0.927	0.749
	X2.2	0.894			
	X2.3	0.915			
	X2.4	0.810			
	X2.5	0.817			
Purchase (Y)	Y1	0.785	0.880	0.881	0.677
	Y2	0.866			
	Y3	0.837			
	Y4	0.813			
	Y5	0.810			
Trust (Z)	Z1	0.883	0.926	0.928	0.774
	Z2	0.902			
	Z3	0.896			
	Z4	0.808			
	Z5	0.906			

Source: SmartPLS Output 4 (2026)

All outer loadings range from 0.769 to 0.915 and exceed the recommended 0.70 threshold. Indicator reliability is therefore acceptable. Convergent validity is AVE values range from 0.677 to 0.765, exceeding 0.50 for all constructs. Together with the outer loadings, these results support convergent validity.

4.1.2 Discriminant Validity

Table 3 reports cross-loadings rather than HTMT values. Every indicator loads more strongly on its intended construct than on the other constructs, which provides preliminary evidence of discriminant validity. However, cross-loadings alone are not sufficient; report HTMT and its bootstrapped confidence interval as the primary assessment [17].

Table 3. Cross Loading

Indicators	AI Curated e-WOM (X1)	Organic e-WOM (X2)	Purchase (Y)	Trust (Z)
X1.1	0.837	0.464	0.603	0.514
X1.2	0.896	0.511	0.649	0.548
X1.3	0.899	0.564	0.674	0.569
X1.4	0.769	0.466	0.588	0.481
X1.5	0.857	0.576	0.656	0.565
X2.1	0.542	0.887	0.480	0.394
X2.2	0.571	0.894	0.558	0.449
X2.3	0.537	0.915	0.505	0.417
X2.4	0.368	0.810	0.377	0.291
X2.5	0.564	0.817	0.568	0.467
Y1	0.581	0.384	0.785	0.627
Y2	0.593	0.435	0.866	0.655
Y3	0.643	0.497	0.837	0.636
Y4	0.641	0.580	0.813	0.616
Y5	0.602	0.504	0.810	0.595
Z1	0.499	0.376	0.642	0.883
Z2	0.583	0.435	0.686	0.902
Z3	0.543	0.416	0.690	0.896
Z4	0.574	0.461	0.621	0.808
Z5	0.565	0.404	0.703	0.906

Source: SmartPLS Output 4 (2026)

The cross-loading pattern is consistent with construct distinctiveness. The manuscript no longer labels this table as convergent validity and does not claim that unreported HTMT values meet a threshold.

Table 4. Heterotrait-Monotrait Ratio (HTMT)

Indicators	AI Curated e-wom (X1)	Organic e-wom (X2)	Purchase (Y)
AI Curated e-wom (X1)			
Organic e-wom (X2)	0.654		
Purchase (Y)	0.833	0.638	
Trust (Z)	0.686	0.506	0.842

Source: SmartPLS Output 4 (2026)

Table 5. Criteria Fornell-Larcker

Indicators	AI Curated e-wom (X1)	Organic e-wom (X2)	Purchase (Y)	Trust (Z)
AI Curated e-wom (X1)	0.853			
Organic e-wom (X2)	0.607	0.866		
Purchase (Y)	0.745	0.585	0.823	
Trust (Z)	0.629	0.476	0.761	0.880

Source: SmartPLS Output 4 (2026)

The Fornell–Larcker criterion shows that the square root of AVE for each construct exceeds its correlations with other constructs, confirming adequate discriminant validity.

4.2 Structural Model Assessment

4.2.1 Coefficient of Determination (R^2)

R^2 evaluates the model's in-sample explanatory power for each endogenous construct. Table 6 presents the results.

Table 6. Coefficients of determination

Endogenous construct	R^2	Adjusted R^2
Purchase decision (Y)	0.708	0.705
Customer trust (Z)	0.410	0.405

Source: SmartPLS Output 4 (2026)

The R^2 value for customer trust is 0.410 (adjusted $R^2 = 0.405$), indicating that AI-curated and organic e-WOM jointly explain 41.0% of its variance. This represents moderate explanatory power in the present behavioral context. The R^2 value for purchase decision was 0.708 (adjusted $R^2 = 0.705$), indicating substantial in-sample explanatory power. Thus, the three predictors jointly explain 70.8% of purchase-decision variance, indicating substantial in-sample explanatory power. This statement concerns explanation and should not be interpreted as evidence of out-of-sample predictive performance.

4.2.2 Effect Sizes (f^2)

Effect sizes quantify each predictor's incremental contribution to an endogenous construct. Values around 0.02, 0.15, and 0.35 are conventionally interpreted as small, medium, and large, respectively [18].

Table 7. Effect sizes

Predictor	Purchase decision	Customer trust
AI-curated e-WOM (X1)	0.223	0.311
Organic e-WOM (X2)	0.043	0.024
Purchase decision (Y)		
Customer trust (Z)	0.432	

Source: SmartPLS Output 4 (2026)

AI-curated e-WOM has medium effects on purchase decisions ($f^2 = 0.223$) and customer trust ($f^2 = 0.311$). Organic e-WOM has small effects on purchase decisions ($f^2 = 0.043$) and trust ($f^2 = 0.024$). Customer trust has a large effect on purchase decisions ($f^2 = 0.432$). These classifications replace the earlier general description and follow [18].

4.3 Hypothesis Testing: Direct & Indirect Effects

We evaluated the hypotheses using nonparametric bootstrapping in SmartPLS 4. The path coefficient (β), t-statistic, and p-value were used to assess the direction and statistical significance of each hypothesized relationship. A two-tailed criterion of $t > 1.96$ and $p < 0.05$ was applied. Figure 2 displays the bootstrapped

structural model. The figure should be exported directly from SmartPLS at publication resolution, with legible coefficients, t statistics, and p values.

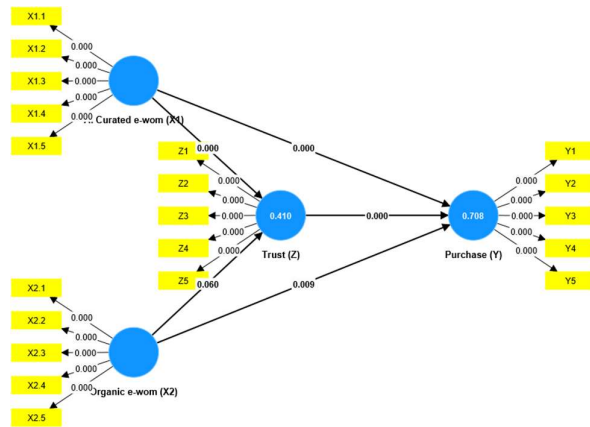


Figure 2. Bootstrapping Results of Structural Models
Source: SmartPLS Output 4 (2026)

Table 8 shows that H1, H2, H3, and H5 are supported, whereas H4 is not supported at the 5% level. The larger coefficient for AI-curated e-WOM is descriptive; a formal coefficient-difference test would be required to claim that one effect is statistically stronger than another.

Table 8. Direct and Indirect Effects of the Structural Model

Hipotesis	Path	b	T	p	Results
H1	AI-curated e-WOM → Purchase	0.348	6.273	<0.001	Supported
H2	Organic e-WOM → Purchase	0.142	2.625	0.009	Supported
H3	AI-curated e-WOM → Trust	0.539	6.945	<0.001	Supported
H4	Organic e-WOM → Trust	0.148	1.879	0.060	Not supported
H5	Trust → Purchase	0.462	8.720	<0.001	Supported
H6	AI-curated e-WOM → Trust → Purchase	0.249	5.254	<0.001	Supported
H7	Organic e-WOM → Trust → Purchase	0.069	1.874	0.061	Not supported

Source: SmartPLS Output 4 (2026)

The direct-effect results show that AI-curated e-WOM positively and significantly affects purchase decision ($\beta = 0.368$, $t = 6.273$, $p < 0.001$), supporting H1. Organic e-WOM also has a positive and significant direct effect on purchase decision ($\beta =$

0.142 , $t = 2.625$, $p = 0.009$), supporting H2. AI-curated e-WOM positively and significantly affects customer trust ($\beta = 0.539$, $t = 6.945$, $p < 0.001$), supporting H3, whereas the effect of organic e-WOM on customer trust is positive but not statistically significant ($\beta = 0.148$, $t = 1.879$, $p = 0.060$), leading to rejection of H4. Customer trust has a positive and significant effect on purchase decision ($\beta = 0.462$, $t = 8.720$, $p < 0.001$), supporting H5.

The mediation results further show that customer trust significantly mediates the relationship between AI-curated e-WOM and purchase decision ($\beta = 0.249$, $t = 5.254$, $p < 0.001$), supporting H6. Because the corresponding direct effect is also positive and significant ($\beta = 0.368$, $t = 6.273$, $p < 0.001$), the mediation is complementary partial mediation. In contrast, the indirect effect of organic e-WOM through customer trust is not statistically significant ($\beta = 0.069$, $t = 1.874$, $p = 0.061$), so H7 is rejected. Nevertheless, the direct effect of organic e-WOM on purchase decision remains significant ($\beta = 0.142$, $t = 2.625$, $p = 0.009$), indicating that organic e-WOM influences purchase decision primarily through a direct rather than trust-mediated pathway.

4. DISCUSSION

The findings reveal two distinct information-processing routes in AI-enabled social commerce. AI-curated e-WOM affects purchase decisions both directly and indirectly through trust, whereas organic e-WOM affects purchase decisions directly but not through trust. This pattern refines research that treats e-WOM as a single undifferentiated cue and is consistent with the S-O-R proposition that different stimuli can activate different organism states before producing a response.

5.1 AI-Curated e-WOM Builds Customer Trust

AI-curated e-WOM positively affects customer trust ($\beta = 0.539$, $p < 0.001$). A plausible mechanism is informational fit: ranking based on prior behavior can surface reviews and product content that users perceive as timely and personally relevant. This reduces search effort and helps users organize an otherwise excessive information environment. The finding is consistent with research showing that trust is central to AI acceptance and that users evaluate algorithmic competence when deciding whether to rely on an AI-enabled system [11].

The result should not be interpreted as unconditional endorsement of opaque personalization. Explainable-AI research suggests that transparency, comprehensibility, and opportunities to recognize bias help users calibrate trust [10]. Thus, relevance may explain the positive average relationship, while transparency and user control likely serve as boundary conditions for sustainable trust. The study extends the S-O-R account by identifying algorithmically organized consumer information as a distinct technological-information stimulus.

5.2 Organic e-WOM Doesn't Always Build Customer Trust

Findings H4 showed that organic e-WOM had no statistically significant effect on Customer Trust ($\beta = 0.148$; $t = 1.879$; $p = 0.060$). These results show that, in the context of TikTok Shop, consumer-generated reviews alone are not enough to build customer trust. One possible explanation is information overload among Generation Z consumers. TikTok Shop users are

constantly exposed to a large volume of product reviews, comments, promotional videos, and influencer-generated content, making it increasingly difficult to identify truly relevant and trustworthy information. As a result, consumers tend to rely more on algorithmically selected recommendations that reduce cognitive effort and present information that suits their personal preferences. These findings align with the Human AI Interaction perspective, which shows that users increasingly collaborate with intelligent systems when evaluating digital information and making purchasing decisions [20]. Similarly, recent studies on Algorithmic Trust argue that consumers are more willing to rely on AI-generated recommendations when they perceive them to be accurate, transparent, and relevant [10].

These findings differ from previous studies that generally reported a positive relationship between organic e-WOM and consumer trust [21] [22]. This difference may be explained by the rapidly evolving nature of AI-based social commerce, where personalised recommendations are increasingly competing with traditional peer-generated reviews. Therefore, while organic e-WOM continues to provide valuable social proof, its ability to directly reinforce customer trust appears to be declining in an environment where algorithmic recommendation systems dominate consumer information exposure.

From a theoretical perspective, these findings challenge the traditional assumption that all forms of electronic word-of-mouth communication affect consumer trust similarly. Instead, the study shows that the mechanisms that generate and deliver information play an important role in shaping trust. In AI-based social commerce, trust is influenced not only by interpersonal communication but also by consumer trust in intelligent recommendation systems that are able to filter and personalize information according to individual needs.

5.3 Customer Trust as the Strongest Predictor of Purchase Decision

Findings H5 showed that Customer Trust had a positive and significant effect on Purchase Decisions ($\beta = 0.462$; $t = 8.720$; $p < 0.001$), suggesting that trust was the strongest determinant of purchasing behavior among TikTok Shop Generation Z users. These findings suggest that while consumers are exposed to a variety of digital information sources, including AI-curated recommendations and organic consumer reviews, purchasing decisions ultimately depend on whether they perceive the information, vendors, and platforms as trustworthy. In a digital environment characterized by uncertainty and limited opportunities for direct product evaluation, trust serves as a psychological mechanism that reduces perceived risk and increases consumer confidence in completing online transactions.

These findings are consistent with previous studies that emphasized the important role of trust in social commerce. Ref. [13] argue that trust allows consumers to overcome uncertainty in digital transactions by increasing trust in both information sources and online vendors. Similarly, [22] show that customer trust significantly influences consumers' willingness to engage in online purchasing behavior in social commerce platforms.

In practical terms, these findings imply that social trading platforms should prioritize strategies aimed at strengthening customer trust. Improving recommendation accuracy, improving algorithm transparency, ensuring information credibility, and

maintaining a secure transaction environment are likely to drive stronger purchasing behavior among digital consumers.

5.4 Mediation, Theoretical Contribution, and the Unexpected Pattern

Trust partially mediates the AI-curated e-WOM effect but does not mediate the organic e-WOM effect. This asymmetry indicates that algorithmic relevance may first strengthen confidence and then support purchase, while peer-authored content may trigger a more immediate response through social proof, informativeness, affect, or urgency. These alternative mediators were not tested and should be examined in future research.

Theoretically, the study contributes by differentiating two information stimuli and locating trust as an organism mechanism only for the AI-curated route. It does not demonstrate that the AI coefficient is statistically larger than the organic coefficient because no formal difference test was conducted. TAM remains a supporting explanation for receptivity to the recommender interface, whereas S-O-R provides the tested causal ordering. This tighter boundary resolves the mismatch between the previous theoretical claims and the measured constructs.

5. CONCLUSIONS, IMPLICATIONS, AND LIMITATIONS

6.1 Conclusion

Among the surveyed Generation Z TikTok Shop users in Surabaya, AI-curated e-WOM is associated with both trust and purchase decisions. Organic e-WOM is associated directly with purchase decisions but not significantly with trust. Customer trust strongly predicts purchase decisions.

Trust provides complementary partial mediation for AI-curated e-WOM and no mediation for organic e-WOM. The evidence therefore supports differentiated rather than uniform treatment of e-WOM in AI-enabled social commerce. The conclusions are limited to the sampled context and do not establish that algorithmic curation is universally superior to organic consumer communication.

6.2 Theoretical implications

The study extends e-WOM research by separating authorship from algorithmic exposure, applies S-O-R to a dual-stimulus model, and shows that trust carries only the AI-curated route. It also clarifies TAM's limited role: usefulness and ease-of-use concepts provide background for technology receptivity, but the model tests no TAM constructs. Future models can explicitly add perceived usefulness, perceived ease of use, social presence, information diagnosticity, and source credibility.

6.3 Managerial and Policy Implications

These findings provide several practical implications for social commerce platforms, online businesses, digital marketers, and policymakers. For platform providers like TikTok Shop, improving the quality of AI recommendation systems should be a strategic priority. Recommendation algorithms must continuously improve personalization accuracy, information

relevance, transparency, and explanations to strengthen user trust in AI-generated recommendations. Building consumer trust through a transparent and reliable recommendation system can ultimately drive stronger purchasing decisions.

For online sellers and digital marketers, the results show that relying solely on organic consumer reviews is no longer enough to maximize buying performance in AI-driven marketplaces. Businesses must optimize product information, visual presentation, customer engagement, and interaction quality to improve compatibility with AI recommendation algorithms while maintaining authentic customer reviews. Integrating algorithm optimization with consumer-generated content can provide greater marketing effectiveness in attracting Generation Z consumers.

From a policy perspective, these findings highlight the growing importance of responsible Artificial Intelligence in digital trade. As consumers increasingly rely on algorithmically curated information, digital platform providers and policymakers must drive greater transparency, accountability, fairness, and explanation in AI recommendation systems to maintain public trust and support the sustainable development of AI-based social commerce ecosystems.

6.4 Limitations and Future Research

The cross-sectional, self-report, nonprobability design limits causal inference and generalizability. The single-city, single-platform setting may not represent other cohorts or markets, and researchers must assess common-method and nonresponse bias using the available raw data. The operational distinction between curated and organic e-WOM should be validated further because even consumer-authored content can be algorithmically distributed. Future research should use experiments or longitudinal designs, probability or stratified sampling, multi-group analysis, and formal tests of coefficient differences; distinguish trust targets; and evaluate transparency, privacy concern, perceived manipulation, social presence, and review authenticity as moderators or alternative mediators.

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