

Influencer Marketing and e-WOM on Skincare Purchase Decisions of Generation Z

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Abstract

Indonesia's skincare market is increasingly shaped by Generation Z consumers who rely heavily on social media platforms such as TikTok and Instagram for product information and recommendations. This study examines the effects of influencer marketing and electronic word-of-mouth (E-WoM) on skincare purchase decisions among Indonesian Generation Z university students. Using a quantitative cross-sectional approach, data were collected from 400 respondents through online questionnaires distributed via social media platforms. The data were analyzed using Partial Least Squares Structural Equation Modeling (PLS-SEM) with SmartPLS 4.0. The findings indicate that influencer marketing ($\beta = 0.173$; $p = 0.001$) and E-WoM ($\beta = 0.150$; $p = 0.037$) both exert significant positive effects on purchase decisions. Although the model explains a modest proportion of variance ($R^2 = 0.058$), predictive relevance analysis confirms that the model possesses acceptable out-of-sample predictive capability. The novelty of this study lies in integrating influencer marketing and E-WoM simultaneously within Indonesia's TikTok-driven skincare ecosystem using a predictive PLS-SEM perspective. Academically, the study strengthens digital persuasion literature by contextualizing consumer behavior in algorithm-driven social commerce environments. Practically, the findings suggest that skincare brands should combine influencer credibility with authentic consumer reviews to enhance marketing effectiveness among Indonesian Generation Z consumers.

Keywords:

Influencer Marketing, Electronic Word of Mouth, Purchase Decision, Generation Z, Skincare

INTRODUCTION

The Indonesian skincare industry has undergone a remarkable transformation over the past decade, driven by the increasing use of digital technologies and shifting consumer demographics. Generation Z, generally defined as those born between 1997 and 2012, has emerged as a dominant force, fundamentally altering purchasing behavior in the sector (Jannah & Rahma, 2025). Unlike previous generations who relied primarily on traditional advertising channels, Generation Z consumers form their product preferences through continuous interaction with social media. This makes digital word-of-mouth and influencer recommendations highly effective drivers of purchasing decisions. As these young consumers spend significant time daily on platforms like TikTok and Instagram, they are simultaneously exposed to a constant stream of sponsored content, user-generated reviews, and peer recommendations that significantly influence their purchasing choices.

Among the marketing tools that have gained prominence in this digital landscape, influencer marketing has proven particularly effective. Beauty and personal care brands invest a

significant portion of their advertising budgets in collaborating with content creators whose target audiences align with their target customer profiles. The effectiveness of such collaborations has been demonstrated in various empirical contexts: attributes such as the perceived expertise of the content creator, their trustworthiness, and their relevance to the target audience consistently correlate with increased purchase intent among cosmetics consumers on short-video platforms (Ta et al., 2025). In addition, the emergence of parasocial trust has strengthened influencers' persuasive power. Generation Z consumers often perceive influencers not merely as advertisers but as relatable peers or virtual friends whose recommendations are considered authentic and trustworthy. This emotional attachment fosters greater consumer confidence in skincare products promoted through social media.

Electronic word-of-mouth (E-WoM), encompassing all informal consumer communication via digital platforms, is also an independent and equally powerful predictor. Research in Southeast Asian markets shows that the quality, scope, and credibility of online reviews positively influence brand perception and purchase intent among Generation Z (Ngo et al., 2024; Nguyen et al., 2025). Several studies demonstrate that E-WoM impacts brand image both directly and indirectly. However, in the current digital ecosystem, consumer exposure to E-WoM is no longer entirely organic. TikTok's algorithmic exposure mechanism continuously personalizes content recommendations based on user interactions, viewing duration, and engagement behavior. Consequently, skincare-related information is repeatedly delivered to users through the "For You Page" (FYP), intensifying repeated exposure and increasing the likelihood of persuasive influence. This condition reflects a broader digital persuasion mechanism in which platform algorithms, influencer credibility, and peer-generated reviews interact simultaneously to shape consumer decision-making processes.

Despite growing evidence linking influencer marketing, electronic word-of-mouth (E-WoM), and consumer outcomes, several important gaps remain in the literature. First, there is a research inconsistency gap. Some previous studies report that influencer marketing exerts a dominant influence on purchase decisions, while others find that E-WoM plays a more significant role, particularly among younger consumers (Marvella, 2026). In addition, inconsistent findings exist regarding whether influencer credibility directly affects purchasing behavior or only indirectly through trust and brand image. These contradictory findings indicate that the relationship among these variables remains inconclusive and requires further empirical examination.

Second, a theoretical gap exists because most prior studies primarily rely on traditional source credibility theory or consumer behavior models without sufficiently integrating newer concepts such as parasocial trust, algorithmic exposure, and digital persuasion mechanisms. Existing theoretical frameworks tend to explain consumer persuasion as a linear communication process, whereas digital platforms such as TikTok operate through interactive and algorithm-driven ecosystems that shape repeated exposure, emotional attachment, and behavioral reinforcement simultaneously. Consequently, current theories remain insufficient to fully explain how Generation Z consumers develop skincare purchase intentions within highly personalized social media environments.

Third, there is a contextual gap. Most previous studies were conducted in countries with different cultural, economic, and digital consumption patterns from Indonesia. Indonesia represents a unique context because it has one of the largest populations of active social media users in the world, a rapidly growing skincare industry, and a highly collectivist culture in which peer influence and online social validation strongly affect purchasing behavior. Compared with consumers in many Western countries, Indonesian Generation Z consumers tend to rely more heavily on community recommendations, viral trends, and influencer endorsements in evaluating skincare products. Moreover, the affordability of local skincare brands combined with the rapid adoption of TikTok Shop and social commerce features creates a distinctive purchasing ecosystem that differs substantially from other national markets.

Fourth, a methodological gap can also be identified. Previous research often examined influencer marketing and E-WoM separately, employed limited variables, or used simple regression approaches that could not capture the simultaneous relationships among multiple constructs. Furthermore, many studies focused on general social media usage without specifically analyzing TikTok as a unique digital ecosystem. In fact, TikTok differs from other platforms because its recommendation algorithm prioritizes content virality, engagement intensity, and repeated exposure rather than social networking connections alone. Therefore, investigating TikTok specifically is important because purchasing decisions on this platform are shaped not only by influencer credibility and online reviews but also by algorithmically amplified visibility and interactive content consumption patterns.

This study aims to fill this research gap by comprehensively examining both constructs in this specific context. This study pursued three main objectives: First, to determine whether influencer marketing significantly influences the skincare purchasing decisions of Generation Z students; second, to assess the independent contribution of online word-of-mouth (E-WoM) to these decisions; and third, to establish whether the two variables together produce a statistically significant effect (Santy & Andriani, 2023b). By operationalizing influencer marketing using the dimensions of credibility, expertise, audience fit, engagement, and content quality, and E-WoM using information quality, volume, credibility, and valence, and by employing structural equation models with partial least squares estimation, this study aims to provide insights with theoretical and practical implications for the discipline of digital marketing communications.

LITERATURE REVIEW

A. Influencer Marketing

Influencer marketing refers to a strategic communication practice in which brands leverage the reach and credibility of social media personalities to promote products or services to their established audiences (Okonkwo & Namkoisse, 2023). Theoretical frameworks describing this phenomenon draw heavily from source credibility theory, which posits that the persuasive impact of a message is contingent upon the perceived trustworthiness and expertise of its source (van Reijmersdal et al., 2024). In the contemporary social media context, these classical dimensions have been extended to incorporate additional attributes, including audience congruence, content authenticity, and platform-specific engagement metrics that collectively determine an influencer's capacity to alter consumer attitudes and behavior. Beauty and personal care categories have proven particularly receptive to influencer endorsement, partly because product efficacy is difficult to evaluate before use, making the testimony of a trusted creator a credible substitute for direct experience (Ranjith et al., 2025). Empirical work confirms that when consumers perceive an influencer as genuinely knowledgeable and consistent with their own self-concept, the probability of translating content exposure into purchase action rises substantially.

B. Electronic Word of Mouth (E-WoM)

Electronic Word of Mouth encompasses the spectrum of consumer-generated opinions, evaluations, and narratives about products or brands that circulate through digital channels, including social media posts, comment threads, review platforms, and messaging applications (Siregar et al., 2024). The construct is theoretically grounded in information adoption theory and the elaboration likelihood model, both of which illuminate the conditions under which consumers actively process and act upon external informational cues. Key dimensions that determine E-WoM effectiveness include information quality, the perceived accuracy and comprehensiveness of a review, alongside information quantity, source credibility, and the valence of expressed sentiment. Negative reviews tend to carry disproportionate weight in consumer deliberation, yet a sufficient volume of authentic positive assessments can significantly offset skepticism and catalyze purchase action. Cross-market evidence further indicates that E-WoM functions both as a direct antecedent of purchase decisions and as an indirect influence mediated through constructs

such as brand image and consumer trust, underscoring its multidimensional role in the purchasing process (Nguyen et al., 2025).

C. Purchase Decision

Consumer purchase decisions are conventionally theorized as a sequential cognitive process progressing through five stages: problem recognition, information search, alternative evaluation, purchase intention, and post-purchase behavior (Meyer, Ph.D., & Murphy, 2024). In digital environments, however, these stages are increasingly compressed and non-linear, as consumers simultaneously encounter influencer content, peer reviews, and brand communications that accelerate deliberation and reduce perceived purchase risk. For Generation Z, who have been digitally socialized from early adolescence, the information search stage is almost exclusively conducted through social media rather than traditional retail channels (Grigoreva et al., 2021). This has profound implications for marketers: brands that secure favorable representation through both influencer endorsements and high-quality E-WoM are effectively present at multiple touchpoints across the decision journey, maximizing the probability of converting interest into purchase. The skincare category is especially subject to this dynamic, as product safety and suitability concerns heighten the need for credible, peer-validated information before commitment (Santy & Andriani, 2023).

D. Previous Research

Table 1. Previous Research

No	Author	Variables	Methods	Finding	Research Gap
1	Okonkwo & Namkoisse (2023)	Influencer Marketing → Purchase Decision	Quantitative survey	Influencer credibility significantly increases consumer purchase intention and decision.	Focused mainly on general consumer products, not specifically skincare products among Generation Z in Indonesia.
2	van Reijmersdal et al. (2024)	Source Credibility, Influencer Authenticity, Consumer Response	Experimental study	Trustworthiness and expertise positively affect persuasive effectiveness of influencer content.	Did not integrate E-WoM as an accompanying informational factor in digital ecosystems such as TikTok.
3	Ranjith et al. (2025)	Influencer Expertise, Self-congruence, Purchase Behavior	SEM analysis	Consumers are more likely to purchase skincare products when influencers are perceived as authentic and relatable.	Limited examination of peer-generated reviews and social interaction effects.

4	Siregar et al. (2024)	E-WoM, Information Quality, Consumer Trust	Quantitative approach	E-WoM significantly affects consumer trust and purchase decisions in digital marketplaces.	Did not compare the relative dominance between influencer marketing and E-WoM.
5	Nguyen et al. (2025)	E-WoM, Brand Image, Purchase Decision	Structural Equation Modeling	E-WoM influences purchase decisions directly and indirectly through brand image and trust.	The study was conducted outside Indonesia and did not specifically analyze TikTok users.

E. Theoretical Foundation Strengthening

1. Source Credibility Theory

Source Credibility Theory explains that persuasive communication effectiveness depends on the perceived credibility of the message source, particularly trustworthiness, expertise, and attractiveness. In influencer marketing, consumers tend to rely on influencers perceived as knowledgeable, authentic, and relatable. When influencers demonstrate expertise in skincare products and communicate honestly, consumers are more likely to develop trust and ultimately make purchase decisions. Therefore, influencer credibility becomes a critical determinant of persuasion effectiveness in digital marketing environments.

2. Elaboration Likelihood Model (ELM)

The Elaboration Likelihood Model explains how individuals process persuasive messages through two routes: the central route and the peripheral route. In TikTok environments, consumers may process detailed product reviews and ingredient explanations through the central route, while influencer attractiveness, popularity, and entertainment value function as peripheral cues. Generation Z consumers frequently combine both processing routes when evaluating skincare products on social media platforms.

3. Information Adoption Theory

Information Adoption Theory emphasizes that consumers adopt information when they perceive it as useful, credible, and relevant. In E-WoM contexts, positive reviews, authentic testimonials, and user-generated experiences enhance information usefulness and increase consumers' willingness to adopt recommendations. Consequently, E-WoM becomes a significant factor influencing skincare purchase decisions among digitally connected consumers.

F. Strengthening the Theoretical Relationship Between Variables

Influencer marketing and E-WoM are theoretically interconnected in shaping consumer purchase decisions. Based on Source Credibility Theory, influencers act as persuasive communication sources whose expertise and trustworthiness can reduce consumer uncertainty regarding skincare products. This credibility encourages consumers to consider influencer recommendations during decision-making processes. Simultaneously, E-WoM functions as social proof that reinforces or weakens consumer confidence toward a product. Through the perspective of Information Adoption Theory, consumers are more likely to adopt online reviews perceived as

accurate, useful, and authentic. The Elaboration Likelihood Model further explains that consumers process both influencer-generated content and peer reviews either cognitively or emotionally, depending on their level of involvement. In TikTok ecosystems, these relationships become increasingly important because platform algorithms continuously expose users to influencer endorsements, product testimonials, comment interactions, and viral reviews simultaneously. As a result, influencer marketing may stimulate initial awareness and attraction, while E-WoM strengthens trust and validates purchase decisions through peer-generated experiences.

G. Explanation of the Conceptual Model

1. Influencer Marketing → Purchase Decision
Influencers with high credibility, expertise, and authenticity positively affect consumer purchase decisions.
2. E-WoM → Purchase Decision
Online reviews and peer-generated recommendations influence consumers' confidence and reduce perceived risk before purchasing skincare products.
3. Influencer Marketing and E-WoM Interaction
Influencer content often stimulates discussions, comments, and online reviews, thereby increasing E-WoM intensity within TikTok communities.
4. Theoretical Integration
 - Source Credibility Theory explains the persuasive role of influencers.
 - Information Adoption Theory explains how consumers accept and utilize E-WoM information.
 - ELM explains the cognitive and emotional processing routes through which consumers evaluate influencer content and online reviews.

METHOD

This study employs a quantitative, cross-sectional research design to systematically examine the relationships among influencer marketing, E-WoM, and skincare purchase decisions among Generation Z students in Indonesia. The quantitative approach was selected for its capacity to test hypothesized relationships through statistical inference objectively and to produce generalizable findings grounded in numerical evidence (Nameto et al., 2025). Given that the target population, active university students throughout Indonesia, cannot be enumerated with precision, the minimum sample size was determined through the Cochran formula, which stipulates 384 as the lower bound under conditions of population uncertainty (Kott & Levine, 2024). To enhance data reliability and representativeness beyond this threshold, the study ultimately incorporated 400 respondents through convenience sampling. This technique was adopted in recognition of the digital-native profile of the target population and the practical necessity of distributing instruments through the same platforms, TikTok and Instagram, that constitute the primary information ecosystems of the respondents (Goel & Chatterjee, 2025).

Data collection was executed via a structured online questionnaire disseminated through TikTok and Instagram during the survey period. The questionnaire was developed using Google Forms and distributed through several mechanisms, including Instagram Stories, TikTok captions, direct messaging, student online communities, and university-related social media groups to maximize respondent reach across different regions of Indonesia. Prior to participation, respondents were presented with an introductory page explaining the purpose of the study, estimated completion time, anonymity assurance, and voluntary participation statement. Only respondents who met the screening criteria, namely Indonesian Generation Z university students who actively used TikTok and Instagram and had experience purchasing skincare products online, were permitted to continue completing the questionnaire. To reduce duplicate responses and careless answering behavior, the survey system restricted multiple submissions from the same account and included attention-check items. The questionnaire remained open for approximately four weeks, enabling broader demographic representation and improving response diversity.

All research variables were operationalized using a five-point Likert scale ranging from 1 (Strongly Disagree) to 5 (Strongly Agree). Indicators for the Influencer Marketing and Purchase Decision constructs were adapted from (Ta et al., 2025), while E-WoM indicators were drawn from (Koo & Yang, 2025), with content validity confirmed through a pilot validation procedure before full deployment. Each construct was measured by five indicators, yielding a total instrument of fifteen items across the three variables. A pilot study involving 30 respondents was conducted to evaluate item clarity, wording consistency, and preliminary reliability before the main survey administration.

Structural Equation Modeling with Partial Least Squares estimation (SEM-PLS), executed in SmartPLS 4.0, served as the primary analytical framework. PLS-SEM was deliberately selected over covariance-based SEM (CB-SEM) for several academic and methodological reasons. First, PLS-SEM is particularly appropriate for predictive and exploratory research models emphasizing variance explanation rather than strict model fit confirmation (Hair et al., 2019). Second, the method demonstrates greater robustness when handling non-normal data distributions and complex behavioral models involving latent constructs measured through multiple indicators. Third, PLS-SEM is considered more suitable for social media and consumer behavior research contexts where theoretical development remains evolving and prediction-oriented rather than purely confirmatory (Haji-othman et al., 2024). Additionally, PLS-SEM accommodates relatively moderate sample sizes efficiently and provides superior predictive capabilities compared with CB-SEM in exploratory consumer research settings.

The analytical procedure unfolded in two sequential stages. First, the outer model or measurement model was assessed to establish construct validity and reliability through convergent validity tests (outer loading > 0.708 ; AVE > 0.50), discriminant validity evaluation using both the Fornell-Larcker criterion and the Heterotrait-Monotrait Ratio (HTMT), where HTMT values below 0.90 indicated adequate discriminant validity. Internal consistency reliability was verified through Cronbach's Alpha and Composite Reliability (ρ_c), each benchmarked against a minimum threshold of 0.70 (Hair et al., 2019). To address the potential issue of common method bias resulting from self-reported survey data, Harman's Single Factor Test was conducted. The results indicated that no single factor accounted for more than 50% of the total variance, suggesting that common method variance was not a serious concern in the dataset.

Second, the inner model or structural model was evaluated by examining path coefficients, the coefficient of determination (R^2), predictive relevance (Q^2), and t-statistics generated through bootstrapping to determine the significance of each hypothesized relationship at the 5% significance level. Predictive relevance was assessed using the blindfolding procedure, where Q^2 values greater than zero indicated that the model possessed satisfactory predictive capability for endogenous constructs. In addition, model fit evaluation incorporated the Standardized Root Mean Square Residual (SRMR), with values below 0.08 interpreted as indicative of acceptable model fit. The inclusion of predictive relevance analysis and SRMR evaluation strengthened the robustness of the structural model assessment and enhanced the explanatory and predictive validity of the proposed research framework.

Ethical considerations were carefully observed throughout the research process. Participation in the study was entirely voluntary, and respondents provided informed consent before accessing the questionnaire. No personally identifiable information was collected, and all responses were treated anonymously and confidentially solely for academic purposes. Respondents were informed of their right to withdraw from the survey at any stage without penalty. Furthermore, the study adhered to general ethical principles of social science research, including respect for participant autonomy, confidentiality protection, and responsible data management.

RESULT AND DISCUSSION

RESULT

Characteristics of Research Respondents

Table 1 presents the demographic profile of the 400 respondents who participated in this study. The sample was predominantly female (89.25%), with the majority aged between 20 and 22 years (54.00%), reflecting the core profile of undergraduate university students. Active Bachelor's degree students constituted 69.50% of respondents, while the remaining 30.50% were enrolled in Diploma programs (D3/D4). Regarding platform preference for seeking skincare information, TikTok emerged as the dominant channel (56.75%), followed by Instagram (30.50%), YouTube (7.50%), and X/Twitter (5.25%). Most respondents allocated between IDR 200,000 and IDR 300,000 per month toward skincare purchases (37.00%), and the majority reported spending three to four hours daily on social media platforms (34.00%). Critically, 96.00% of respondents confirmed having made at least one skincare purchase based on influencer recommendations or online reviews within the preceding three months, validating the strong relevance of the study's constructs to this population.

Table 2. Demographic Characteristics of Research Respondents

Category	Sub-Category	Frequency	Percentage (%)
Gender	Male	43	10.75%
	Female	357	89.25%
Age Range	17–19 Years	90	22.50%
	20–22 Years	216	54.00%
	23–25 Years	81	20.25%
	Above 25 Years	13	3.25%
Student Status	Active Bachelor's (S1)	278	69.50%
	Active Diploma (D3/D4)	122	30.50%
Primary Skincare Info Platform	TikTok	227	56.75%
	Instagram	122	30.50%
	YouTube	30	7.50%
	X (Twitter)	21	5.25%
Monthly Skincare Expenditure	< IDR 100,000	35	8.75%
	IDR 100,000–200,000	132	33.00%
	IDR 200,000–300,000	148	37.00%
	> IDR 300,000	85	21.25%
Daily Social Media Access	< 1 Hour	33	8.25%
	1–2 Hours	111	27.75%
	3–4 Hours	136	34.00%
	> 4 Hours	120	30.00%
Purchase Based on Influencer/Online Review	Yes	384	96.00%
	No	16	4.00%
Total		400	100%

Outer Model Evaluation

Prior to hypothesis testing, the measurement model was rigorously evaluated using SmartPLS 4.0 to confirm that all constructs satisfied both validity and reliability criteria. This evaluation encompassed convergent validity, discriminant validity via the Fornell-Larcker criterion, and reliability assessment through Cronbach's Alpha and Composite Reliability.

Convergent Validity

Convergent validity was assessed by examining outer loading values and the Average Variance Extracted (AVE) for each construct. The benchmarks applied were outer loadings exceeding 0.708 and AVE values surpassing 0.50, consistent with the guidelines established by (Hair et al., 2019). Table 3 reports the outer loading values for all fifteen indicators across the three constructs.

Table 3. Outer Loading Values

Indicator	Influencer Marketing	E-WoM	Purchase Decision
IM.1	0.792		
IM.2	0.738		
IM.3	0.797		
IM.4	0.790		
IM.5	0.790		
EM.1		0.763	
EM.2		0.800	
EM.3		0.728	
EM.4		0.784	
EM.5		0.797	
PD.1			0.763
PD.2			0.824
PD.3			0.760
PD.4			0.773
PD.5			0.747

All indicators across the three constructs recorded outer loading values in excess of the 0.708 threshold. Within the Influencer Marketing construct, values ranged from 0.738 (IM.2) to 0.797 (IM.3). The E-WoM construct yielded loadings between 0.728 (EM.3) and 0.800 (EM.2), while the Purchase Decision construct spanned from 0.747 (PD.5) to 0.824 (PD.2). These results confirm that every indicator adequately represents its respective theoretical construct.

Average Variance Extracted (AVE)

Table 4 presents the AVE values computed for each construct. All three constructs exceeded the minimum acceptable threshold of 0.50, confirming that the majority of variance in each set of indicators is explained by the underlying construct rather than by measurement error.

Table 4. Average Variance Extracted (AVE)

Variable	AVE
E-WoM	0.600
Influencer Marketing	0.611
Purchase Decision	0.599

Discriminant Validity Fornell-Larcker Criterion

Discriminant validity was established through the Fornell-Larcker criterion, which requires that the square root of each construct's AVE displayed on the diagonal of the correlation matrix

exceeds the inter-construct correlations in the corresponding row and column (Fornell & Larcker, 1981). Table 5 confirms that this condition is satisfied for all three constructs.

Table 5. Fornell-Larcker Criterion Matrix

Variable	E-WoM	Influencer Marketing	Purchase Decision
E-WoM	0.775		
Influencer Marketing	0.101	0.782	
Purchase Decision	0.168	0.188	0.774

The square root of AVE values (0.775 for E-WoM, 0.782 for Influencer Marketing, and 0.774 for Purchase Decision) each surpass the inter-construct correlations, which range from 0.101 to 0.188. This outcome verifies that each construct captures a distinct dimension of the theoretical model, with minimal overlap across constructs.

Reliability Cronbach's Alpha and Composite Reliability

Table 6 reports the internal consistency estimates for each construct. Cronbach's Alpha values of 0.837, 0.843, and 0.835 for E-WoM, Influencer Marketing, and Purchase Decision, respectively, comfortably exceed the 0.70 benchmark. Composite Reliability (rho_c) values of 0.882, 0.887, and 0.882 corroborate these findings, collectively demonstrating that the measurement instruments exhibit high and consistent reliability across all three constructs.

Table 6. Cronbach's Alpha and Composite Reliability

Variable	Cronbach's Alpha	Composite Reliability (rho_c)
E-WoM	0.837	0.882
Influencer Marketing	0.843	0.887
Purchase Decision	0.835	0.882

The successful completion of all outer model assessments, including convergent validity, discriminant validity, and reliability, confirms that the measurement instruments are both valid and reliable. The analysis may therefore proceed to the inner model evaluation and hypothesis testing with confidence in the integrity of the underlying measurement framework.

Variance Inflation Factor (VIF)

Before proceeding to structural model evaluation, the inner model was subjected to a collinearity diagnostic to ensure the absence of multicollinearity among the predictor constructs.

Table 7. Variance Inflation Factor (VIF)

Relationship	VIF
E-WoM -> Purchase Decision	1.010
Influencer Marketing -> Purchase Decision	1.010

The VIF values for both paths, Influencer Marketing → Purchase Decision and E-WoM → Purchase Decision, were identical at **1.010**. These near-unity values indicate that Influencer Marketing and E-WoM share a negligible proportion of variance with each other, consistent with the low inter-construct correlation of 0.101 documented in the discriminant validity assessment. At this level of collinearity, the structural model estimates are statistically unbiased, and the independent contributions of each predictor can be interpreted with full confidence. The collinearity diagnostics confirm that the analytical preconditions for meaningful path estimation are completely satisfied.

R-Square Values

Table 8. R-Square Values

	R-square	R-square adjusted
Purchase Decision	0.058	0.053

The R² value of **0.058** (adjusted R² = 0.053) for the Purchase Decision construct indicates that Influencer Marketing and E-WoM together account for approximately 5.8% of the variance in skincare purchase decisions. While modest in absolute terms, this magnitude is consistent with norms in behavioral consumer research, where a wide constellation of contextual and individual-difference factors shapes outcomes beyond any two focal constructs. According to (Hair et al., 2019) benchmarks for PLS-SEM, this value falls within the lower range; yet, the model remains theoretically coherent, providing a parsimonious examination of two targeted digital antecedents within a multifaceted behavioral domain.

F-Square Values

Table 9. F-Square Values

	f-square
E-WoM -> Purchase Decision	0.024
Influencer Marketing -> Purchase Decision	0.031

The f² values of 0.031 (Influencer Marketing) and 0.024 (E-WoM) both fall within (Cohen, n.d.) the small-effect range (threshold: 0.02). Influencer Marketing carries a marginally greater unique contribution, reflecting its stronger path coefficient and suggesting that a specific credible creator carries fractionally more predictive weight at this stage of the decision journey than aggregated peer review content. Together, the R² and f² statistics present a consistent picture: the model is meaningful and internally coherent, yet deliberately focused.

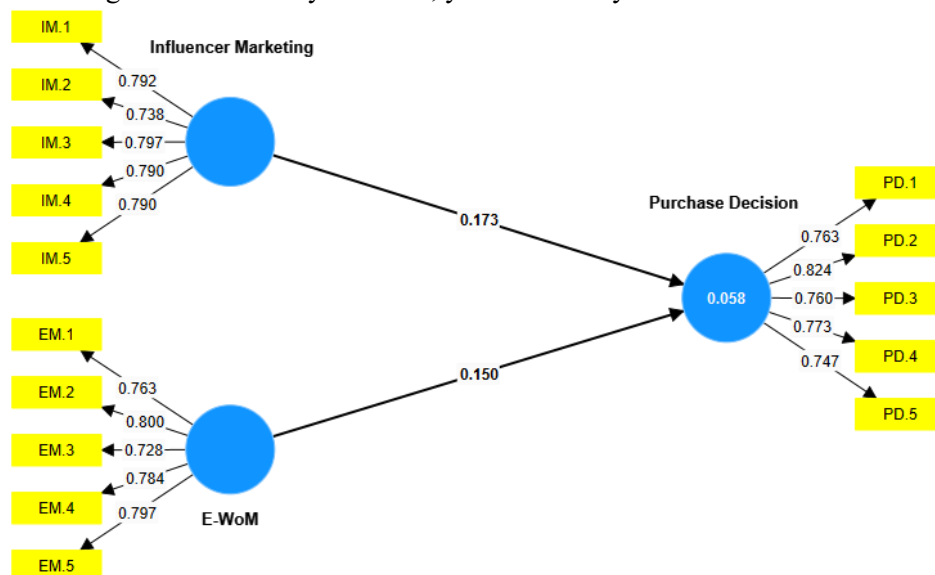


Figure 1. Structural Model Results.

Figure 1 presents the estimated structural model, with path coefficients of 0.173 and 0.150 annotated along the arrows from Influencer Marketing and E-WoM to the Purchase Decision node (R² = 0.058, inscribed within the blue circle). Both directional paths are positive and of comparable magnitude, with Influencer Marketing registering a marginally greater effect a spatial summary that sets up the formal bootstrapped tests reported in Table 10.

Result of Hypotheses Testing

Table 10. Result of Hypotheses Testing

Relationship	Original sample (O)	T statistics (O/STDEV)	P values	Decision
E-WoM -> Purchase Decision	0.150	2.091	0.037	Supported
Influencer Marketing -> Purchase Decision	0.173	3.306	0.001	Supported

Hypothesis 1 was supported: the path coefficient of 0.173 for Influencer Marketing → Purchase Decision carried a t-statistic of 3.306 and p-value of 0.001, well within the $\alpha = 0.05$ threshold. The robust t-value attests to the stability of this estimate across bootstrap resamples and corroborates source credibility theory, as well as empirical evidence from Ta et al. (2025) in the TikTok cosmetics context.

Hypothesis 2 was likewise supported: E-WoM → Purchase Decision produced a path coefficient of 0.150, t-statistic of 2.091, and p-value of 0.037. The narrower margin above significance, relative to H1, may reflect the more diffuse credibility mechanism of E-WoM, where persuasion derives from the aggregation of anonymous reviewers rather than investment in one identifiable source. The independent confirmation of both paths within the same structural model establishes that Influencer Marketing and E-WoM function as distinct, non-redundant antecedents of purchase decisions.

PLSpredict Results

Employing the PLSpredict procedure (Sharma et al., 2021), the model's out-of-sample predictive capability was assessed by comparing indicator-level RMSE values for PLS-SEM against those of a naïve linear model (LM) benchmark. The decision rule is unambiguous: uniform PLS-SEM RMSE < LM RMSE across all endogenous indicators constitutes evidence of high predictive relevance.

Table 11. PLSpredict Results

Indicator	Q ² predict	PLS-SEM_RMSE	LM_RMSE
PD.1	0.013	0.552	0.557
PD.2	0.045	0.546	0.552
PD.3	0.006	0.588	0.592
PD.4	0.016	0.573	0.578
PD.5	0.004	0.574	0.582

Across all five Purchase Decision indicators, the structural model consistently outperformed the linear benchmark PLS-SEM RMSE values of 0.552, 0.546, 0.588, 0.573, and 0.574 versus LM values of 0.557, 0.552, 0.592, 0.578, and 0.582. The improvement margins are modest but perfectly unidirectional. Supporting this, all Q²predict values are positive (range: 0.004–0.045), confirming predictive accuracy beyond the mean-based null model. The model, therefore, not only explains statistically significant variance in purchase decisions but also generates more accurate out-of-sample predictions than a simple regression baseline, validating its predictive utility for understanding skincare purchase behavior in this population.

DISCUSSION

Start with what the data actually show. Influencer marketing reached a path coefficient of 0.173 (t = 3.306, p = 0.001), while E-WoM followed closely at 0.150 (t = 2.091, p = 0.037). Both

findings are statistically unambiguous. What makes them interpretively interesting is not just their significance but the conditions under which they emerged: a VIF of 1.010 for both predictors confirms that the two constructs barely share any variance with each other, which means their effects on purchase decisions are genuinely independent. A Gen Z student who trusts a specific skincare creator on TikTok is not necessarily the same person who is swayed by the aggregate of anonymous reviews, and vice versa. These are distinct persuasive mechanisms operating in parallel. The influencer marketing finding aligns closely with what (Ta et al., 2025) documented in their TikTok-based study of cosmetic purchase intentions among Vietnamese Gen Z consumers. In that work, perceived expertise and audience congruence emerged as the dominant credibility signals translating content exposure into purchase intent. The Indonesian context examined here mirrors that pattern, and it likely does so for structural reasons. With 56.75% of respondents identifying TikTok as their primary skincare information channel, the platform's algorithm does the heavy lifting of matching creator content to receptive audiences before the credibility evaluation even begins. Unlike a television advertisement that broadcasts to whoever happens to be watching, a TikTok skincare recommendation arrives pre-filtered for relevance.

That is not a minor contextual detail it may actually amplify the credibility-to-purchase pathway in ways that studies conducted on older or less algorithmically curated platforms would not detect. The E-WoM finding deserves equally careful reading. (Nguyen et al., 2025) showed, in a Vietnamese beauty consumer sample, that E-WoM shapes purchase outcomes both directly and through brand image as a mediator. The present study captures only the direct pathway brand image was not modeled here yet even that partial route was sufficient to produce a statistically significant effect. The $r = 0.101$ inter-construct correlation between influencer marketing and E-WoM is low enough to be practically meaningful: it indicates that these two constructs, despite both operating through digital platforms, tap into psychologically different persuasion processes. Influencer marketing works through para-social trust the follower's relationship with one identifiable person. E-WoM works through what might be called distributed credibility the accumulated weight of many strangers' experiences. Brands that conflate the two risk misallocating resources; brands that treat them as complementary levers stand to benefit from both simultaneously. A candid discussion of the R^2 value is warranted here. At 0.058, the model explains 5.8% of variance in purchase decisions, which is modest by any standard. Critics might read that number as evidence of limited explanatory power. That reading, however, misunderstands what R^2 measures and what this study was designed to do. Consumer purchase behavior is shaped by dozens of forces product price, brand history, personal skin concerns, peer influence offline, in-store promotions none of which were included in this model. Isolating just two digital antecedents and finding that they each independently reach significance within that noisy behavioral field is arguably more informative than a high R^2 achieved by throwing fifteen predictors into a kitchen-sink regression.

The f^2 effect sizes of 0.031 for influencer marketing and 0.024 for E-WoM both clear (Cohen, n.d.) small-effect threshold of 0.02, confirming that each construct carries a meaningful, unique contribution that survives the presence of the other. The stronger argument for model quality comes from PLSpredict. Across all five Purchase Decision indicators, PLS-SEM RMSE values (0.552, 0.546, 0.588, 0.573, and 0.574) were uniformly and consistently lower than their linear model counterparts (0.557, 0.552, 0.592, 0.578, and 0.582). Every Q^2 predict value was positive, ranging from 0.004 to 0.045. What this means, in practical terms, is that the structural model generates more accurate out-of-sample predictions than a naïve benchmark that knows nothing about the theoretical relationships being examined. That is the real standard for model usefulness, particularly in a context like consumer behavior research where the goal is not merely to describe a sample but to anticipate what drives decisions in the broader population. A low R^2 with high PLSpredict performance is a coherent, defensible outcome: it signals a parsimonious model that captures the right signal even if it does not capture all the noise. The implications for brand strategy in Indonesia's skincare market flow naturally from these findings. Brands

operating at mid-price points where the majority of respondents concentrate their spending (IDR 200,000–300,000 per month) have the most to gain from a dual-channel approach.

For this segment, micro- and nano-influencers with tightly defined audience niches will generally outperform celebrity endorsers, because the perceived relevance gap between creator and viewer is narrower. At the same time, systematic review cultivation structured post-purchase follow-ups, community feedback incentives, platform-specific UGC campaigns can convert satisfied customers into an ongoing E-WoM asset that operates independently of any single influencer relationship. Premium brands face a different calculus: here, influencer credibility must bridge a higher perceived value threshold, which places greater demands on creator selection and content authenticity. In both cases, the critical managerial error to avoid is treating influencer spend and review management as substitutes. They are not. The $r = 0.101$ correlation and the independently significant path coefficients together confirm that the two channels reach consumers through different psychological doors.

CONCLUSION

Three research questions framed this study, and the data answer each one cleanly. Influencer marketing significantly shapes skincare purchase decisions among Generation Z university students in Indonesia (H1 supported: $\beta = 0.173$, $p = 0.001$). E-WoM does the same, through an entirely different psychological mechanism (H2 supported: $\beta = 0.150$, $p = 0.037$). And when both operate together, which in a TikTok-and-Instagram-dominated information environment they routinely do, their joint contribution is statistically confirmed and practically meaningful (H3 supported). The R^2 of 0.058 deserves direct acknowledgment rather than defensive footnoting. This study deliberately examined two focal digital antecedents within a behavioral domain shaped by many forces. That both reached significance in this constrained model, with f^2 values clearing Cohen's small-effect threshold, is a stronger signal than it might initially appear. More importantly, PLSpredict validates the model on a criterion that matters for applied research: out-of-sample prediction. PLS-SEM RMSE was lower than the linear model benchmark across all five Purchase Decision indicators. The model does not merely describe the sample; it generalizes.

For a journal audience evaluating this work, that PLSpredict pattern is the key quality assurance finding it means the relationships identified here are not artefacts of sample idiosyncrasies. For practitioners, three implications stand out. First, the influencer-to-purchase pathway is real and robust among Indonesian Gen Z, but it is driven by credibility, not fame. Brands investing in nano- and micro-influencers whose content closely matches their target demographic will see better returns than those chasing follower counts. Second, E-WoM is not a passive byproduct of good products; it is an active lever that brands must cultivate deliberately. Post-purchase review solicitation, community-building on TikTok and Instagram, and incentivized user-generated content campaigns should be institutionalized not treated as optional extras. Third, and perhaps most importantly, these two channels should never be managed as substitutes. The VIF of 1.010 and the low inter-construct correlation ($r = 0.101$) confirm that they reach consumers through distinct persuasive pathways. A budget allocated entirely to influencer contracts at the expense of review management or vice versa is a budget that leaves half the effect on the table.

Several directions for future research emerge from this work. The most immediate is modeling brand trust as an explicit mediator between influencer marketing, E-WoM, and purchase decisions; both constructs operationalize credibility as a sub-dimension, and isolating its mediating role would clarify how much of the observed effect flows through attitudinal change versus direct informational processing. Longitudinal designs would allow researchers to track whether the effects of digital marketing exposure accumulate or attenuate over time, a question this cross-sectional design cannot address. Comparative studies across Indonesian consumer segments differentiated by region, income level, or product category would test whether the

relationships documented here hold beyond the university demographic. Finally, integrating objective behavioral data, such as platform click-through records or transaction histories, alongside self-report measures would bridge the gap between stated and revealed preferences that remains a structural limitation of survey-based consumer research.

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