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Electronic Word-of-Mouth and Consumer–Brand Relationships in the Indonesian Cosmetic Industry

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Keywords:
electronic word-of-mouth; brand trust; customer loyalty; consumer resistance to innovation.

Abstract

Indonesia's expanding cosmetics market is increasingly shaped by digital interactions, making negative electronic word-of-mouth (e-WOM) an important influence on consumer–brand relationships and responses to product innovation. This study aimed to examine the relationships among negative e-WOM, brand trust, customer loyalty, and consumer resistance to innovation in the Indonesian cosmetics industry. A quantitative causal-relational design was employed, with data collected through a structured online questionnaire. Respondents were cosmetics consumers aged 17 years or older who had encountered online reviews or digital discussions concerning cosmetic products and were selected through purposive sampling. Data were measured using a five-point Likert scale and analyzed using partial least squares structural equation modeling (PLS-SEM), including measurement model assessment, structural model evaluation, and bootstrapping. All four hypothesized relationships were positive and statistically significant. Negative e-WOM had a significant effect on brand trust ($\beta = 0.669$, $p < 0.001$) and customer loyalty ($\beta = 0.474$, $p < 0.001$); brand trust had a significant effect on customer loyalty ($\beta = 0.476$, $p < 0.001$); and customer loyalty had a significant effect on resistance to innovation ($\beta = 0.670$, $p < 0.001$). These findings demonstrate an interconnected relational pathway and suggest that customer loyalty may create inertia toward unfamiliar or newly introduced products. Cosmetics companies should therefore integrate proactive online reputation management, trust-building initiatives, and gradual, educationally oriented innovation strategies.

INTRODUCTION

This chapter explains the background and significance of the study by situating the research within the context of Indonesia's cosmetics industry and the evolving digital marketing environment (Aprilialay et al., 2025; Hasrudin & Sagena, 2023; Muhajir et al., 2026; Nurfadhila, 2024; Saparuddin et al., 2025). It focuses on the growing influence of negative electronic word-of-mouth (e-WOM) on consumer perceptions and behavior, particularly in relation to brand trust and responses to innovation. The chapter also presents relevant real-world industry phenomena that underpin the research problem and provide the foundation for developing the conceptual framework (Ngulube, 2026; Robson, 2024; Salawu et al., 2023; Surdey et al., 2026).

Historically, marketing strategies in the cosmetics and skin care industry were predominantly transactional; however, they have increasingly shifted toward relationship-oriented approaches supported by digital technologies (Davis, 2026; Nguyen, 2026; Santini, 2023; Uddin & Zafar, 2026). Marketing 5.0, as explained by Kotler, Kartajaya, and Setiawan (2021), emphasizes the integration of technology, data, and human-centered engagement, meaning that consumers are no longer merely recipients of corporate messages but also active participants in shaping brand narratives. This transformation is particularly significant in the cosmetics industry, where product image is closely associated with personal identity, lifestyle, and self-expression, resulting in relatively high levels of consumer involvement. As digital platforms increasingly serve as key channels for brand–consumer interaction, marketing communication has shifted from predominantly firm-controlled communication toward more peer-driven exchanges. Consequently, managing consumer–brand relationships has become a major strategic priority for cosmetics companies operating in digitally networked environments (Kotler et al., 2021).

Emerging online trends and increasing digital engagement have enhanced the importance of user-generated content as a major source of information in consumer decision-making (Gunawan, 2024; Sahai et al., 2024; Shukun & Loang, 2024; Suyuthi, 2024; Tran & Pham, 2026). Online reviews are often perceived as more authentic and credible than conventional advertising because they are generally associated with the experiences and opinions of other consumers rather than direct promotional messages from companies. Rosario et al. (2021) showed that online peer reviews are systematically incorporated into consumer evaluation processes, particularly when products involve perceived functional or psychological risks. Such information is especially influential in the cosmetics industry, where consumers frequently consider issues such as skin compatibility, product safety, and effectiveness. This development has reduced companies' control over brand narratives and requires them to manage increasingly complex networks of interpersonal communication alongside traditional promotional activities.

Electronic word-of-mouth (e-WOM) provides opportunities for brands to increase visibility and consumer engagement; however, academic research has also highlighted the potentially adverse effects of negative e-WOM. According to Weitzl et al. (2022), negative information tends to exert a stronger cognitive and emotional influence than positive information because it is often perceived as more diagnostic in reducing uncertainty. This negativity bias can be particularly pronounced in online environments, where information may remain accessible for extended periods and circulate widely across platforms. Dissatisfaction with cosmetic products may further increase consumers' sensitivity to risk because product evaluations are closely related to physical appearance, perceived health, and personal well-being. Therefore, negative e-WOM can function as an important relational mechanism that influences trust formation, brand attachment, and the stability of long-term consumer–brand relationships (Weitzl et al., 2022; Rosario et al., 2021).

These global marketing developments have also become increasingly apparent in Indonesia's cosmetics and skin care industry in recent years. The national beauty industry experienced substantial growth, supported by increasing demand for locally produced products and the growing competitiveness of domestic brands (Coordinating Ministry for Economic Affairs of the Republic of Indonesia, 2025). Online interactions between brands and consumers have been further strengthened by Indonesia's high levels of Internet and social media use. As digital platforms have become important sources of product and service information, consumers increasingly discuss brands online, making such interactions an integral component of brand perception. Consequently, the Indonesian cosmetics market has developed into a highly interconnected and digitally mediated environment.

From an industry perspective, Indonesia's cosmetics sector is characterized by the rapid growth of local brands and small and medium-sized enterprises that actively use digital marketing channels. The Ministry of Industry of the Republic of Indonesia (2025) identified several important factors influencing industry competitiveness, including innovation capability, product diversification and branding strategies, and waste management. To strengthen the industry ecosystem, the government has also introduced initiatives such as Cosmetic Day to improve the competitiveness, export potential, and product quality of local manufacturers. However, rapid industry expansion has also intensified competition and increased brands' exposure to reputational risks. In this environment, maintaining strong consumer relationships is no longer merely an additional marketing activity but a strategic requirement for sustaining competitiveness.

Pre-purchase information-seeking behavior among cosmetics consumers in Indonesia is relatively high, with many consumers searching for information online and reviewing comments from other consumers or influencers before making purchasing decisions. Such behavior reflects consumers' increasing concern with product suitability, quality, credibility, and brand authenticity. Customer loyalty therefore represents an important relational asset, as loyal consumers are generally more likely to repurchase products and engage in positive brand advocacy, even in highly competitive markets. However, loyalty is not necessarily permanent and may change in response to developments in the information environment. In digitally connected markets, ongoing online discussions may play an increasingly important role in reinforcing or weakening loyalty alongside consumers' previous purchasing experiences.

Negative e-WOM represents a particular relationship-management challenge for cosmetics companies operating in digital environments. Negative reviews, public complaints, and discussions surrounding controversies can spread rapidly across platforms and reach large audiences within a short period. According to Rosario et al. (2021), negative online content may be perceived as relevant information when consumers assess product-related risks. The cosmetics industry is particularly susceptible to such effects because consumers often place considerable emphasis on product safety, health implications, and personal suitability. Consequently, negative e-WOM may undermine relationship stability by weakening brand trust, reducing attachment, and altering consumers' evaluations of the brand.

Several cases involving negative e-WOM among cosmetics brands in Indonesia have demonstrated the practical relevance of this issue, including the widely discussed case involving Rose All Day. The brand faced national media attention and calls for consumer boycotts following social media discussions concerning the perceived political position of one of its co-founders (Suara.com, 2023). The incident generated extensive online discussion and demonstrated how digital discourse can quickly develop into a reputational threat. The company's subsequent clarifications and humanitarian initiatives were interpreted as efforts to mitigate further relational damage and restore consumer trust. This case illustrates how e-WOM can influence consumer–brand relationships beyond immediate purchasing behavior and highlights the broader reputational consequences of digitally mediated consumer discourse.

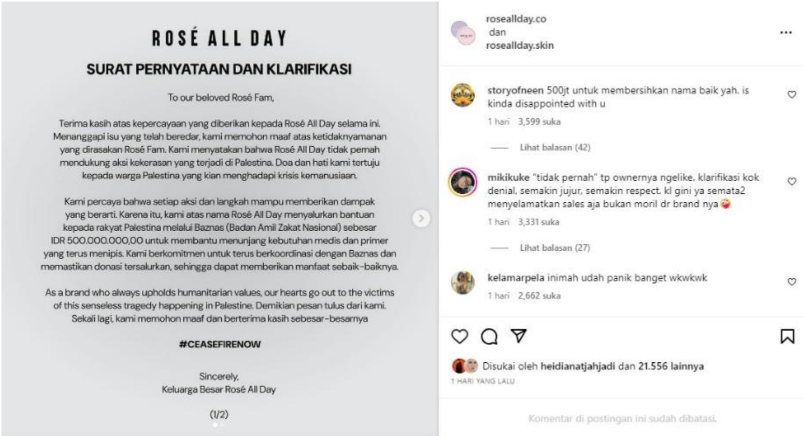

Figure 1. The illustrative example of this negative e-WOM phenomenon

Negative e-WOM not only affects short-term consumer impressions but also influences relational constructs such as brand trust and customer loyalty. Brand trust reflects the extent to which consumers are confident in a brand's ability to fulfill its promises and act responsibly and reliably under conditions of uncertainty. When negative information challenges these beliefs, consumers may reassess their commitment to the brand and reduce their level of loyalty. Conversely, a high level of brand trust may buffer the adverse effects of negative information. Therefore, understanding the relationships among e-WOM, brand trust, and customer loyalty is crucial for examining the stability of consumer–brand relationships in the cosmetics industry.

The erosion of brand trust and customer loyalty may also influence consumers' responses to new products. Relational uncertainty may increase consumers' doubts about the brand, potentially delaying product adoption or increasing resistance to innovative offerings. In this study, consumer resistance to innovation refers to consumers' cautiousness, hesitation, or reluctance to adopt new or unfamiliar products. In an innovation-intensive industry such as cosmetics, resistance to innovation may constrain a company's long-term competitiveness and growth. Accordingly, because electronic word-of-mouth can influence consumers' evaluations of brands and their relational responses, it is important to examine its broader implications for consumer resistance to innovation in the Indonesian cosmetics industry.

METHOD

Research Design

This study employed a quantitative causal-relational design to examine the structural relationships among electronic word-of-mouth (e-WOM), brand trust, customer loyalty, and consumer resistance to innovation in the Indonesian cosmetics industry. A survey method was used because the study focused on examining relationships among latent variables without experimental manipulation. Partial least squares structural equation modeling (PLS-SEM) was applied as the primary analytical technique to test the proposed relationships among the constructs.

The research framework was developed based on relevant theories concerning relationship marketing, electronic word-of-mouth, attribution, brand trust, customer loyalty, and consumer resistance to innovation. These theoretical foundations were used to formulate four testable hypotheses. Primary data were collected through a structured online questionnaire distributed to consumers who had been exposed to online information or reviews concerning cosmetic brands in Indonesia. The questionnaire consisted of indicators representing each construct and was measured using a Likert scale.

The collected data were screened for completeness and consistency before analysis. PLS-SEM analysis was conducted in two stages. First, the measurement model (outer model) was evaluated to assess construct reliability and validity. Second, the structural model (inner model) was evaluated to test the hypothesized relationships using path coefficients, the coefficient of determination (R^2), and bootstrapping significance tests. The analysis provided empirical evidence regarding the relationships among e-WOM, brand trust, customer loyalty, and consumer resistance to innovation in the Indonesian cosmetics industry.

Data Collection Method

In this study, the data obtained is primary data, obtained by making a structured online questionnaire to consumers in the cosmetic and skin care market in Indonesia. The survey method is chosen because it is the best method for measuring the latent constructs like electronic word-of-mouth, brand trust, customer loyalty, and consumer resistance to innovation with standardized indicators. The target population includes consumers who have bought or used cosmetics, and who have received information and/or reviews on cosmetic brands online. The respondents are selected by non-probability sampling technique, purposive sampling, to ensure that the respondents fulfill the criteria that is relevant to the research objective. The respondents must meet the following criteria: have at least 17 years of age and have had previous experience with online reviews and/or digital conversations about cosmetic products.

The research instrument is constructed using existing measurement scales that have been validated from previous research literature on electronic word-of-mouth, brand trust, customer loyalty and consumer resistance to innovation. To get a consistent perception and attitude from respondents, all items are measured via a five-point Likert scale from 1 (strongly disagree) to 5 (strongly agree). In order to have a construct validity and reliability in SEM-PLS analysis, the questionnaire has multiple indicators to each construct. The instrument can be subject to preliminary review before being fully distributed to ensure the instrument is understandable and relevant in the context of the Indonesian Cosmetics market. The final data set consists of responses from completed and valid questionnaires with data that have been screened.

As for the sample size, this study is guided by Hair et al. (2022) which suggest minimum sample size for SEM-PLS analysis as a function of the maximum number of structural paths pointing toward a latent construct in the model. The most complicated construct in this study has two structural routes and therefore the minimum sample size needed is determined based on this; the final sample size is above this minimum value, providing statistical strength. The method guarantees sufficient statistical power for testing the structural relationships as well as reliable estimation of path coefficients. The data is collected through digital distribution channels and easily distributed among the active cosmetic consumers through social media and online communities. Responses are anonymous and self-reported and follow ethical guidelines for research.

RESULTS AND DISCUSSION

The results of the research and their discussion on the data got from the respondents from the questionnaire will be presented in this chapter. The data analysis is performed on the proposed research model to test the research model, research hypotheses and for the formulation of business solutions which is based on the empirical results obtained by using the Partial Least Squares Structural Equation Modeling (PLS-SEM) method.

Analysis

The analysis of the research model is the analysis of the partial least squares structural equation modeling (PLS-SEM). Analysis involved an evaluation of the measurement model, the structural model assessment and hypothesis testing to test the relationships between the proposed constructs.

Measurement Model Evaluation

Assessment of the validity and reliability of the measurement instrument was carried out first before investigating the structural relationships between the proposed constructs, by conducting the measurement model evaluation. The Partial Least Squares Structural Equation Modeling (PLS-SEM) method is considered as an appropriate method for the evaluation of the measurement model, with the goal of its appropriate measurement for each construct, by testing the indicators for reliability, they are evaluated in terms of internal consistency reliability, convergent validity, and discriminant validity. Before jumping into the assessment of the structural model and solving the hypotheses testing, Hair et al. (2022) mentioned that it was a basic requirement to evaluate the measurement model first.

Outer Loadings

Table 1. Outer Loadings

	BT	CL	CRI	EWOM
BT 1	0.725			
BT 2	0.673			
BT 3	0.819			
BT 4	0.821			
BT 5	0.810			
BT 6	0.770			
BT 7	0.830			
CL 1		0.819		
CL 2		0.738		
CL 3		0.615		
CL 4		0.695		
CL 5		0.798		
CL 6		0.533		
CRI 1			0.841	
CRI 2			0.774	
CRI 3			0.714	
CRI 4			0.835	
CRI 5			0.785	
CRI 6			0.839	
CRI 7			0.810	
EWOM 1				0.664
EWOM 10				0.627

	BT	CL	CRI	EWOM
EWOM 2				0.757
EWOM 3				0.790
EWOM 4				0.815
EWOM 5				0.798
EWOM 6				0.588
EWOM 7				0.764
EWOM 8				0.805
EWOM 9				0.759

Source: Processed by Author (2026)

The outer loading values for the indicators in the final measurement model are shown in Table 4.1. If the indicator loadings are ≥0.70, it suggests acceptable indicator reliability (Hair et al., 2022). However, Hair (2022) states that indicators, which scores fall in the range of 0.40 - 0.70, are not deleted without considering a number of factors, such as the theoretical value of the indicator being investigated and the Composite Reliability (CR) and Average Variance Extracted (AVE). Thus, it is essential to have a statistical assessment of the suitability of an indicator, as well as the benefit therefor from a theoretical perspective, when determining whether to keep an indicator.

Table 4.1 shows that majority of the indicators had outer loading values greater than 0.70 which signifies satisfactory indicators reliability. Several indicators, namely BT2 (0.673), CL3 (0.615), CL4 (0.695), CL6 (0.533), EWOM1 (0.664), EWOM6 (0.588), and EWOM10 (0.627), exhibited loading values between 0.40 and 0.70. However, these indicators were retained as the overall measurement model scored reliably and validly with results that met the recommended level for Composite Reliability and Average Variance Extracted to conduct analysis further (Hair et al., 2022). In general, the outer model validation results indicate that the model validation process obtains useful measurement results and has a sufficient supporting basis to support the next steps in subsequent model validation processes based on PLS-SEM, namely construct model validation, common method bias, and factor loadings.

Reliability & Convergent Validity

Table 2. Internal Consistency Reliability and Convergent Validity Results

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
BT	0.893	0.904	0.916	0.609
CL	0.792	0.805	0.854	0.500
CRI	0.907	0.914	0.926	0.641
EWOM	0.908	0.918	0.923	0.548

Source: Processed by Author (2026)

Results of internal consistency reliability in Table 4.2 shows that the internal consistency reliability of all of the constructs is satisfactory. All values of Cronbach's alpha are between 0.792 and 0.908, and the values of the Composite Reliability are between 0.854 and 0.926, both showing that all latent constructs are consistently measuring their respective indicators (Hair et al., 2022). The convergent validity of all constructs meets the threshold of 0.50, as recommended. The Customer Loyalty construct has an AVE of exactly 0.500, which is still satisfactory from the proposed minimum value by Hair et al. (2022) that the construct has an AVE of more than 50%. The measurement model has good reliability and convergent validity, so it can be used to test discriminant validity and the structural model.

Discriminant Validity

Table 3. HTMT

	BT	CL	CRI	EWOM
BT				
CL	0.921			
CRI	0.638	0.790		
EWOM	0.681	0.906	0.654	

Source: Processed by Author (2026)

The assessment of discriminant validity was carried out using Heterotrait-Monotrait Ratio (HTMT) as shown in Table 3. Henseler et al. (2015) suggested HTMT as a more stringent criterion in judging discriminant validity, and suggested that when the HTMT value is below 0.90, it can be judged that it has adequate discriminant validity. Additionally, Hair, et al. (2022) discuss the use of a combination of measurement model evaluation metrics, rather than one.

The majority of pairs of constructs had HTMT values below the suggested cut-off of 0.90, as shown in Table 4.3, which suggested good discriminant validity. The correlation value between the variables of “Brand Trust” with “Customer Loyalty” (0.921) and “Customer Loyalty” with “Negative Electronic Word-of-Mouth” (0.906) were slightly above the threshold (0.9) as recommended by Ozerall. The results suggest that the constructs described above have about the same level of conceptual similarity. This finding logically makes sense as Brand Trust has been shown to be a strong antecedent of customer loyalty in relationship marketing (Morgan & Hunt, 1994; Chaudhuri & Holbrook, 2001) and negative EWOM could also have a negative effect on the level of loyalty towards a brand.

Table 4. Fornell-Larcker

	BT	CL	CRI	EWOM
BT	0.780			
CL	0.793	0.707		
CRI	0.591	0.670	0.801	
EWOM	0.669	0.792	0.630	0.741

Source: Processed by Author (2026)

To measure the discriminant validity, the Fornell-Larcker criterion was used and is shown in Table 4.4. To confirm that each construct has more variance with its indicators than with other latent constructs, for each construct, the square root of the Average Variance Extracted (AVE) needs to be higher than the correlation values of each construct with other constructs (Fornell and Larcker, 1981).

Table 4.4 shows that the Consumer Resistance to Innovation (CRI) construct fulfils the Fornell-Larcker criterion (the square root of AVE is greater than the correlations with the other constructs). This is because, there is slight overlaps between ‘Brand Trust' and ‘Customer Loyalty', and between ‘Customer Loyalty' and ‘Negative Electronic Word-of-Mouth', with margins higher than inter-construct correlations of the related AVE square roots. These results are echoed by the results of the HTMT assessment, which does not seem to indicate any significant measurement issues, but rather some conceptual and theoretical overlap between constructs. The discriminant validity results suggest that, overall, although some overlapping was found between some of the theoretically related constructs, the present measurement model shows good internal consistency reliability and convergent validity.

Given the overall measurement model (MM) evaluation and the theoretical relationships among the constructs, the model was considered appropriate for subsequent structural model (SM) evaluation and testing of the hypotheses (Hair et al., 2022).

Structural Model Evaluation

After evaluation of the measurement model, the structural model is evaluated concerning the explanatory potential of the proposed research model. This evaluation comprises of an assessment of Variance Inflation Factor (VIF), coefficient of determination (R^2) and effect size (f^2) according to Hair et al. (2022). In the following subsection, bootstrapping is used to confirm the significance of the hypothesized relationships; these measures are used as preliminary indicators of a model's ability to explain relationships.

Collinearity Statistics (VIF)

Table 5. VIF Inner Model

	BT	CL	CRI	EWOM
BT		1.809		
CL			1.000	
CRI				
EWOM	1.000	1.809		

Source: Processed by Author (2026)

The Variance Inflation Factor (VIF) is used to check for collinearity in a structural model as shown in Table 5. As per Hair et al (2022) [14], the VIF scores are employed for checking the multicollinearity of the predictor constructs, when the value is less than 3.0, it is not specified that multicollinearity is a problem for the structural model.

Like shown in Table 5, all the predictor constructs yield the VIF values which fall within the acceptable range of 1.000-1.809. Specifically, the relationship between Negative Electronic Word-of-Mouth and Brand Trust showed an acceptable value of VIF; the relationship between Negative Electronic Word-of-Mouth and Customer Loyalty, Brand Trust and Customer Loyalty showed an acceptable value of VIF; and the relationship between Customer Loyalty and Consumer Resistance to Innovation showed an acceptable value of VIF. These results suggest that there is no multicollinearity between the constructs which act as predictors, so each predictor brings its own information for the model to explain.

In general, the structural model meets the requirements of the collinearity assumption and can be used to further analyze the explanatory and predictive power of the model (Hair et al., 2022).

Coefficient of Determination (R^2)

Table 6. Coefficient of Determination (R^2)

	R-square	R-square adjusted
BT	0.447	0.442
CL	0.753	0.748
CRI	0.449	0.443

Source: Processed by Author (2026)

The coefficient of determination (R^2) for endogenous constructs of the proposed structural model is reported in Table 6. The coefficient of determination (R^2) is a measure indicating the share of the variance in an endogenous construct attributable to its predictor constructs. Hair et al. (2022) suggest that R^2 (explanatory power) of about 0.75, 0.50, and 0.25 are respectively substantial, moderate, and weak levels of explanatory power.

The model's R^2 value of 0.447 for Brand Trust suggested moderate explanatory power as 44.7% of the model's variance is explained by the dependent variable, or Negative Electronic Word-of-Mouth. The R^2 value for Customer Loyalty was 0.753, showing that the explanatory power of the two variables, Negative Electronic Word-of-Mouth and Brand Trust was fairly high. In the meantime, Consumer Resistance to Innovation had an R^2 value of 0.449, which means that 44.9% of their variance can be explained by Customer Loyalty and that it had a moderate level of explanatory power

Results of the R2 showed that in general, the proposed structural model has moderate to high explanatory ability, which means the proposed structural model is able to explain the endogenous constructs used in this research well.

Effect Size (f^2)

Table 7. Effect Size (f^2)

	BT	CL	CRI	EWOM
BT		0.508		
CL			0.814	
CRI				
EWOM	0.809	0.502		

Source: Processed by Author (2026)

Table 7 displays the specified effect size (f^2) values of the exogenous constructs and the endogenous constructs that are dependent on these. Effect size (f^2) indicates the amount of explained variance (R^2 change) in an endogenous construct after removing from the structural model each predictor construct, by other words the predictive power of each predictor construct in the equation. The values of 0.02, 0.15, and 0.35 have been used by Cohen, 1986 (adopted by Hair et al., 2022) as small, medium, and large effect sizes, respectively.

All structural relationships showed the f^2 value greater than the recommended threshold of 0.35 indicating large effect sizes as presented in Table 4.7. In particular, Negative Electronic Word of Mouth is found to have significant effect on both Brand Trust (f2=0.809) and Customer Loyalty (f2=0.502). Similarly, Consumer Resistance to Innovation counts as a significant contributor to Customer Loyalty (f^2 = 0.814), and Brand Trust also makes a significant contribution to Consumer Resistance to Innovation ($f^2 = 0.508$). These results reveal that each predictor constructs contributes in meaningful way towards understanding the endogenous constructs in its respective structural model for the endogenous constructs.

In general, the results of the effect size test showed that all constructs of the predictors have high practical contributions to the endogenous constructs, which makes the proposed structural model have a good capability of explaining.

Hypothesis Testing

After the examination of the measurement and structural models, the significance of the proposed hypotheses needs to be explored. The bootstrapping function is used in PLS-SEM to test the significance of the structural relationships, where it generates a range of t statistics and p values for each of the path coefficients. The path coefficient (β), t statistic, and p value results from the bootstrapping results are used to evaluate the significance of each hypothesized relationship, according to Hair et al., 2022. These findings allow for the empirical test of the proposed hypothesis to either support or reject them.

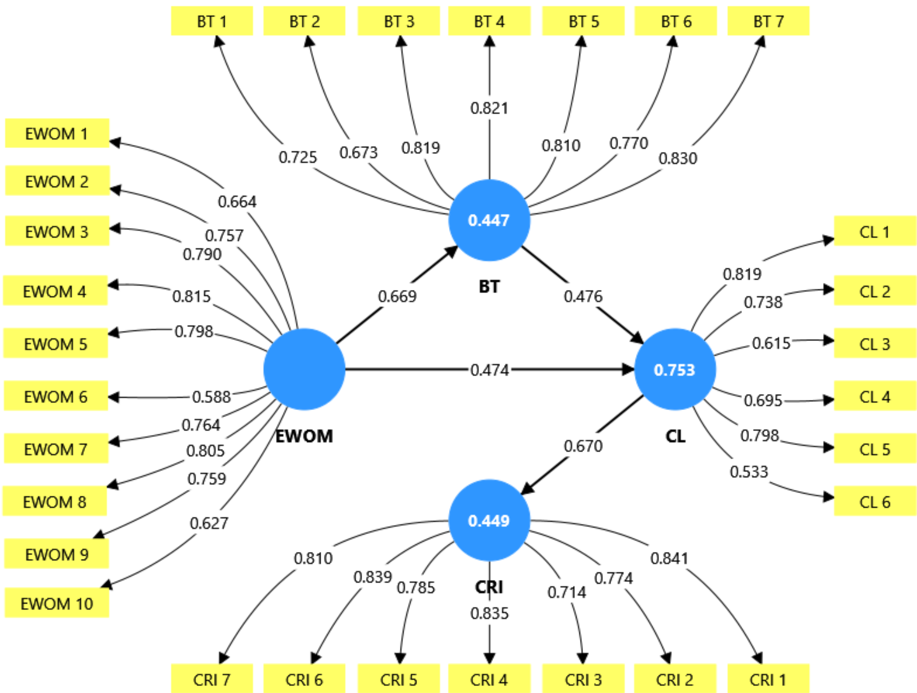

Figure 2. Final Structural Model

The final structural model is given in Figure 4.1 and was generated by PLS-SEM algorithm. The path diagram shown above depict the standardized path coefficients and the coefficient of determination (R^2) that are associated with each endogenous construct, and thus, provide an overview of the correlation between the proposed constructs. These relationships are further analyzed statistically using the bootstrapping procedure as shown in Table 4.8.

Bootstrapping

Table 8. Bootstrapping Results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
BT > CL	0.476	0.480	0.076	6.243	0.000
CL > CRI	0.670	0.668	0.080	8.341	0.000
EWOM > BT	0.669	0.683	0.058	11.557	0.000
EWOM > CL	0.474	0.468	0.086	5.531	0.000

Source: Processed by Author (2026)

Table 8 summarizes the bootstrapping results for the proposed structural relationships. The results indicate that all hypothesized paths are statistically significant, as evidenced by t-statistics ranging from 5.531 to 11.557 and p-values below 0.001. Moreover, all standardized path coefficients are positive, indicating that the relationships among the constructs are in the hypothesized direction. Therefore, all proposed hypotheses (H1–H4) are supported, providing empirical evidence for the structural relationships specified in the research model.

H1. Negative e-WOM has a positive effect on Brand Trust

Positive results of bootstrapping show that Negative e-WOM has positive significant relationship with Brand Trust ($\beta = 0.669$, $t = 11.557$ and P-value < 0.001). Therefore, H1 is supported. The standardized path coefficient data reveal that there is a strong positive relationship between the two constructs and that consumers' reactions to the negative electronic word-of-mouth are closely tied to their respective trust levels for cosmetic brands. This path is one of the strongest among the relationships studied here which indicates the significance of negative online review and consumer feedback control to keep consumer trust.

H2. Negative e-WOM has a positive effect on Customer Loyalty

The bootstrapping result is further confirmed that Customer Loyalty has a significant positive impact with a value of $\beta = 0.474$, $t = 5.531$, $p < 0.001$ from the Negative e-WOM results of the study. Thus, H2 is favoured. The results showed that the correlation coefficient of the positive path coefficient significantly influences the customer loyalty, which means, the improvement of consumer perception of negative eWOM has significant effect on the customer loyalty. The results showed that the relationship was statistically significant, however, it was also found that the effect of it was not as high as the relationship between Negative e-WOM and Brand Trust, so it seemed that there were other factors influencing customer loyalty that were not related to negative online information

H3. Brand Trust has a positive effect on Customer Loyalty

The results reveal that brand trust has a significant positive effect on customer loyalty ($\beta = 0.476$, $t = 6.243$, $p<0.001$). Based on this, H3 shall be supported. The positive relationship that emerged suggests that more trust for the consumers means more loyalty towards cosmetic brands. Overall, developing consumers' trust is crucial to improving the quality of long-term relationships with customers and promoting ongoing brand loyalty and behavior.

H4. Customer Loyalty has a positive effect on Consumer Resistance to Innovation

For the bootstrapping result, the Customer Loyalty has significant positive impact on Consumer Resistance to Innovation ($\beta = 0.670$, $t = 8.341$ and $p< 0.001$). So it can be concluded that H4 is the supported hypothesis. This relationship has the largest standardized path coefficient of all the structural relationships, suggesting that customer loyalty has the highest association with the consumers' resistance to innovation among all others analyzed in this study. The discovery indicates that loyal customers are more likely to carry out their familiar products and buying practices that could lead to the resistance for new product innovations.

In general, the bootstrapping approach supports all the proposed hypotheses. The results show that from a statistical point of view, the proposed structural model has been validated, given that significant positive relationships between negative e-WOM, brand trust, Customer Loyalty and Consumer Resistance to Innovation are found. These conclusions show that the hypothesized relationships in this study are supported by empirical data and can be used as reference in developing business solutions in the cosmetic industry sector in Indonesia to overcome negative electronic word of mouth.

Business Solution

Findings from the previous section of the empirical work highlight the importance of exploring a consumer-focused approach to the challenge of negative electronic word of mouth for cosmetic firms that will help to reduce negative eWOM effects, consolidate customer relationships in the long term and usher in the adoption of innovations. The study proposes a consumer-centered business strategy for managing the negative impact of eWOM, capable of promoting the long-term relationships that are crucial for cosmetic companies. The relationships between the constructs in the structural model that are statistically significant are used to shape the development of the proposed strategy in this instance called the Integrated Consumer Trust and Innovation Strategy (ICTIS). The strategy seeks to tackle each of the findings of the empirical studies in a linked, mutually reinforcing way that ultimately helps boost online reputation management, strengthen brand trust and increase the likelihood of adopting innovation by loyal brand consumers. Therefore, the next section provides the proposed strategic initiatives obtained from the empirical results of this study.

Table 9. Summary of Research Findings and Proposed Business Solutions

Research Findings	Business Implication	Proposed Strategic Response
Negative e-WOM significantly influences Brand Trust.	Negative online reviews can weaken consumer trust toward cosmetic brands.	Strengthen online reputation management and proactive customer engagement.
Brand Trust significantly influences Customer Loyalty.	Building consumer trust is essential for maintaining long-term customer relationships.	Enhance trust-building initiatives through transparency, consistent product quality, and responsive customer service.
Customer Loyalty significantly influences Consumer Resistance to Innovation.	Loyal customers may become hesitant to adopt newly introduced products.	Develop customer-centered innovation programs that reduce uncertainty and encourage product adoption.

Source: Developed by the researcher based on the SEM analysis (2026).

Managing Negative e-WOM through Proactive Online Reputation Management

The first one of the strategic initiatives is helping companies grow their ability to deal with negative electronic word of mouth while it is still a small fish around their ears. The empirical results revealed that Negative e-WOM has a significant negative effect on Brand Trust, this means that cosmetic companies need to take the proactive measures for online reputation management on digital platforms as their primary concerns. It involves managing and keeping an eye on product reviews people post online on eCommerce websites and social media, rapidly reacting to customer concerns, and clearly communicating product-related issues and communicating with trusted beauty influencers or dermatology experts to educate customers on your product and its features. The aim of these things is for online conversations to not have as much of an effect on consumers, but not to make them lose faith in the brand.

Strengthening Brand Trust to Sustain Customer Loyalty

The second strategic goal is to build the Brand Trust as the basis for Customer Loyalty over the long term. The results of the research action show the significant contribution of Brand Trust to Customer Loyalty; this means that when the consumer has a sense of confidence in the brand, then he tends to keep a long association with the brand. Hence, companies in the cosmetic industry must reinforce the trust by ensuring product quality over time, giving clear and suitable information about their product, putting itself at the service of its customers and engaging in ongoing dialogue with them via communication channels in digital media. Customer relation programmes should not only reward the consumers for the transactions they make but should also build emotions and trust in the brand that the consumers will have for the next best transaction.

Supporting Innovation Adoption among Loyal Customers

The third strategic will be towards Customer Resistance to Innovation with loyal customers. In spite of the fact that customers' loyalty is regarded as a cost competitive advantage, the outcomes show that highly loyal customers might be more resistant towards new cosmetic products entering the market. Companies should, therefore, engage customer related innovation approaches which eliminate the uncertainty at the novelties market launches. Some strategies include product trial programs, educational content on new product benefits and formulation advances, limited product trial sampling, and events just to loyal customers to introduce new products. This can help consumers feel more comfortable with new innovations and therefore less resistivit and boost the uptake of innovations.

Loyal Customers' Consumer Resistance to Innovation is covered in the third strategic pillar. The results showed that while customer loyalty is a business asset, there might be consumers that show increased resistance to new products in the company's portfolio should loyalty be mission-critical. Thus, cosmetic companies must go for one of the innovative strategies of customer satisfaction, gradually launching new products while minimizing consumers' uncertainty. Practical steps could involve trialing products, educating consumers on products, undergoing limited sampling and including an only-for-loyal-customers launches event. The activities allow consumers to immerse themselves into the use of innovations without entering an unfamiliar world of new products, which helps mitigate the behaviour resistance to innovation and facilitates adoption.

In summary, the proposed Integrated Consumer Trust and Innovation Management Strategy by the current study is a managerial practice derived from the empirical results. Incorporating proactive reputation management, building trust programs, and adopting innovative strategies for the usage of electronic word-of-mouth will help companies effectively deal with the negative effects of such communication while enhancing the relationship and opportunities for sustainable business growth. The strategy is also discussed as the background to the implementation plan that sets out in the next section.

CONCLUSION

This study examined the relationships among negative electronic word-of-mouth (e-WOM), brand trust, customer loyalty, and consumer resistance to innovation (CRI) in the Indonesian cosmetics industry using a quantitative causal-relational design and partial least squares structural equation modeling (PLS-SEM). The results showed that all four hypothesized relationships were positive and statistically significant: negative e-WOM strengthened brand trust and customer loyalty, brand trust further strengthened customer loyalty, and customer loyalty, in turn, increased resistance to innovation. These findings indicate that e-WOM, brand trust, customer loyalty, and resistance to innovation form an interconnected relational pathway rather than functioning as isolated constructs. They also suggest that strong consumer–brand relationships may create inertia toward unfamiliar or newly introduced products. The findings extend the relationship marketing literature by positioning resistance to innovation as a downstream relational outcome and suggest that cosmetics companies should integrate online reputation management, brand trust maintenance, and gradual, educationally oriented innovation strategies rather than managing these activities separately. This study was limited by its cross-sectional design, reliance on self-reported data, broad focus on the cosmetics industry, and exclusive attention to negative e-WOM. Future research should employ longitudinal designs, compare the effects of positive and negative e-WOM, test the model across specific cosmetic product categories, and incorporate external factors such as pricing, promotional activities, and influencer endorsements.

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