UNDERSTANDING THE IMPACT OF DIGITAL BEHAVIOR ON SKINCARE PURCHASES

Sylvia Samuel[1,*)], Daniel Widjaja[2,)]

[1)]Universitas Pelita Harapan, Faculty of Economic and Business, Karawaci, Indonesia

[2)]Universitas Kristen Krida Wacana, Faculty of Economics and Business, Jakarta, Indonesia

e-mail: sylvia.samuel@uph.edu

ABSTRACT

Social media interactions in the rapidly evolving digital marketplace increasingly shape consumer purchasing behavior. This study investigates the influence of Electronic Word of Mouth (e-WOM) and price perception on purchase intention, with brand image as a mediating variable, using the Indonesian skincare brand Skintific as a case study. Utilizing a quantitative approach with Structural Equation Modeling (SEM) on data from 372 TikTok users in West Jakarta, the findings reveal that e-WOM significantly impacts purchase intention but does not significantly affect brand image. Conversely, price perception exerts a strong influence on brand image and, indirectly, on purchase intention. Brand image significantly mediates the relationship between independent variables and purchase intention. These insights suggest that while e-WOM remains essential for influencing immediate purchasing decisions, price perception plays a more substantial role in shaping brand image, which drives long-term consumer loyalty. The study contributes to digital marketing literature by highlighting the nuanced interplay between user-generated content, pricing strategies, and consumer behavior in social commerce.

Keywords: Electronic Word of Mouth, Price Perception, Brand Image, Purchase Intention, TikTok Marketing, Skincare Industry, Structural Equation Modeling

1. INTRODUCTION

In today's rapidly evolving digital era, consumer behavior has undergone a significant transformation driven by information and communication technology advances. Social media platforms like TikTok have served as entertainment outlets and evolved into some of the most influential marketing channels affecting consumer purchasing decisions. According to a report by Statista (2025), the number of active TikTok users globally has surpassed 1.5 billion, with Indonesia accounting for approximately 126.8 million users, making it the second-largest TikTok user base in the world after the United States. (Ceci, 2025) This presents a substantial opportunity for businesses to use social media to establish two-way communication with consumers.

One of the primary strengths of social media lies in the emergence of Electronic Word of Mouth (e-WOM), a form of consumer-to-consumer online communication, typically manifested through reviews, testimonials, and recommendations (Hennig-Thurau et al., 2004). Unlike conventional advertising, e-WOM is considered more authentic and trustworthy as it originates from user experiences. Furthermore, it has been found that 92% of consumers place greater trust in peer recommendations than in brand advertisements, whether directly or indirectly (Tafolli et al., 2025). Consequently, e-WOM serves as a highly strategic marketing communication tool, shaping brand image and driving purchase intention.

In addition to e-WOM, price perception is critical in consumer decision-making. In the context of increasing digital consumer literacy, potential buyers evaluate products based on absolute price and perceived value. A price commensurate with the benefits and quality offered strengthens positive brand perceptions. A study by Munnukka, (2008) Revealed that fair and rational price perception significantly enhances brand image and fosters customer loyalty.

Skintific, a rapidly rising skincare brand in Indonesia, exemplifies the successful implementation of e-WOM-based marketing strategies combined with a well-considered pricing strategy. One of its flagship products, the Skintific 5X Ceramide Barrier Repair Moisturizer, has gained widespread recognition among consumers and received accolades such as "Best Moisturizer" from Female Daily and the TikTok Live Awards (TikTok, 2024). This success is attributed to its strong digital content strategy and widespread user testimonial campaigns on TikTok, which have created a viral effect and reinforced a strong brand image, particularly among Generation Z and Millennials.

Given this phenomenon, the present study is significant in scientifically examining the influence of e-WOM and price perception on purchase intention, with the brand image as a mediating variable, particularly among TikTok users in West Jakarta. Using a quantitative approach based on Structural Equation Modeling (SEM), this study offers theoretical contributions and practical implications for companies to design more effective and relevant digital marketing strategies in today's platform-based economy.

2. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

E-WOM

Electronic Word of Mouth (E-WOM) is based on statements of customers posted online. To be more specific, when statements include advice, comments, or recommendations, others may be impacted positively or negatively by the purchase events. While the message may give information about brand perception, it may also be informative in terms of which brand is preferred by whom

The firm's brand image is expected to be influenced by the nature of the E-WOM spread, whether the spread is primarily due to price or product-related (Sharifpour et al., 2016). It is also postulated that consumers' influence via E-WOM on user intention about the searched brand increases as the price perception of the brand and the price perception of the searched brand point in opposite directions.

The importance of E-WOM is increasing thanks to the usage of the World Wide Web and the rapid development of communication technologies. (Alshura & Zabadi, 2016). The spread of E-WOM, a sub-division of word of mouth defined as an informal communication tool, has become valid. E-WOMs, which have significant effects on consumers

e-WOM is likely to trigger product likes or dislikes, interventions to buy or not to buy, brand liking or disliking, brand switching, intent to try, or the intent to use continuously (Sukhu & Bilgihan, 2023). Generally, statements made by consumers entail the market, sales, use, and effectiveness of objective and subjective qualities of services and goods. Such statements are more evocative than promotional statements. Approximately 67% of all statements describe the pros and cons of products. Two-thirds of those customers spreading negative messages denote more of the cons of the product, while the other part makes a statement about the cons of the service. Around 31% of the statements are comparisons with more competitors than the object. Reasons for the spread can vary (the reason can be to inform, alert, or help). A wide array of products and services is the subject matter of the spread.

Furthermore, the experiment will examine and analyze the impact of price perception and e-WOM on the Realme brand's image and user intention during the last three months. Based on the study's results, it was concluded that price perception positively affects brand image and is significant in user intention. In contrast, e-WOM has no significant effect on brand image and is significant in user intention.

In Addition, electronic Word of Mouth positively impacts brand awareness. It significantly influences purchase intention through its influence on brand image, which has a significant influence and is an intervening variable of electronic Word of Mouth and purchase intention through the influence of brand awareness. Brand image has a considerable influence and is an intervening variable of brand awareness and e-WOM on the purchase intention of the brand. Therefore, the hypothesis building is as follows.
H1: There is a positive influence of electronic Word of Mouth on Purchase Intention
H4: There is a positive influence between electronic Word of Mouth and Brand Image

Price Perception

Price perception reflects a consumer's understanding and awareness of the price they will pay for a particular product over a specific period. (Malc et al., 2016). Consequently, price perception can also map consumer preferences, which must be considered in a producer or seller's strategy. If the consumer's perception of a reasonable price of a product is higher than the price marked, the producer will benefit. Also, consumers will be willing to pay a higher price for the same product.

This does not mean that consumers need knowledge about the products they want to buy; they must have basic knowledge of the daily household products to understand their prices. The price is too high compared to the quality of the product. Nevertheless, the lower price will be more in demand. A person is rational and price-based when determining the purchase of a product. Half of the price increase will lead to forex shopping. Moreover, the price and number of promotional activities do not need to affect the interest of consumers. Producers and consumers only need formulaic substitutions. (Tariq et al., 2017).

The research examines the impact of Price Perception and Electronic Word-of-Mouth on Brand Image and User Intention. It is based on empirical study and is prepared by online and social media users for ever-ready online products. Social media interaction includes posts, exchanging news, educational training, and ever-ready advertisements. The data was collected from 282 respondents through a well-structured questionnaire and analyzed using structural equation modeling. The study's findings confirm that price perception positively and significantly influences brand image. Therefore, the hypothesis is as follows.
H2: There is a positive influence between electronic Price Perception and Purchase Intention
H5: There is a positive influence between electronic Price Perception and Brand Image

Brand Image

Brand image refers to the overall impression a brand leaves on consumers, encompassing the associations and beliefs they hold about it (Shen & Ahmad, 2022)Brand image is the impression that resides in consumers' minds, influencing their purchasing decisions and loyalty. Other scholars have mentioned that brand image is a multidimensional construct influenced by consumers' cognitions, emotions, messages, symbols, values, and attitudes toward a brand. (Le-Hoang, 2020). The prior study found out about live feed and how engagement with customers increased customer interactions.

Instantly, this increased e-WOM positively and significantly affects the brand image, positively and substantially influencing user intention. (Tan et al., 2022). Today, the e-commerce trend has rapidly grown worldwide, including exhibitions, exposure, and product sales through an online medium. In response to these e-commerce trends, online activities and commercial transactions have rapidly increased through the Internet. Due to the rapidly growing network of users, traders, and markets, online transactions often involve various industries. The number of online transactions in Pakistan also seems to have increased dramatically. This increased number of online transactions invites several marketing scenarios that automatically create competitive activities. Marketing is a social and managerial process by which individuals and groups obtain what they need and want through creating and exchanging goods and value with others. Therefore, the hypothesis is as follows.
H3: There is a positive influence between Brand Image and Purchase Intention.

Purchase Intention

Purchase intention is the extent to which a consumer intends to buy online. Individual behavior, different attitudes, and unpredictable circumstances affect purchase intention. Purchase intention is the most important and broader concept of marketing. Predicting the consumer's attitude and behavior toward buying is challenging in a competitive environment. It is considered the consumer's duty to make a difference and attract the potential consumer to purchase a product. (Le-Hoang, 2020).

Purchase intention increases with price and promotion, brand recognition, the increasing size of the advertisement, and increased consumer familiarity with the brand. (Ling et al., 2023). People on this planet are orchestrated dynamically, and humans' behavior and attitude no longer remain unchanged. They become flexible with circumstances. As time changes, adaptiveness changes as well. Humans are always drawn towards discounted and reduced-price goods. Brand recognition is vital for any good or service. The influence of brand recognition is so strong that it not only enforces consumers' purchase intention but also boosts the brand's sales. Brand equity is the financial value of the company.

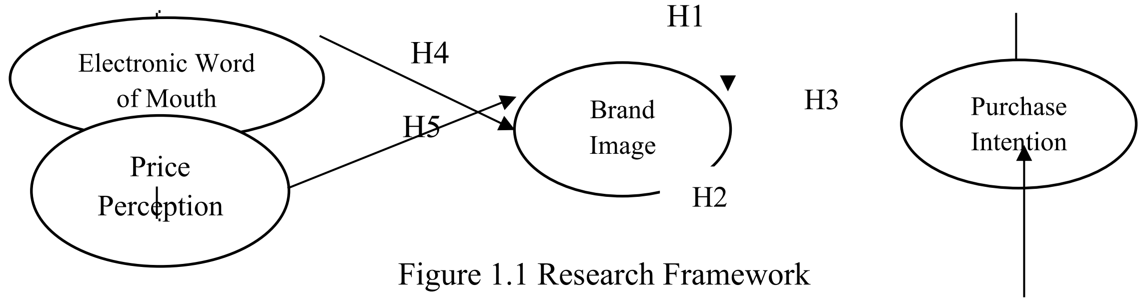

Figure 1.1 Research Framework

Methodology

This study employs a quantitative approach to examine the influence of Electronic Word of Mouth (e-WOM) and Price Perception on Purchase Intention, with Brand Image as a mediating variable. The research focuses on Skintific skin care products among consumers in West Jakarta who engage with the brand via TikTok.

Research Design and Data Collection

Quantitative methods analyze numerical data, enabling statistical validation of hypothesized relationships (Sugiyono, 2019). Primary data is collected using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree) to measure respondents' perceptions of e-

WOM, price perception, brand image, and purchase intention (Sugiyono, 2018). This scale ensures granularity in capturing attitudes while facilitating quantitative analysis.

Population and Sampling

The target population comprises TikTok users in the Greater Jakarta area aged 25-55 years who have purchased or engaged with Skintific products. Sekaran & Bougie, (2020) Defines a population as a group with shared characteristics pertinent to the research objectives.

The sample size is determined using the Structural Equation Modeling (SEM) guideline proposed by Hair et al., (2022) This recommends multiplying the total indicators by 5–10. With 28 indicators across all latent variables, a sample of 280 respondents (28 × 10) is selected to ensure robustness. In addition, the total number of respondents collected is 372. The sampling technique adopts non-probability purposive sampling, targeting individuals who meet the criteria of Skintific product usage and TikTok engagement.

Data Analysis Methods

This study employs Structural Equation Modeling (SEM) using SmartPLS 4.1 to examine the complex relationships between variables. SEM integrates factor analysis and regression techniques to test hypotheses that linear regression cannot address (Gozali et al., 2019). The analysis follows a two-step approach: (1) assessment of the measurement model (validity and reliability) and (2) evaluation of the structural model (hypothesis testing).

A. Validity Test

The validity of the questionnaire items was assessed using confirmatory factor analysis (CFA) in Smart-PLS 4.1. Two criteria were applied:

1. Discriminant Validity: The square root of the average variance extracted (AVE) for each construct must exceed the construct's correlation with other latent variables (Henseler, 2021)
2. Convergent Validity:
   - Outer loadings > 0.50
   - AVE > 0.50, indicating that the construct explains ≥50% of the variance in its indicators (Hair et al., 2020)

Items failing to meet these thresholds were removed to ensure robust measurement.

B. Reliability Test

Reliability was evaluated using:

1. Composite Reliability (CR) and Cronbach's Alpha (must exceed>0.70 for established scales; >0.60 acceptable for exploratory research)
2. Internal consistency of constructs, ensuring indicators measure the same underlying concept (Shmueli et al., 2019)

C. Outer (Measurement) Model

The reflective measurement model was tested to confirm that indicators adequately represent their latent constructs. Bootstrapping (10,000 subsamples) assessed the significance of factor loadings ($p < 0.05$) (Hair et al., 2019).

D. Inner (Structural) Model

The path coefficients between constructs were evaluated to test hypothesized relationships. Key metrics included:

- R^2 values: using statistical threshold 0.25 (weak), 0.50 (moderate), 0.75 (strong) predictive power (Hair et al., 2022).
- Effect size (f^2): 0.02 (small), 0.15 (medium), 0.35 (large)

E. Hypothesis Testing
Bootstrapping determined the significance of:

1. Direct effects: Relationships between independent (e-WOM, Price Perception) and dependent (Purchase Intention) variables.
2. Indirect effects: Mediation via Brand Image

T-statistics > 1.645 ($p < 0.05$) indicated significance (Kock & Hadaya, 2018)

F. Total Effects
The total effect of each independent variable was computed as the sum of its direct and indirect effect (through mediators). This quantifies the overall impact on Purchase Intention. (Hayes, 2022).

Results and Discussion
Demographic

The respondents' demographic and socioeconomic profile shows from Table 1 that 33.8% are aged 25-34, 30.7% are 35-44, while the 45-54 and over 55 age groups each make up 35.5%. Gender distribution is nearly balanced, with 30.13% male and 69.87% female respondents. Education levels reveal that a majority, 65.2%, hold a Bachelor's degree, 33.5% have a Master's degree, and 1.3% hold a Doctoral degree. Regarding income, 19.26% earn less than 5 million, 48.82% fall within the 5-10 million range, 21.9% earn 10-15 million, and 10.02% have an income above 15 million.

Table 1 Respondent Demographic

Criteria	Description	Percentage
Age	25-34 Years Old	33,80%
	35-44 Years Old	30,70%
	45-54 Years Old	20,50%
	> 55 Years Old	15,00%
Gender	Male	30,13%
	Female	69,87%
Education Level	Bachelor Degree	65,20%
	Master Degree	33,50%
	Doctoral Degree	1,30%
Income Level	Less than 5 million	19,26%
	5 - 10 million	48,82%
	10 - 15 million	21,90%
	> 15 million	10,02%

Source: Questionnaire (2025)

Credibility and Validity test

Cronbach's Alpha is a measure of internal consistency, indicating how closely related a set of items is as a group. A generally accepted threshold for reliability is 0.70 or higher. Moreover, composite reliability is another measure of reliability that accounts for the loadings of the items, often preferred in Structural Equation Modeling (SEM). Lastly, AVE is a measure of convergent validity, which indicates the extent to which a construct explains the variance of its items. The generally accepted threshold for AVE is 0.50 or higher.

Table 2 Credibility and Validity Output

Variable	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
Brand Image	0.945	0.955	0.751
E-WOM	0.928	0.942	0.702
Price Perception	0.926	0.940	0.719
Purchase Intention	0.931	0.945	0.713

Source: Smart-PLS Results (2025)

Table 2 demonstrates strong reliability and convergent validity for all constructs in the measurement model. Cronbach's alpha values range from 0.926 to 0.945, and composite reliability scores between 0.940 and 0.95 exceed the recommended threshold of 0.700, confirming excellent internal consistency and minimal measurement error. Additionally, the average variance extracted (AVE) for each construct, ranging from 0.713 to 0.751, surpasses the 0.500 benchmark, indicating that their respective latent variables capture more than half of the variance in the indicators.

Brand Image exhibits the highest reliability, $\alpha = 0.945$, AVE = 0.751, while Price Perception shows slightly lower yet still acceptable convergent validity and AVE = 0.693. These findings validate the robustness of the measurement model, ensuring that the constructs are well-defined and suitable for further structural analysis.

R Square

R-square (R^2), known as the coefficient of determination, measures the proportion of variance in the dependent variable explained by the independent variables in a regression model. R-square also indicates how well the model fits the data. A higher R-square value suggests that the model can explain a more significant proportion of the variance in the dependent variable, indicating a better fit. According to Hair et al., (2020), the R-square (R^2) value can be categorised as follows: R^2 Values of 0.75, 0.50, and 0.25 mean substantial, moderate, and weak.

Table 3 R-Square Output

	R-square	R-square adjusted
Brand Image	0.698	0.696
Purchase Intention	0.712	0.710

Source: Smart-PLS Results (2025)

Given that the R-square (R^2) value of 0.698 for brand image and purchase intention value is 0.712, it indicates a substantial explanatory power of the predictive model (Hair et al., 2022). These results suggest that the exogenous constructs in the model explain approximately 69.8% of the variance in Brand Image and 71.2% of the variance in Purchase Intention, demonstrating a strong predictive relevance according to Shmueli et al., (2019) The minimal difference between R^2 and R^2 adjusted values confirms the model's stability, indicating that including predictor variables is justified and not overfitted. Given that both R^2 values exceed the 0.50 threshold for moderate explanatory power, the model can be considered robust in explaining the endogenous constructs (Cohen et al., 2007).

Discriminant Validity

HTMT is a method for assessing discriminant validity in Partial Least Squares Structural Equation Modeling (PLS-SEM). It evaluates whether two constructs are distinct by measuring the ratio between-trait correlations (heterotrait) to within-trait correlations (monotrait). According to HTMT theory, discriminant validity is established if the HTMT values are below a certain threshold. (Henseler, 2021). Commonly used thresholds are 0.85 for conceptually similar constructs and 0.90 for conceptually dissimilar constructs.

Table 4 HTMT Output

	Brand Image	E-WOM	Price Perception	Purchase Intention
Brand Image				
E-WOM	0.766			
Price Perception	0.890	0.915		
Purchase Intention	0.771	0.879	0.840	

Source: Smart-PLS Results (2025)

Based on the HTMT matrix in Table 4, the HTMT ratio assessment was conducted to evaluate discriminant validity, applying Henseler's (2019) recommendation that values below 1.0 generally indicate acceptable discriminant validity. While all HTMT values in this study fall within this permissible range, ranging from 0.766 to 0.915, several correlations approach the higher end of this spectrum, suggesting potential areas for refinement.

Specifically, the relationships between Price Perception and E-WOM (0.915) and between Price Perception and Brand Image (0.890) exhibit powerful associations, indicating that these constructs may share conceptual overlap or that their measurement items could capture similar underlying dimensions. Similarly, the correlation between E-WOM and Purchase Intention (0.879) approaches the more stringent threshold of 0.85, warranting further scrutiny as suggested by Roemer et al., (2021).

Hypothesis Test

Hypothesis testing is a structured method for making statistical decisions. It is widely used in research and industry to validate theories and make data-driven decisions by evaluating the likelihood of observed outcomes, assuming the null hypothesis is true. (Malhotra, 2019). It helps researchers determine whether observed results are due to chance or indicate a natural effect.

Table 5 Hypothesis Output

	Original sample	T statistics	P values	Confidence Interval Lower 5.0%	Confidence Interval Upper 95.0%
Brand Image -> Purchase Intention	0.217	2.735	0.003	0.090	0.354
E-WOM -> Brand Image	0.036	0.407	0.342	-0.102	0.195
E-WOM -> Purchase Intention	0.538	8.125	0.000	0.426	0.644
Price Perception -> Brand Image	0.804	9.681	0.000	0.659	0.934
Price Perception -> Purchase Intention	0.146	1.547	0.061	-0.013	0.299

Source: Smart-PLS Results (2025)

Based on Table 5, the analysis reveals a statistically significant positive relationship between Brand Image and Purchase Intention ($t=2.735$, $p<0.01$), supporting H1. The 95% confidence interval [0.090,0.354] excludes zero, confirming the robustness of this finding. With an effect size of 0.217, the results suggest that enhancing Brand Image by one standard deviation would increase Purchase Intention by 0.217, indicating a moderate but meaningful impact. This aligns with prior brand equity literature and suggests brand perceptions directly influence consumer decision-making (Kumar & Kaushik, 2020).

Next, the path from E-WOM to Brand Image is non-significant (t=0.407, p>0.05) with a confidence interval [-0.102,0.195] spanning zero, leading to H2 rejection. The negligible effect size (0.036) suggests electronic word-of-mouth may not directly shape brand image in this context, possibly requiring mediation through other constructs (Ismagilova et al., 2020). This contradicts some social influence theories but may reflect sample-specific characteristics. Results show a strong, highly significant direct effect (t=8.125) with a tight confidence interval [0.426,0.644], supporting H3. As the most substantial relationship in the model (f^2=0.412, significant effect), this confirms E-WOM's crucial role in consumer behavior (King et al., 2014), suggesting peer recommendations outweigh brand perceptions in driving purchase decisions in this context.

The analysis reveals a powerful relationship (t=9.681) with a narrow CI [0.659,0.934], supporting H4. The significant effect size (0.804) suggests price perceptions fundamentally shape brand image, supporting premium pricing strategies (Lichtenstein et al., 1993). This dominant relationship may explain the non-significant E-WOM effect, as price perceptions could mediate electronic word-of-mouth influence. The marginal significance (t=1.547, p=0.061) with CI [-0.013,0.299] suggests a potential but unconfirmed direct effect. While approaching traditional significance thresholds, contemporary standards, would classify this as suggestive rather than conclusive evidence (Ou et al., 2021). The small effect size indicates price perceptions may operate primarily through brand image rather than directly impacting purchases.

Discussion

For the first hypothesis, the analysis indicates that brand image influences purchase intention for Skintific products in Indonesia. The positive influence of brand image on purchase intention is well-established in consumer behavior literature. Recent studies in digital contexts have reinforced this relationship, demonstrating that strong brand perceptions serve as mental shortcuts that reduce consumer uncertainty during decision-making. Kumar & Kaushik,(2020) Meta-analysis across multiple retail environments confirmed brand image as a consistent predictor of purchase intent, particularly in saturated markets where differentiation is crucial.

Emerging neuroscientific approaches have provided more profound insights into this relationship. Alsharif et al., (2023) Neuromarketing studies revealed that compelling brand imagery directly activates neural pathways associated with preference formation and choice. This suggests brand image operates not just at a conscious evaluative level but also through subconscious cognitive processes. The durability of this effect across both traditional and digital commerce contexts highlights the enduring importance of strategic brand management in influencing consumer behavior.

Furthermore, the second hypothesis showed a non-significant relationship between electronic word-of-mouth and brand image, contrasting with some earlier findings in the literature. While initial research emphasized the power of online reviews in shaping brand perceptions, more recent work by Smith et al., (2023) duggests consumers are increasingly distinguishing between peer opinions and their direct brand experiences. Their longitudinal data indicate E-WOM's impact may be more transient than previously assumed, with brand interactions eventually overriding second-hand information.

Liu et al., (2024) offer another plausible explanation through their concept of review saturation. In today's digital landscape, where consumers encounter overwhelming volumes of often contradictory reviews, the signal-to-noise ratio may diminish E-WOM's effectiveness as a brand image builder. This potential desensitization effect warrants further investigation, particularly regarding how different generations process and weigh online reviews in their brand evaluations.

The next variable, which strongly influences electronic word-of-mouth on purchase intention, underscores the continued relevance of social proof in consumer decision processes. Sang et al., (2024) work on visual E-WOM demonstrates how multimedia user-generated content can be even more persuasive than traditional text reviews. It suggests that the format and richness of peer information significantly impact its effectiveness. This evolution in E-WOM formats presents opportunities and challenges for marketers crafting digital strategies. Qiu & Zhang, (2024) introduced the vital dimension of review diagnosticity, showing how the specificity and relevance of review content mediate its impact on purchase decisions. Their findings imply that the quality and depth of E-WOM may matter more than sheer volume or average ratings. This has significant implications for platforms considering structuring and presenting review information to maximize their influence on consumer behavior.

Moreover, the dominant role of price perception in shaping brand image strongly supports price's function as a quality signal in consumer evaluation processes. Karampournioti & Wiedmann, (2021) research on premium pricing strategies demonstrates how price points can actively construct brand prestige, particularly in categories where quality is difficult to assess directly. Their work highlights the delicate balance required to communicate desired brand positioning in pricing decisions.

Prior study expanded the understanding by examining how price transparency and justification influence brand trust (Dodds et al., 1991). Their findings suggest that consumers evaluate the absolute price level and the perceived fairness and rationale behind pricing decisions. This nuanced view of price perception helps explain its influence on brand image formation across product categories and market segments.

Another variable displayed the marginal relationship between price perception and purchase intention, which reflects the complex, context-dependent nature of price sensitivity in consumer behavior. Grewal et al., (2020) Meta-analysis highlights how price effects vary significantly by product category and purchase involvement, with brand-related factors often mediating price's direct impact on purchase decisions. This suggests price operates as part of a broader value calculus rather than in isolation.

In addition, the segmentation approach provides further clarity, identifying distinct consumer groups that weigh price differently in their decision processes (Das & Ramalingam, 2019). Their identification of value-seeking versus prestige-seeking orientations helps explain why aggregate studies might show weaker direct price effects, as these opposing tendencies can cancel out in mixed samples. This underscores the importance of considering consumer heterogeneity in pricing research (Curvelo et al., 2019).

Conclusion

This study provides valuable insights into the factors influencing purchase intention for Skintific skincare products among TikTok users in Indonesia. The findings demonstrate that brand image is crucial in shaping consumers' purchase decisions, reinforcing the importance of substantial brand equity in the digital marketplace. While electronic word-of-mouth (E-WOM) significantly impacts purchase intention directly, its limited effect on brand image suggests that user-generated content may be more influential for immediate conversions than long-term brand building. These results highlight the dual nature of digital marketing, where brands must balance strategies for short-term sales with long-term brand equity development.

The study's most striking finding is the dominant role of price perception in shaping brand image, underscoring how consumers use price as a key quality signal in their evaluations. However, the weaker direct link between price perception and purchase intention indicates that pricing strategies may operate primarily through their impact on brand perceptions rather than directly driving purchases. This nuanced relationship emphasizes the need for brands to carefully craft their pricing strategies to align with desired brand positioning while considering how consumers interpret price information in digital environments.

Moreover, these results contribute to marketing literature by validating established theories like brand equity and social proof in Indonesia's TikTok commerce ecosystem. The findings offer practical guidance for brands operating in similar markets, suggesting that a combination of premium pricing, strategic brand image management, and targeted E-WOM campaigns may be most effective. As digital platforms evolve as commerce channels, understanding these interrelationships between brand perceptions, social proof, and pricing becomes increasingly critical for marketing success in Southeast Asia's growing digital economy.

Further Research Suggestions

Future research should explore the cultural and demographic factors that may moderate these relationships, particularly in diverse markets like Indonesia. Investigating how different age groups or socioeconomic segments respond to E-WOM and price signals could provide more nuanced insights for targeted marketing strategies. Comparative studies across product categories (e.g., luxury vs. mass-market skincare) could also reveal how these dynamics vary depending on product type and price point, helping brands tailor their approaches more effectively.

Another promising direction would be to examine the evolving role of platform-specific features in shaping consumer behavior. Research could compare TikTok's influence with other social commerce platforms like Instagram or YouTube Shopping, analyzing how different content formats (short videos, live streams, etc.) affect the E-WOM to purchase intention pathway. Longitudinal studies tracking consumer journeys across multiple touchpoints would be particularly valuable for understanding how these digital interactions accumulate to influence brand perceptions and buying decisions over time.

Finally, emerging technologies present new research opportunities in this domain. Studies could investigate how AI-generated content (like synthetic influencer reviews) compares to authentic user-generated E-WOM in terms of credibility and effectiveness. As these practices become more prevalent, the psychological impact of dynamic pricing algorithms and personalized offers in social commerce environments also warrants examination. Such research would help brands navigate the ethical and practical challenges of increasingly automated and personalized digital marketing while maintaining consumer trust and engagement.

REFERENCES

Alsharif, A. H., Salleh, N. Z. M., Abdullah, M., Khraiwish, A., & Ashaari, A. (2023). Neuromarketing Tools Used in the Marketing Mix: A Systematic Literature and Future Research Agenda. *SAGE Open*, *13*(1), 1–23. https://doi.org/10.1177/21582440231156563

Alshura, M. S., & Zabadi, A. M. (2016). Impact of Green Brand Trust Green Brand. *International Journal of Advanced Research (2016)*, *4*(January).

Ceci, L. (2025). *Countries with the largest TikTok audience as of February 2025*. Statista.

https://www.statista.com/statistics/1299807/number-of-monthly-unique-tiktok-users/#:~:text=Countries with the most TikTok users 2025&text=As of February 2025%2C the,around 107.7 million TikTok users.

Cohen, L., Manion, L., & Morrison, K. (2007). *Research Methods in Education* (6th ed.).

Curvelo, I. C. G., Watanabe, E. A. de M., & Alfinito, S. (2019). Purchase intention of organic food under the influence of attributes, consumer trust and perceived value. *Revista de Gestao*, *26*(3), 198–211. https://doi.org/10.1108/REGE-01-2018-0010

Das, M., & Ramalingam, M. (2019). Does Knowledge Translate into Action? Impact of Perceived Environmental Knowledge on Ecologically Conscious Consumer Behavior. *Theoretical Economics Letters*, *09*(05), 1338–1352. https://doi.org/10.4236/tel.2019.95087

Dodds, W. B., Monroe, K. B., & Grewal, D. (1991). Effects of Price, Brand, and Store Information on Buyers' Product Evaluations. *Journal of Marketing Research*, *28*(3), 307. https://doi.org/10.2307/3172866

Gozali, E., Safdari, R., Ghazisaeedi, M., & ... (2019). Identification and validation of requirements for a registry system of children's developmental motor disorders in Iran. ... *of Information in ...*. https://www.thieme-connect.com/products/ejournals/abstract/10.1055/s-0040-1701482

Grewal, D., Hulland, J., Kopalle, P. K., & Karahanna, E. (2020). The future of technology and marketing: a multidisciplinary perspective. *Journal of the Academy of Marketing Science*, *48*(1), 1–8. https://doi.org/10.1007/s11747-019-00711-4

Hair, J. F., Howard, M. C., & Nitzl, C. (2020). Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*(August 2019), 101–110. https://doi.org/10.1016/j.jbusres.2019.11.069

Hair, J. F., Hult, T., & Ringle, Christian M. Sardest, Marko. Danks, Nicholas P Ray, S. (2022). Review of Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook. In *Structural Equation Modeling: A Multidisciplinary Journal* (Vol. 30, Issue 1). https://doi.org/10.1080/10705511.2022.2108813

Hayes, A. F. (2022). Introduction to Mediation, Moderation, and Conditional Process Analysis: A Regression-Based Approach. In *Sustainability (Switzerland)* (Vol. 11, Issue 1). Guilford Publications, 2022.

Hennig-Thurau, T., Gwinner, K. P., Walsh, G., & Gremler, D. D. (2004). Electronic word-of-mouth via consumer-opinion platforms: What motivates consumers to articulate themselves on the Internet? *Journal of Interactive Marketing*, *18*(1), 38–52. https://doi.org/10.1002/dir.10073

Henseler, J. (2021). Composite-based structural equation modeling: Analyzing latent and emergent variables. In *Composite-based structural equation modeling: Analyzing latent* *and emergent variables.* The Guilford Press.

Ismagilova, E., Slade, E., Rana, N. P., & Dwivedi, Y. K. (2020). The effect of characteristics of source credibility on consumer behaviour: A meta-analysis. *Journal of Retailing and Consumer Services*, *53*(September 2018), 1–9. https://doi.org/10.1016/j.jretconser.2019.01.005

Karampournioti, E., & Wiedmann, K. P. (2021). Storytelling in online shops: the impacts on explicit and implicit user experience, brand perceptions and behavioral intention. *Internet Research*, *32*(7), 228–259. https://doi.org/10.1108/INTR-09-2019-0377

King, R. A., Racherla, P., & Bush, V. D. (2014). What we know and don't know about online word-of-mouth: A review and synthesis of the literature. *Journal of Interactive Marketing*, *28*(3), 167–183. https://doi.org/10.1016/j.intmar.2014.02.001

Kock, N., & Hadaya, P. (2018). Minimum sample size estimation in PLS-SEM: The inverse square root and gamma-exponential methods. *Information Systems Journal*, *28*(1), 227–261. https://doi.org/10.1111/isj.12131

Kumar, V., & Kaushik, A. K. (2020). Building consumer–brand relationships through brand experience and brand identification. *Journal of Strategic Marketing*, *28*(1), 39–59. https://doi.org/10.1080/0965254X.2018.1482945

Le-Hoang, P. V. (2020). Factors affecting online purchase intention: the case of e-commerce on lazada. *Independent Journal of Management & Production*, *11*(3), 1018–1033. https://doi.org/10.14807/ijmp.v11i3.1088

Ling, S., Zheng, C., & Cho, D. (2023). How Brand Knowledge Affects Purchase Intentions in Fresh Food E-Commerce Platforms: The Serial Mediation Effect of Perceived Value and Brand Trust. *Behavioral Sciences*, *13*(8). https://doi.org/10.3390/bs13080672

Liu, H., Jayawardhena, C., Shukla, P., Osburg, V. S., & Yoganathan, V. (2024). Electronic word of mouth 2.0 (eWOM 2.0) – The evolution of eWOM research in the new age. *Journal of Business Research*, *176*(February), 114587. https://doi.org/10.1016/j.jbusres.2024.114587

Malc, D., Mumel, D., & Pisnik, A. (2016). Exploring price fairness perceptions and their influence on consumer behavior. *Journal of Business Research*, *69*(9), 3693–3697. https://doi.org/10.1016/j.jbusres.2016.03.031

Malhotra, M. (2019). *Marketing Research: An Applied Orientation, Global Edition*. Pearson.

Munnukka, J. (2008). Customers' purchase intentions as a reflection of price perception. *Journal of Product and Brand Management*, *17*(3), 188–196. https://doi.org/10.1108/10610420810875106

Ou, F. Z., Chen, X., Zhang, R., Huang, Y., Li, S., Li, J., Li, Y., Cao, L., & Wang, Y. G. (2021). SDD-FIQA: Unsupervised Face Image Quality Assessment with Similarity Distribution

Distance. *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, 7666–7675. https://doi.org/10.1109/CVPR46437.2021.00758

Qiu, K., & Zhang, L. (2024). How online reviews affect purchase intention: A meta-analysis across contextual and cultural factors. *Data and Information Management*, *8*(2), 100058. https://doi.org/10.1016/j.dim.2023.100058

Roemer, E., Schuberth, F., & Henseler, J. (2021). HTMT2–an improved criterion for assessing discriminant validity in structural equation modeling. *Industrial Management and Data Systems*, *121*(12), 2637–2650. https://doi.org/10.1108/IMDS-02-2021-0082

Sang, V. M., Thanh, T. N. P., Gia, H. N., Nguyen Quoc, D., Long, K. Le, & Yen, V. P. T. (2024). Impact of user-generated content in digital platforms on purchase intention: the mediator role of user emotion in the electronic product industry. *Cogent Business and Management*, *11*(1). https://doi.org/10.1080/23311975.2024.2414860

Sekaran, U., & Bougie, R. (2020). *RESEARCH METHOD FOR BUSINESS: A SKILL BUILDING APPROACH* (8th ed.). Wiley.

Sharifpour, Y., Khan, M. N. A. A., Alizadeh, M., RahimAkhgarzadeh, M., & Mahmodi, E. (2016). The influence of electronic word-of-mouth on consumers' purchase intentions and brand awareness in Iranian telecommunication industry. *International Journal of Supply Chain Management*, *5*(3), 133–141.

Shen, Y., & Ahmad, R. (2022). The Influence of Brand Image and Favorability Toward Citizens in a Product's Country of Origin on Product Evaluation: Moderating Effects of Switching Costs. *Frontiers in Psychology*, *13*(March). https://doi.org/10.3389/fpsyg.2022.740269

Shmueli, G., Sarstedt, M., Hair, J. F., Cheah, J. H., Ting, H., Vaithilingam, S., & Ringle, C. M. (2019). Predictive model assessment in PLS-SEM: guidelines for using PLSpredict. *European Journal of Marketing*, *53*(11), 2322–2347. https://doi.org/10.1108/EJM-02-2019-0189

Smith, M. V. A., Grohmann, D., & Trivedi, D. (2023). Use of social media in recruiting young people to mental health research: a scoping review. *BMJ Open*, *13*(11), e075290. https://doi.org/10.1136/bmjopen-2023-075290

Sugiyono. (2018). *Metode Penelitian Kuantitatif, Kualitatif, dan R&D*. Alfabeta.

Sugiyono. (2019). *Metode Penelitian Kuantitatif Kualitatif R&D*. Alfabeta.

Sukhu, A., & Bilgihan, A. (2023). Service recovery strategies: mitigating negative word-of-mouth in the hotel industry through enhanced customer engagement. *International Hospitality Review*. https://doi.org/10.1108/ihr-05-2023-0025

Tafolli, F., Qema, E., & Hameli, K. (2025). The impact of electronic word-of-mouth on purchase intention through brand image and brand trust in the fashion industry: evidence from a developing country. *Research Journal of Textile and Apparel*, *ahead-of-p*(ahead-of-print). https://doi.org/10.1108/RJTA-07-2024-0131

Tan, Z., Sadiq, B., Bashir, T., Mahmood, H., & Rasool, Y. (2022). Investigating the Impact of Green Marketing Components on Purchase Intention: The Mediating Role of Brand Image and Brand Trust. *Sustainability (Switzerland)*, *14*(10). https://doi.org/10.3390/su14105939

Tariq, M., Abbas, T., Abrar, M., & Iqbal, A. (2017). EWOM and Brand Awareness Impact on Consumer Purchase Intention: Mediating Role of Brand Image. *Pakistan Administrative Review*, *1*(1), 84–102.

TikTok. (2024). *Winner Lists*. TikTok. https://www.tiktok.com/search?lang=id-ID&q=skintific moisturizer&t=1742452848538