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THE IMPACT OF SOCIAL MEDIA MARKETING ACTIVITIES ON *SKINTIFIC* PRODUCTS: PLS-SEM APPROACH

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ABSTRACT

The swift expansion of the internet has markedly facilitated communication, thereby evolving social media from a tool for personal interaction into a formidable platform for product promotion. This research aims to investigate the effects of social media marketing endeavors on brand awareness, brand image, and brand loyalty about Skintific, a well-regarded skincare brand. Considering its growing significance, formulating a robust marketing strategy—especially within social media—is essential for enhancing brand visibility and cultivating customer loyalty. This study analyzes data from online questionnaires collected from June to July 2024 using Structural Equation Modeling (SEM) through Partial Least Squares (PLS). The sample for this investigation comprises 170 consumers of Skintific residing in Yogyakarta, with data gathered through questionnaires disseminated on platforms including Instagram, Twitter, LINE, and WhatsApp. The results indicate a positive and statistically significant correlation between social media marketing activities and brand metrics: awareness, image, and loyalty.

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1. INTRODUCTION

The rapid evolution of social media has profoundly altered marketing methodologies across diverse industries, with particular emphasis on the cosmetics and skincare domains. This alteration is distinguished by the advent of social media marketing activities (SMMA) that exploit platforms such as Instagram, TikTok, and Facebook to engage consumers through innovative approaches. The ramifications of these activities on consumer behavior, brand perception, and purchase intentions have emerged as a central theme of scholarly inquiry as brands endeavor to acclimate to the digital milieu and capitalize on the influence of social media personalities. A principal advantage of social media marketing is its capacity to enhance brand and product visibility. It highlights that social media advertising enables firms to access a wider audience, thereby improving the visibility and recognition of their products [1].

Skintific, a new player in the Indonesian beauty market, is known for its skincare formulations that focus on repairing and strengthening the skin barrier, the outermost epidermal layer. *Skintific* uses social media as a primary marketing tool to reach consumers effectively. Its social media marketing initiatives, emphasizing key aspects such as brand awareness, perception, and consumer loyalty, are a testament to the brand's proactive approach. *Skintific* actively promotes its products through two major social media platforms: Instagram (@skintificid), with a following of 921,000, and TikTok (@skintific_id), which boasts an impressive 3 million followers.

Recent empirical investigations have elucidated the pivotal function of social media in influencing consumer preferences for skincare products. For example, Alamer's research accentuates the transformation of social media into an indispensable medium for beauty influencers and makeup artists, facilitating the demonstration of products and interaction with a broader audience than conventional advertising methodologies permitted [2]. This transition augments brand visibility and cultivates a sense of community among consumers, who increasingly depend on social media for product endorsements and evaluations.

Furthermore, the efficacy of social media marketing within the skincare sector is highlighted by findings from Zheng, who examined the correlation between skincare brands' SMMA and consumers' perceived brand equity as well as electronic word-of-mouth [3]. This investigation reveals that informational components within social media marketing significantly elevate the perception of brand equity, consequently enhancing consumer engagement and intentions to purchase. In a similar vein, Boonpreda and Ruan's exploration of organic skincare brands in Thailand demonstrates that social media instruments offer enterprises cost-efficient marketing avenues, permitting them to initiate tailored campaigns that resonate with their intended demographic [4].

The impact of social media transcends essential advertising; it envelops the intricacies of consumer interaction and engagement. Jin et al. discuss how social media influencers adeptly connect with consumers by generating relatable content, thereby nurturing brand loyalty, especially among individuals possessing varying degrees of self-discrepancy [5]. This underscores the significance of authenticity and relatability within influencer marketing, as consumers exhibit a greater propensity to trust and engage with brands that align with their narratives.

Considering these advancements, the current study aspires to examine the ramifications of SMMA on *Skintific* products through a Structural Equation Modeling-Partial Least Squares (PLS-SEM). The PLS-SEM represents a versatile, resilient, and predictive modeling paradigm that is particularly advantageous in exploratory investigations or when dealing with intricate, limited-sample, or non-normally distributed datasets. Conversely, Covariance-Based Structural Equation Modeling (CB-SEM) may be more appropriately aligned with theoretical validation and hypothesis examination objectives under stringent prerequisites. In contrast, PLS-SEM is particularly effective in contexts where the emphasis is placed on prediction, exploratory inquiry, or pragmatic application.

By scrutinizing the complex interrelations between SMMA, brand perception, and purchase intentions, this research provides valuable insights into how skincare brands may refine their marketing strategies in the digital epoch. Comprehending these dynamics is imperative for brands aspiring to bolster their market presence and effectively interact with consumers within an increasingly competitive environment.

2. RESEARCH METHODS

2.1 Instrument Validation for Research

The validation of instruments is essential in guaranteeing the precision and uniformity of analytical results. Evaluation includes the examination of both the accuracy and consistency of the measurement instruments employed. Validity is the extent to which an experimental tool accurately measures what it is designed to measure. Validity can be classified into numerous forms, such as content validity, which examines if the instrument encompasses all elements of the topic under investigation, and construct validity, which evaluates how accurately the instrument represents the theoretical foundation of the research. One frequently utilized statistical technique in this context is Pearson's correlation coefficient, which evaluates the magnitude and orientation of the linear association between two continuous variables. Using Pearson correlation in validity assessment yields significant insights into the reliability and construct validity of survey instruments. We use Pearson's correlation for the validity test in this study, applying the following formula [6]:

$$r_{val} = \frac{n\sum_{i=1}^{n} X_i Y_i - (\sum_{i=1}^{n} X_i)(\sum_{i=1}^{n} Y_i)}{\sqrt{(n\sum_{i=1}^{n} X_i^2 - (\sum_{i=1}^{n} X_i)^2)(n\sum_{i=1}^{n} Y_i^2 - (\sum_{i=1}^{n} Y_i)^2)}} \tag{1}$$

where r_{val} is the correlation coefficient between variables X and Y, n is the number of respondents, X_i is the total score of the i-th indicator, and Y_i is the total score of each i-th variable. If the value of $r_{val} > r_{(df,n)}$ we reject the null hypothesis, which means the indicator is not valid. The $r_{(df,n)}$ is the r critical value table for Pearson's correlation. Lordello et al. employed Pearson correlation coefficients to evaluate the construct validity of the Self-esteem/Self-image Female Sexuality (SESIFS) questionnaire by examining its correlation with Rosenberg's self-esteem scale, revealing significant associations that substantiate the construct validity of the SESIFS [7].

The reliability pertains to the instrument's capacity to maintain consistency and stability throughout time. In a consistent environment, a dependable tool will yield comparable outcomes. Typical techniques to assess dependability include Cronbach's alpha test for internal consistency and test-retest reliability for evaluating stability via repeated measurements, establishing that a coefficient above 0.60 indicates acceptable reliability [6]. Through the integration of validity and reliability testing, researchers ascertain the accuracy and dependability of their instruments, thus enhancing the credibility of their findings [8].

$$\alpha = \left(\frac{k}{k-1}\right)\left(1 - \frac{\sum_{i=1}^{k} S_i}{S_t}\right) \tag{2}$$

The k is the number of questionnaires, $\sum_{i=1}^{k} S_i$ is the total variance of scores for each questionnaire, and S_t is total variance.

2.2 Partial Least Squares Structural Equation Modelling (PLS-SEM)

The PLS-SEM is a flexible statistical method that enables researchers to examine intricate connections among several variables, considering both reflecting and formative measurement models. This approach offers significant benefits when working with limited sample sizes and data that do not follow a normal distribution, making it a favored option for exploratory research [9], [10]. The PLS-SEM represents a variance-oriented methodology for structural equation modeling. The PLS algorithm derives component score outcomes for each latent construct by applying indicator weights that maximize explained variance while concurrently minimizing residual variance associated with the dependent variable [11].

A notable advantage of PLS-SEM is its capacity to evaluate both the measurement and structural models concurrently, offering valuable insights into the validity and dependability of the constructs under consideration. The measurement model evaluates observational indicators regarding their underlying latent variables, while the structural model investigates the relationships among the latent variables themselves [12], [13]. The twofold evaluation is essential to verify that the constructs employed in a study precisely mirror the theoretical framework and that the empirical evidence supports the links proposed in the research hypotheses.

The SEM consists of two types of variables: latent variables and manifest variables or constructs, which are illustrated in Figure 1 below. Latent variables refer to factors assessed using indicators and lack direct observation, often exogenous and endogenous variables. Exogenous variables (ξ), often known as independent variables, are independent variables that exert external effects on other variables. The endogenous variables (η) or dependent variables are subject to the effect of other factors due to their inherent limitations. Manifest factors, such as gender, age, and occupation, can be directly quantified through each relevant indicator [14].

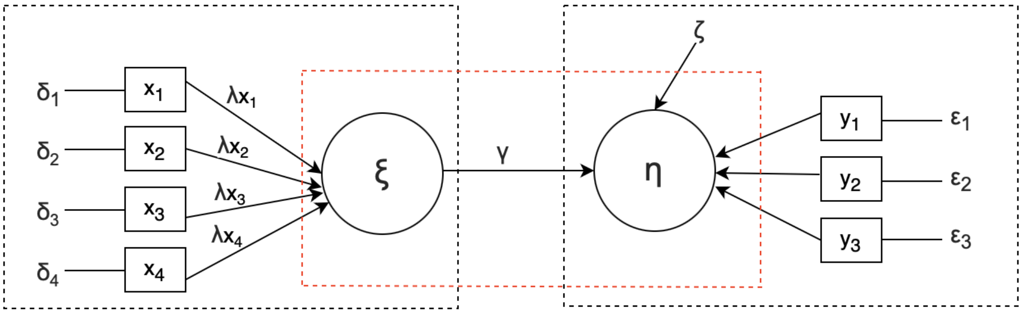

Figure 1. The PLS-SEM Model

The measurement model (or outer model) evaluates the association between latent variables and their corresponding indicators [15]. Its foremost aim is to assess the reliability and validity of these indicators, which constitute the overarching framework.

$$\boldsymbol{\eta} = \boldsymbol{\beta}\boldsymbol{\eta} + \boldsymbol{\gamma}\boldsymbol{\xi} + \boldsymbol{\zeta} \tag{3}$$

where:

$\boldsymbol{\eta}$: $mx1$ random vector of endogenous latent variables
$\boldsymbol{\beta}$: mxm coefficient matrix of endogenous latent variables
$\boldsymbol{\gamma}$: mxn coefficient matrix of exogenous latent variables
$\boldsymbol{\xi}$: $nx1$ random vector of exogenous latent variables
$\boldsymbol{\zeta}$: $mx1$ random error vector

The indicators' validation is conducted through convergent validity and discriminant validity assessments, whereas reliability is quantified via composite reliability and Cronbach's alpha. Convergent validity is established when various indicators of a construct exhibit a strong correlation with one another. In PLS-SEM, convergent validity is generally evaluated by the Average Variance Extracted (AVE) and the outer loadings of the indicators. An AVE value of 0.50 or above signifies that the construct accounts for more than half of its indicators' variation, affirming convergent validity [16]. Furthermore, outer loadings should preferably surpass 0.70 to indicate that each indicator substantially contributes to the build [17]. Discriminant validity evaluates whether conceptions intended to be unrelated are distinct. This can be assessed in many ways, including the Fornell-Larcker criterion and the Heterotrait-Monotrait (HTMT) ratio. The Fornell-Larcker criterion posits that each construct's square root of the AVE must exceed its correlations with other constructs [18]. The HTMT ratio offers a rigorous assessment of discriminant validity, with values under 0.85 signifying adequate discriminant validity [19]. Reliability denotes the consistency of the measurement. In PLS-SEM, this is frequently evaluated by Cronbach's alpha and composite reliability. A Cronbach's alpha exceeding 0.70 is often deemed acceptable, and composite reliability must likewise surpass 0.70 to validate that the indicators reliably measure the latent construct [20].

Conversely, the structural model (or inner model) delineates the connections between exogenous and endogenous variables. Arrows between latent variables signify regression relationships [15].

$$\boldsymbol{y} = \Lambda_y\ \boldsymbol{\eta} + \boldsymbol{\varepsilon} \tag{4}$$

$$\boldsymbol{x} = \Lambda_x\ \boldsymbol{\xi} + \boldsymbol{\delta} \tag{5}$$

where:

$\boldsymbol{y}$: the $px1$ indicators for endogenous latent variables and p is the number of endogenous variables
$\boldsymbol{x}$: the $qx1$ indicator for the exogenous latent variables and q is the number of exogenous variables
Λ_y : the pxm loading matrix between endogenous variables and its indicators
Λ_x : the qxn loading matrix between an exogenous variable and its indicators
$\boldsymbol{\varepsilon}$: the $px1$ error measurement vector of the endogenous variables

$\boldsymbol{\delta}$: the px1 measurement error vector of exogenous variables

The regression coefficient linking an exogenous variable to an endogenous variable is represented by the γ (gamma). In contrast, the relationship between one endogenous variable and another is symbolized by the β (beta). This model offers valuable insights into the strength and directionality of relationships among variables within the research framework. The inner model comprises latent variables and unobserved constructs deduced from measured data. Latent variables are generally depicted as circles or ellipses in route diagrams, signifying their function as predictors or outcomes in the model [21]. The inner model delineates the proposed relationships among these latent variables. Each path signifies a direct influence of one latent variable on another, with the intensity of these associations measured by path coefficients. The coefficients denote the amount and direction of the associations, with positive values indicating a direct positive influence and negative values signifying an inverse link. This statistic quantifies the extent to which the independent latent variables account for the variance in the dependent latent variable. Elevated R^2 values signify a superior alignment of the model with the data, indicating that the model accounts for a substantial portion of the variance in the outcome variable [22].

The importance of model evaluation in PLS-SEM cannot be overstated. Researchers are encouraged to report various metrics, including the AVE, Composite Reliability (CR), and goodness-of-fit indices, to provide a comprehensive understanding of the model's performance [12], [23]. The reliability of a construct may be assessed through the computation of a composite reliability (CR) value exceeding 0.6, utilizing the equation provided below [24].

$$\hat{\rho} = \frac{(\sum_i \lambda_i)^2}{(\sum_i \lambda_i)^2 + \sum_i var(\varepsilon_i)} \tag{6}$$

In SEM, the loading factor is a crucial measure of convergent validity. The standardized loading factor quantifies the degree of association between each indicator and its corresponding latent variable. The loading factor values vary between -1 and 1, where numerical values closer to 0 suggest a less strong link between the indicator and the hidden variable. A high loading factor indicates that the indicator is a robust and reliable measure of the underlying variable. In assessing convergent validity through analyzing individual item reliability, insights can be derived from the standardized loading factor. The standardized loading factor elucidates the extent of the association between each measurement item (indicator) and its corresponding construct. The correlation may be deemed valid if it exhibits a value exceeding 0.7 [25].

An evaluation of the discriminant validity of the measurement model using reflecting indicators is conducted by examining the cross-loading of the measurement with the construct. The approach to evaluating discriminant validity involves comparing the square root of the AVE for each construct with the correlation among other constructs in the model. If the AVE root value of each construct exceeds the correlation value between the construct and other constructs in the model; it is considered to possess sufficient discriminant validity. The AVE value should exceed 0.50. Equation (7) shows the formula for AVE [26].

$$AVE = \frac{\sum_i \lambda_i^2}{\sum_i \lambda_i^2 + \sum_i var(\varepsilon_i)} \tag{7}$$

Meanwhile, the composite reliability of a set of indicators measuring a variable is considered good if it exceeds 0.6.

3. RESULTS AND DISCUSSION

3.1 Materials

The study employed one external latent variable alongside three endogenous latent variables. The solitary exogenous latent variable encompasses attributes pertinent to social media marketing. The constructs identified as brand awareness, brand image, and brand loyalty constitute the three endogenous latent variables. This research examines the influence of social media marketing on the dimensions of awareness, branding, and consumer loyalty concerning *Skintific* products.

Table 1. **Research Variables**

Variable	Explanation	Category
X	Social media marketing	1: Strongly Disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly Agree
Y_1	Brand awareness	1: Strongly Disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly Agree
Y_2	Brand image	1: Strongly Disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly Agree
Y_3	Brand loyalty	1: Strongly Disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly Agree

Data for this study were collected through online questionnaires distributed to *Skintific* product users residing in Yogyakarta between June and July 2024. This survey consists of 17 questions, 8 of which pertain to social media marketing, 3 to brand awareness, 3 to brand image, and 3 to brand loyalty. A total of 170 respondents participated, representing a diverse range of demographic characteristics, including gender, occupation, and age.

Table 2. **Overview of the Data**

Age/Gender	Occupation					Total
	Students	Pupils	Employees	Entrepreneur	Other	
Male	**33**	**0**	**0**	**1**	**0**	**34**
<20	11	0	0	0	0	11
21 – 25	22	0	0	1	0	23
>25	0	0	0	0	0	0
Female	**118**	**5**	**9**	**2**	**2**	**136**
<20	47	3	0	0	0	50
21 – 25	71	2	8	2	2	85
>25	0	0	1	0	0	1
Total	**151**	**5**	**9**	**3**	**2**	**170**

Table 2. summarizes the gender, age, and occupation of Survey Participants who use *Skintfic* in Yogyakarta. For example, 22 respondents are male *Skintific* users in Yogyakarta, aged 21-25, and they are students.

3.2 Instrument Validation Test

A validity test is utilized to evaluate the extent to which the variables in this study effectively reflect their intended representations. It assesses the degree to which the acquired data corresponds with the theoretical ideas or notions under investigation. By implementing a validity test, researchers ascertain that the indicators or items employed in the study are pertinent and proficient in encapsulating the fundamental characteristics of the constructs. These tests verify that the associations identified among variables are significant and align with the study's theoretical framework, improving the conclusions' reliability and robustness.

Table 3. Validity Test

Item	r_{val}	Sign	$r_{(168;170)}$
$X_{1.1}$	0.71	>	0.15
$X_{1.2}$	0.70	>	0.15
$X_{1.3}$	0.61	>	0.15
$X_{1.4}$	0.64	>	0.15
$X_{1.5}$	0.65	>	0.15
$X_{1.6}$	0.73	>	0.15
$X_{1.7}$	0.67	>	0.15
$X_{1.8}$	0.69	>	0.15
$Y_{1.1}$	0.57	>	0.15
$Y_{1.2}$	0.64	>	0.15
$Y_{1.3}$	0.55	>	0.15
$Y_{2.1}$	0.59	>	0.15
$Y_{2.2}$	0.679	>	0.15
$Y_{2.3}$	0.69	>	0.15
$Y_{3.1}$	0.769	>	0.15
$Y_{3.2}$	0.63	>	0.15
$Y_{3.3}$	0.67	>	0.15

Table 3 displays r_{val} values ranging from 0.54 to 0.76, with an $r_{(168;170)}$ of 0.15. Therefore, it may be inferred that r_{val} is greater than $r_{(df,n)}$, resulting in the declaration of all items as valid. Based on the declared validity of the items mentioned above, the questionnaire aligns with the data and can be utilized for research purposes, including further reliability testing. The Table of Critical Values for Pearson's r is utilized to ascertain the $r_{(168;170)}$. This table facilitates the assessment of whether the computed r value is statistically significant by considering the degrees of freedom (df) and the predetermined significance level (α conventionally set at 0.05).

Reliability testing aims to demonstrate that a test's measurements maintain consistency when administered repeatedly to individuals under identical circumstances. Considering the acquired Cronbach's alpha coefficient of 0.91, which surpasses the established threshold of 0.60, it can be concluded that all components are considered reliable **[6]**. Thus, the reliability of the previously mentioned components, the questionnaire is suitable for the gathered data.

3.3 Measurement Model Test (Outer Model)

Convergent validity and discriminant validity assessments are utilized within the framework of measurement model evaluation to determine the construct's validity. In contrast, the composite reliability assessment evaluates the construct's reliability.

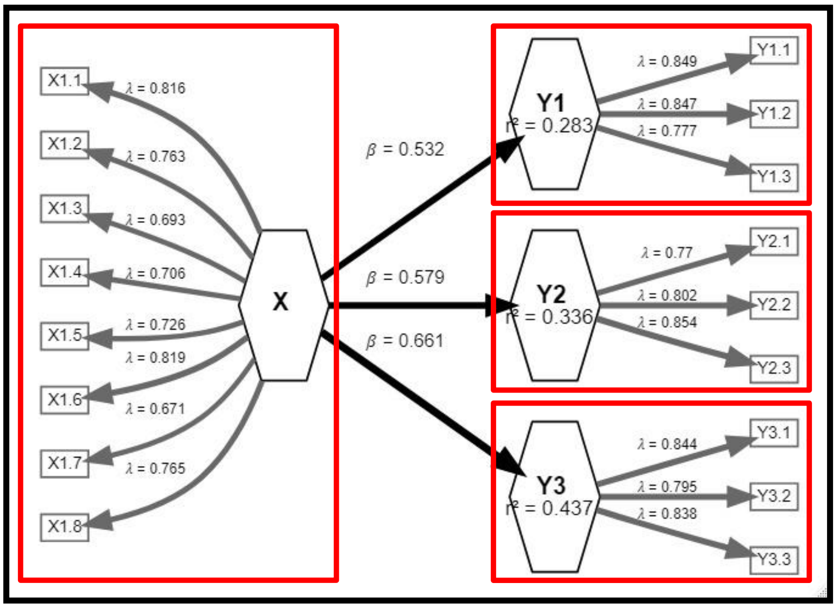

Figure 2. Measurement Model Path Diagram

Figure 2 illustrates that the image is a measurement model of the PLS-SEM model. In the context of PLS-SEM, the outer model elucidates the methodology by which latent variables, categorized as either exogenous (X) or endogenous (Y), are operationalized through their respective indicators (manifest variables). The red-marked result is the outcome of the measurement model investigated in this work. Indicators $X_{1.1}$ to $X_{1.8}$ exhibit loading factors ranging from 0.671 to 0.819, suggesting a substantial to significant influence of the indicators on variable X. Indicators $Y_{1.1}$ to $Y_{1.3}$ have loading factors ranging from 0.847 to 0.849, indicating a solid relationship between endogenous variables Y_1. Indicators $Y_{2.1}$ to $Y_{2.3}$ have loading factors ranging from 0.754 to 0.802, indicating a strong relationship between indicators Y_2. Indicators $Y_{3.1}$ to $Y_{3.3}$ have loading factors ranging from 0.795 to 0.844, indicating a strong relationship between the indicators on the Y_3 variable.

Validity assessment is undertaken to ascertain the extent to which the research inquiries (tools) proposed for quantifying research variables possess validity. The convergent validity of the measurement framework is evaluated based on the outcomes of the loading factor analysis. The loading factor represents the correlation between indicators and their respective constructs; a higher degree of correlation signifies a superior level of validity. In this study, the loading factor used was 0.5, so if the loading factor is > 0.5, it is said to be valid. Based on the Figure 2, the loading factor (λ) for each variable has a value greater than 0.6. Therefore, all constructs are valid.

Knowing the loading factor leads to calculating the AVE value in the discriminant validity test. A variable is considered good if the AVE value equals or exceeds 0.5. The social media marketing construct (X) has an AVE root value of 0.747, higher than the correlation values of 0.532 for X with Y_1, 0.579 for X with Y_2, and 0.660 for X with Y_3. Therefore, it can be concluded that the social media marketing construct has sufficient discriminant validity.

Followed by reliability measurements of the construct are conducted. Based on the eight indicators and loading factor values recorded for the social media marketing variable, it can be inferred that the composite reliability value for the X variable is 0.770. The composite reliability coefficients for the variables of brand awareness, brand image, and brand loyalty are 0.903, 0.895, and 0.904, respectively. With a composite reliability score of ≥ 0.6, each construct demonstrates internal solid consistency and is, therefore, considered reliable.

3.4 Structural Model Test (Inner Model)

The structural model test is performed after the completion of the measurement model test once the validity and reliability of the variables employed have been verified. The objective of the structural model test is to ascertain the correlation between two variables, specifically exogenous variables and endogenous variables. Specifically, there are two tests: the R-square test and the path coefficient test.

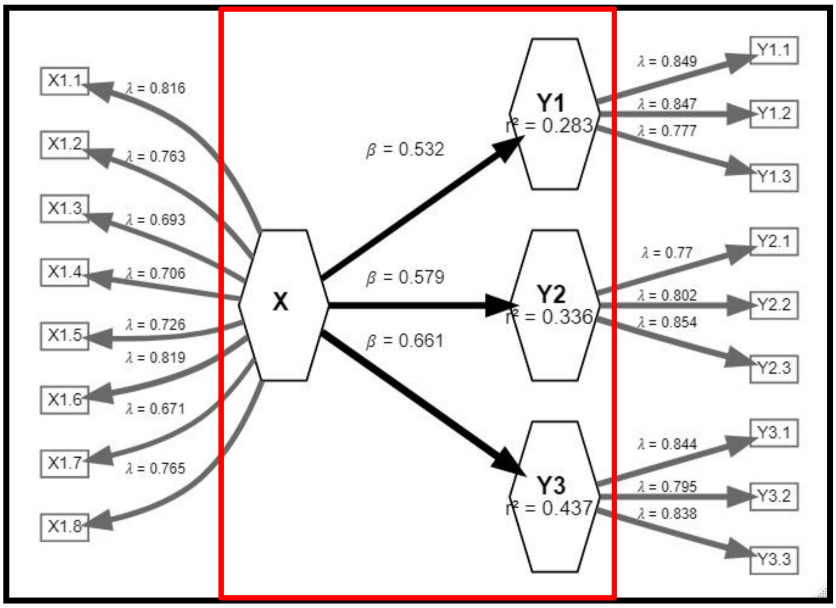

Figure 3. Structural Model Path Diagram

The findings of a structural model in PLS-SEM analysis are depicted in **Figure 3**. This model incorporates a single exogenous variable (X) that impacts the endogenous variables (Y_1, Y_2, Y_3). The path coefficient (β) of 0.532 between X and Y_1 suggests that X exerts a positive and rather significant impact on Y_1. This implies that a rise in X will likely increase Y_1, with a magnitude of 53.2%. The path coefficient of 0.579 between X and Y_2 suggests that X exerts a more pronounced positive impact than Y_2, which accounts for 57.9%. A path coefficient of 0.661 between X and Y_3 suggests that X has the most significant positive impact on Y_3, accounting for 66.1%. The R^2, ranging from 28.3% to 43.7%, suggests that the model well accounts for the variability of endogenous variables, particularly Y_3, which has the greatest R^2.

Statistical path coefficient testing evaluates the magnitude and orientation of the associations between variables in the structural model. Regarding the correlation between social media marketing and brand awareness, the findings indicate that a one-unit rise in social media marketing results in a 0.532 increase in brand awareness. This impact is favorable, moderately strong, and statistically significant. For social media marketing and brand image, it is estimated that a 1-unit increase in social media marketing will lead to a 0.579 increase in brand image. This indicates a highly positive, reasonably robust, and statistically significant effect. A 1-unit increase in social media marketing is associated with a 0.661 rise in brand loyalty, indicating a robust, favorable, and statistically significant impact.

4. CONCLUSIONS

The respondent data from *Skintific* users in Yogyakarta encompasses demographic information, including gender, occupation, and age. Female responders constituted the majority, with 136 women and 34 men. Regarding the respondents' occupations, 89% were students, 5% were employees, 3% were pupils, 2% were entrepreneurs, and 1% were from other professions. For age, most respondents (108) were in the age range of 21 to 25 years old, followed by 61 respondents under the age of 20 and only one respondent above the age of 25.

The investigation unequivocally demonstrates the positive correlation between social media marketing and brand metrics. A one-unit increase in social media marketing results in a corresponding increase of 0.532 units in brand awareness, 0.579 units in brand image, and 0.661 units in brand loyalty. These findings underscore the effectiveness of the social media marketing approach in enhancing brand awareness, brand image, and consumer loyalty.

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