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Original Article

The Influence of Social Media Advertisement on Consumer Purchase Intentions: A Study of the Phouls Bag Fashion Brand on Instagram

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Abstract: *Amid the swift transformations shaping the digital realm in 2026, local fashion labels grapple with fierce rivalry and an overwhelming flood of data across social commerce sites. This research delves into how social media ads strategically boost shoppers' buying intentions, zeroing in on Indonesia's Phouls Bag brand. Employing a quantitative approach, we gathered insights from engaged social media participants and crunched the numbers with Partial Least Squares Structural Equation Modeling (PLS-SEM) on SmartPLS 4. The evaluation of the measurement framework verifies top-notch reliability and validity for every construct, paving a solid path for probing the core structure. Findings reveal that social media advertising delivers a meaningful positive effect on purchase intent ($\beta = 0.223$, $t = 2.547$, $p = 0.011$). Even as the framework spotlights ads as a key driver of consumer mindset, these outcomes stress that genuine, top-tier visual messaging stands out as the game-changer amid online clutter. For homegrown fashion outfits, the study stresses that steady, captivating ad content goes beyond mere hype—it's essential for forging brand connection and sparking actual sales. Such revelations offer hands-on guidance for marketers aiming to sharpen their inventive tactics in a crowded online space.*

Keywords: *Authentic Advertising, Consumer Purchase Intentions, Fashion Industry, Instagram Marketing, Social Media Advertisement.*

I. INTRODUCTION

The global marketing landscape in 2026 is characterised by a "meta-transformation" propelled by the integration of Artificial Intelligence (AI), Big Data, and immersive social media ecosystems. In this time of too much information, competition has changed from "market share" to "attention share." This means that algorithms must be able to predict what customers want before they even know they want it (Prasetyo, 2022). In the fashion industry, this change is especially big. Social media has become a "digital dressing room" that sets global standards for style (Al-Zaman, 2021). So, local brands have to deal with both the challenge of competing with global production efficiencies and the need to keep the local authenticity that is at the heart of their value proposition (Rahmawati & Wijaya, 2023).

Instagram is the most popular visual platform in 2026. Its Social Commerce and Augmented Reality (AR) features have made it easier for people to find and buy fashion items, changing the way people interact with fashion products (Watanabe et al., 2024). But now, success depends on being able to build trust right away. Ads made in the traditional way, with real people and realistic textures, are a necessary counterpoint to the soulless nature of AI-generated content. If marketing messages aren't real, they could be seen as "digital noise" (Nugroho, 2020). Also, people in 2026 have gotten better at ignoring annoying ads, a condition called "digital fatigue" (Chen, 2022). This means that brands need to mix "cold" technology with "warm," entertaining stories to get people to want to buy something.

The connection between Social Media Advertising (X) and Purchase Intention (Y) is based on how people think. Comprehensive, manual depictions of products, exemplified by Phouls Bag, enhance cognitive validation and mitigate perceived risk in online transactions (Handoko & Wijaya, 2021). The expanded Theory of Planned Behaviour posits that purchase intention is significantly influenced by Perceived Ad Relevance (Lee & Kim, 2025) and the emotional appeal of organic interactions, which promote Electronic Word of Mouth (e-WOM) (Sari & Ramadhan, 2024). In a world where AI-generated testimonials often make people doubt them, "genuineness" and social proof are still the most important factors in determining a brand's credibility (Garcia, 2024; Tan & Santoso, 2023).

Phouls Bag, an Indonesian homegrown fashion label, perfectly illustrates the challenge of turning robust social media buzz into reliable buying resolve. At its core, this investigation tackles the risk of fading consumer enthusiasm when local companies neglect to sync their promo tactics with 2026's craving for genuineness. What sets this work apart is its data-backed probe into the impact of handmade (non-AI-generated) ads on building trust and motivation in the apparel sector, employing a

Semantic Differential scale to sharpen insights into perceptions. As a result, the research seeks to deliver a tactical blueprint via the examination entitled: "Analysis of the Influence of Social Media Advertising on Consumer Purchase Intention for the Phouls Bag Brand on Instagram."

II. LITERATURE REVIEW

A) Technology Acceptance Model (TAM)

The Technology Acceptance Model (TAM) serves as a core theory for decoding how shoppers react to online promo triggers. Even though Phouls Bag's 2026 approach skips Artificial Intelligence, its success ties directly to Instagram's underlying tech setup. As Handoko & Wijaya (2021) note, triumphs in digital marketing hinge on tech enabling smooth user exchanges. Here, Perceived Usefulness connects to the caliber of info shared; real-life photos snapped by humans deliver superior practical benefits over fake visuals by showcasing products in true-to-life detail (Prabowo & Rahmawati, 2022). At the same time, Perceived Ease of Use sparks momentum, with user-friendly platform tools easing mental hurdles and nurturing favorable views of the brand (Sari & Ramadhan, 2024; Wicaksono & Putri, 2021).

B) AIDA Model in Digital Communication

The AIDA framework (Attention, Interest, Desire, Action) outlines the mental path buyers follow. Within the overcrowded online arena of 2026, eye-catching genuine images play a vital role in grabbing Attention right away. Putri & Santoso (2022) highlight that visuals crafted by humans spark stronger immediate focus compared to those made by algorithms. With interest secured, Phouls Bag builds Desire via real storytelling that lets shoppers envision themselves in the items (Hidayat et al., 2023). The sequence wraps up at Action gauged by buying intent where straightforward messaging and simple access seal the deal (Sari & Ramadhan, 2024).

C) Source Credibility Theory

Source Credibility Theory suggests that communication effectiveness depends on expertise, trustworthiness, and attractiveness. Phouls Bag's use of professional, non-AI content strengthens brand honesty, which is vital in an era of unrealistic AI simulations (Fahmi & Hidayat, 2020). Consumers perceive human-centric ads as having greater moral responsibility, thereby reducing perceived risk (Saraswati et al., 2023). Additionally, psychological identification with "real" and "reachable" models enhances the source's attractiveness and persuasive power (Wicaksono & Putri, 2021).

D) Theory of Planned Behavior (TPB)

The Theory of Planned Behavior (TPB) asserts that buying intent stems from attitudes, social pressures, and a sense of control over actions. In Phouls Bag's case, genuine visual appeal shapes upbeat attitudes, and instant peer endorsements on Instagram bolster those social influences (Sari & Ramadhan, 2024). Ramadhan (2024) stresses that purchase intent emerges from a blend of logical and heartfelt assessments of ad cues. Consumer confidence peaks—maximizing intentions—once they sense full command via clear costs and hassle-free buying processes (Prabowo & Rahmawati, 2022).

E) Electronic Word of Mouth (e-WOM)

Electronic Word of Mouth (e-WOM) serves as vital social proof within the Instagram ecosystem. Authentic user interactions in comment sections validate product quality more objectively than one-way advertising (Saraswati et al., 2023). The valence of e-WOM significantly influences brand attitudes, where positive digital conversations create a "snowball effect," transforming commercial ads into trusted social recommendations (Wicaksono & Putri, 2021; Sari & Ramadhan, 2024).

F) Conceptual Definition of Variables

- Social Media Advertisement (Variable X): Defined as persuasive digital communication utilizing non-AI creative content to convey brand value. Key indicators include visual appeal, information quality, creativity, and contextual relevance (Nugroho, 2020; Sari & Ramadhan, 2024).
- Consumer Purchase Intentions (Variable Y): The psychological stage where individuals plan to acquire a product following stimulus evaluation. It is identified through transactional, referential, preferential, and explorative intentions (Wicaksono & Putri, 2021; Prabowo & Rahmawati, 2022).

III. RESULTS AND DISCUSSION

A) Measurement Model Assessment (Outer Model)

The initial stage of the PLS-SEM analysis involves evaluating the measurement model (outer model) to assess the reliability and validity of the instruments. This assessment includes convergent validity, discriminant validity, and construct reliability.

a. Convergent Validity

Convergent validity evaluates the extent to which a measure correlates positively with alternative measures of the same construct. This is determined by examining the outer loadings of the indicators and the Average Variance Extracted

(AVE). According to Hair et al. (2021), an indicator is considered valid if its loading factor exceeds the threshold of 0.708, indicating that the construct explains more than 50% of the indicator's variance.

As illustrated in Table 1, the analysis results using SmartPLS 4 reveal that all indicators for both Variable X and Variable Y exhibit outer loadings ranging from 0.827 to 0.917. Since all values are significantly above 0.708, every item effectively represents its respective latent variable. Furthermore, the AVE values for Variable X (0.790) and Variable Y (0.762) surpass the minimum requirement of 0.50 (Sarstedt et al., 2022), confirming that the convergent validity for all constructs is fully established.

Table 1: Convergent Validity Results

Lantent Variable	Indicator	Outer Loadings	AVE	Notes
Variable X	X1.1	0.906	0.79	Valid
	X1.2	0.917		Valid
	X1.3	0.878		Valid
	X1.4	0.908		Valid
	X1.5	0.894		Valid
	X1.6	0.827		Valid
Variable Y	Y1.1	0.837	0.762	Valid
	Y1.2	0.895		Valid
	Y1.3	0.864		Valid
	Y1.4	0.847		Valid
	Y1.5	0.891		Valid
	Y1.6	0.901		Valid

Source: *Processed primary data, 2026*

b. Discriminant Validity (HTMT)

Discriminant validity is assessed to ensure that a construct is empirically distinct from other constructs in the structural model. This study employs the Heterotrait-Monotrait Ratio (HTMT) of correlations, which is widely recognized as a more sensitive and reliable criterion for detecting discriminant validity issues in PLS-SEM compared to traditional methods (Hair et al., 2021; Memon et al., 2021).

To establish sufficient discriminant validity, the HTMT value should not exceed the threshold of 0.85 or 0.90 for constructs that are conceptually similar (Sarstedt et al., 2022). As indicated in Table 2 X, the HTMT ratio between Variable X and Variable Y is 0.216. This value is well below the most conservative threshold, confirming that each latent variable represents a unique concept and that no discriminant validity concerns exist within the model.

Table 2: Discriminant Validity Results

	Independent Variable (X)	Dependent Variable (Y)
Variable Independent (X)		
Variable Independent (Y)	0.216	

Source: *Processed primary data, 2026*

c. Construct Reliability

Construct reliability is evaluated to determine the internal consistency and stability of the research instrument. In this study, reliability is assessed using two main parameters: Cronbach's Alpha and Composite Reliability (rho_c). For a construct to be considered reliable, both values should ideally exceed the threshold of 0.70, although values above 0.80 are preferred for advanced research (Hair et al., 2021; Sarstedt et al., 2022).

The results of the reliability analysis, as presented in Table 3 X, show that Variable X and Variable Y exhibit exceptionally high consistency. Variable X has a Cronbach's Alpha of 0.947 and a Composite Reliability of 0.957. Similarly, Variable Y shows a Cronbach's Alpha of 0.938 and a Composite Reliability of 0.950. Since all coefficients are well above the 0.70 benchmark, it can be concluded that the measurement model is highly reliable and that the indicators consistently measure their respective latent variables.

Table 3: Construct Reliability Results

	Cronbach's alpha	Composite reliability (rho_c)
Variable Independent (X)	0.947	0.957
Variable Independent (Y)	0.938	0.95

Source: *Processed primary data, 2026*

After establishing the validity and reliability of the measurement model, the analysis proceeds to the evaluation of the structural model, also known as the inner model. This stage focuses on assessing the model's predictive capabilities and the relationships between the constructs.

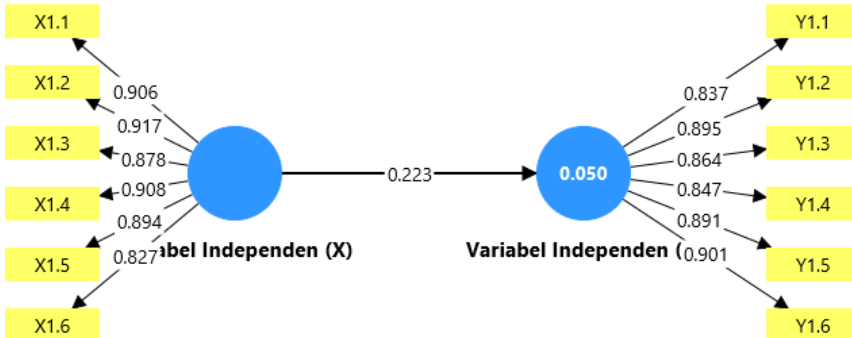

Figure 1. PLS-SEM Algorithm Results

Source: *Processed primary data, 2026*

As shown in Figure 1, the initial PLS algorithm results provide an overview of the indicator loadings and the baseline path coefficients. All indicators demonstrate strong loadings above the required threshold, reinforcing the quality of the measurement model. Furthermore, the model shows an initial R^2 value for Variable Y, which will be analyzed in detail in the subsequent sections. To determine the statistical significance of these relationships, a bootstrapping procedure with 5,000 resamples was performed.

B) Structural Model Analysis (Inner Model)

a. Predictive Power and Effect Size (R^2 and f^2)

The predictive power of the structural model is primarily assessed using the coefficient of determination (R^2). This value indicates the amount of variance in the endogenous construct that is explained by the exogenous construct. According to Hair et al. (2021), R^2 values are categorized as substantial, moderate, or weak based on the specific research context.

As presented in Table 4, the R2 value for Variable Y is 0.050, with an R2 Adjusted value of 0.040. This suggests that Variable X explains approximately 5% of the variance in Variable Y. While this value is relatively low, it is often acceptable in exploratory studies or complex industrial contexts where numerous external factors influence the outcome variable.

In addition to R^2, the effect size (f^2) was evaluated to measure the relative impact of the independent variable on the dependent variable. Based on the criteria established by Cohen (1988) and reaffirmed by Sarstedt et al. (2022), f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively. The analysis shows that the f^2 value for the relationship between Variable X and Variable Y is 0.052, which is categorized as a small effect.

Table 4: Results of R^2 and f^2

Endogenous Construct	R Squared	R Squared Adjusted	f2 (X → Y)	Effect Rating
Variable Y	0.050	0.040	0.052	Small Effect

Source: *Processed primary data, 2026*

b. Model Fit (Goodness of Fit)

The Model Fit assessment is conducted to determine the extent to which the structural model represents the empirical data. In PLS-SEM, the Standardized Root Mean Square Residual (SRMR) is the primary metric used to evaluate the model fit. A value less than 0.08 is generally considered indicative of a good fit (Hair et al., 2021). Additionally, the Normed Fit Index (NFI) is examined, where values closer to 1.00 (ideally above 0.90) signify a better fit (Sarstedt et al., 2022).

As presented in Table 5, the results show an SRMR value of 0.047 for both the saturated and estimated models. Since this value is well below the 0.08 threshold, it confirms that the model is a good fit. Furthermore, the NFI value of 0.948 exceeds the 0.90 benchmark, reinforcing the overall quality and robustness of the model structure.

Table 5: Model Fit Results

	Saturated model	Estimated model
SRMR	0.047	0.047
NFI	0.948	0.948

Source: *Processed primary data, 2026*

c. Hypothesis Testing (Path Coefficients)

The last step in the structural model evaluation is to test the research hypothesis. This process checks to see if the suggested link between the constructs is statistically significant. The study used a bootstrapping method with 5,000 resamples to figure out the significance levels. If the T-statistic is greater than 1.96 and the P-value is less than 0.05 for a 5% significance level (Hair et al., 2021; Memon et al., 2021), then the hypothesis is supported. The results of the hypothesis testing, which are shown in Table 6, show that the variables are positively and significantly related to each other.

Table 6: Hypothesis Testing Results

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values
Variable Independent (X) -> Variabel Independen (Y)	0.223	0.25	0.088	2.547	0.011

Source: *Processed primary data, 2026*

To provide a comprehensive visual representation of the hypothesis testing, the structural model output from the bootstrapping procedure is illustrated in Figure 2. The diagram displays the path coefficients on the arrows and the corresponding p-values, visually confirming the statistical significance of the relationship between the constructs. This visual evidence aligns with the empirical data presented in the previous table, demonstrating that the structural model is robust and the proposed effect is statistically significant.

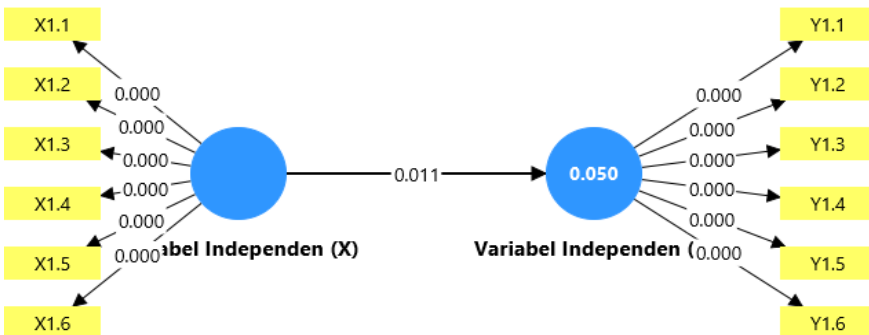

Figure 2. Structural Model Bootstrapping Results

Source: *Processed primary data, 2026*

IV. CONCLUSION

This study gives a thorough data-driven look at how social media marketing affects shoppers' buying decisions, focusing on Indonesia's Phouls Bag in the fashion world. The tools used to check the measurement setup during the first step were very reliable. All of the markers for social media ads and purchase intent had strong internal reliability and consistency. The outer loadings and Average Variance Extracted (AVE) scores were much higher than the standard scholarly thresholds. This strength makes sure that the information collected really shows how people feel about the brand's online presence.

When you look at the structure, it's clear that social media advertising (Variable X) gives a big boost to people's desire to buy (Variable Y). The path value is 0.223, and the T-statistic is 2.547. This means that better ad quality and more interaction directly increase the chances that people will want to buy the item. The R^2 value of 0.050 means that ads explain about 5% of changes in buying plans, but the P-value of 0.011 shows that this link is real and not just a coincidence. It's perfect for the digital world of 2026, which is full of information, shoppers, and "digital burnout."

In conclusion, Phouls Bag's ability to get people interested in buying comes down to making real, eye-catching ads that people made that fit with people's desire for authenticity. The label stands out by focusing on new, heartfelt content that creates emotional connections and eases worries about buying. Overall, even though the effect may seem small, local fashion businesses need to match their promotional triggers with what motivates buyers on a deeper level if they want to turn online hype into long-term sales.

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