
Decoding Purchase Decisions: The Role of Influencer Credibility and Content

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ABSTRACT

The rapid growth of social media has positioned influencer marketing as a key driver of consumer purchase decisions, yet the relative roles of influencer attributes and content characteristics remain unclear. This study investigates the effects of Influencer Credibility, Content Frequency, and Content Relevancy on Purchase Decision using survey data from 516 active social media users analyzed with SEM-PLS 4. The results show that the model explains 58.1% of the variance in Purchase Decision ($R^2 = 0.581$) and demonstrates strong predictive relevance ($Q^2_{\text{predict}} = 0.570$). Hypothesis testing indicates that Content Relevancy has a strong and significant effect on Purchase Decision ($\beta = 0.613$; $t = 11.058$; $p < 0.001$; $f^2 = 0.370$), making it the most influential predictor. Content Frequency has a positive but weak effect ($\beta = 0.121$; $t = 2.192$; $p = 0.014$; $f^2 = 0.014$), while Influencer Credibility does not significantly influence Purchase Decision ($\beta = 0.080$; $t = 1.410$; $p = 0.079$; $f^2 = 0.008$). These findings suggest that content relevance plays a more critical role than influencer credibility in shaping purchase decisions. The study highlights the importance of content strategy in enhancing the effectiveness of influencer marketing.

Keywords: *Influencer Marketing, Content Relevancy, Content Frequency, Influencer Credibility, Purchase Decision*

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INTRODUCTION

Social media's explosive growth has drastically altered how customers get information, engage with brands, and decide what to buy. Influencer marketing, which uses people with sizable fan bases to deliver marketing messages in a more intimate and convincing way, is one of the most notable trends in the field of digital marketing. This tactic is said to be able to close the gap between companies and customers by taking a more genuine and socially conscious approach. (Feng et al., 2023; George et al., 2025).

Despite being widely used by companies, influencer marketing's ability to impact consumer decisions has yielded inconsistent findings in a number of earlier research. While some research highlight the significance of influencer credibility as a major element influencing customer trust and buy intent, other studies demonstrate that the features of the material presented, like frequency and relevancy, really have a more dominant effect (Liu, 2022; Tran & Uehara, 2023). These results' discrepancy points to a research gap that requires more investigation, especially with regard to the variables that have the biggest impact on consumers' decisions to buy in the current social media era.

Additionally, shifts in digital consumer behavior indicate an increasing inclination toward selectivity in marketing content, particularly among younger age groups and active social media users. Customers now consider how relevant the material is to their own needs, interests, and context in addition to the popularity or reputation of influencers. In this situation, high frequency can actually lead to tiredness and lessen the impact of marketing messages, but it can

also boost message exposure if there is insufficient content relevancy (Ilieva et al., 2024; Migkos & Giannakopoulos, 2025).

In light of these circumstances, this study aims to investigate experimentally how consumer purchase decisions are impacted by influencer credibility, content frequency, and content relevancy in the context of influencer-based marketing. In addition to testing the significance of the link between variables, this study uses a Partial Least Squares-based Structural Equation Modeling (SEM-PLS) technique to evaluate the relative contribution and predictive power of each construct in explaining purchase decisions (Abdalla et al., 2025; Ao et al., 2023; Kilumile & Zuo, 2024). It is anticipated that this strategy will offer a more thorough comprehension of influencer marketing techniques.

Theoretically, by offering actual data on the evolving roles of influencers and content in the decision-making process of consumers, this study should enhance the literature on digital marketing (Ilieva et al., 2024). Practically speaking, the study's findings should be taken into account by companies and marketers when creating more successful influencer marketing plans, with a focus on striking a balance between influencer credibility and audience-relevant content.

METHOD

Based on a developed conceptual framework, this study employs a quantitative method with an explanatory research design to examine the causal link between independent and dependent variables. This method was selected because it can employ hypothesis testing based on survey data to scientifically explain the impact of Influencer Credibility, Content Frequency, and Content Relevancy on Purchase Decision. The study was cross-sectional in nature, with data being gathered at a certain point in time (Adaba et al., 2025).

Social media users who have seen influencer material and have either bought or are considering buying promoted goods make up the study's population (Afzal et al., 2024). The sampling strategy combined purposive sampling with non-probability sampling, and the criteria for respondents included using social media regularly, following or being exposed to influencer material, and having prior experience with or interest in buying digitally marketed goods (Gu & Duan, 2024; Tanwar et al., 2021). 516 respondents were successfully gathered and examined, meeting the minimal sample size requirements for SEM-PLS analysis.

An online structured questionnaire was used to collect data. The research instrument was created using indicators that had been verified in earlier studies and modified for the study setting. A five-point Likert scale, with 1 denoting "strongly disagree" and 5 denoting "strongly agree," was used to measure each statement item in order to quantify respondents' opinions about each research construct (Feng et al., 2023; Kilumile & Zuo, 2024).

With the aid of SmartPLS version 4, data analysis was carried out utilizing Partial Least Squares-based Structural Equation Modeling (SEM-PLS). The SEM-PLS approach was selected because it is appropriate for theory construction and prediction, can handle intricate research models with numerous indicators, and does not require stringent data normalcy assumptions (Sohaib & Ali, 2025). The analysis process was conducted in phases: first, the measurement model (outer model) was evaluated by testing its convergent validity, reliability, and discriminant validity; next, the structural model (inner model) was evaluated by testing its R² effect size (f^2), predictive relevance ($Q^2_{predict}$), and hypothesis testing using the bootstrapping technique (Castro Ortigón et al., 2024).

This study's methodological procedures are intended to guarantee that the analytical results have a sufficient degree of validity, reliability, and inferential accuracy. Strong empirical results that are supported by science are anticipated from the analytical methodology and approaches employed in order to explain how influencers and content attributes affect consumer purchasing decisions.

Hypotheses Development

Before making a purchase, shoppers consider a variety of facts. Influencer marketing has emerged as one of the primary information sources influencing digital marketing. Through their personal traits and the content they share, influencers serve as marketing ambassadors with the power to mold customer impressions. Therefore, it's critical to comprehend the elements that determine influencer marketing's efficacy in order to explain customer purchasing behavior (Jos & Oliveira, 2024).

Influencer Credibility is frequently linked to the degree of consumer acceptance and confidence in the message being delivered. Aspects like knowledge, honesty, and attractiveness are typically included in influencer credibility since they are thought to boost consumer trust and affect attitudes and behavior related to purchases. When customers perceive influencers as reliable individuals, the marketing messages they transmit are more likely to be regarded as relevant and trustworthy, which may encourage consumers to make purchases (Jayasingh & Sivakumar, 2025). The first hypothesis is stated as follows in light of this argument:

H1: Purchase decisions are positively impacted by influencer credibility.

Frequency of material is a crucial component in social media marketing, in addition to influencer attributes. The frequency with which marketing messages are presented to the audience is reflected in content frequency, which can boost exposure and brand awareness. Regular exposure to material can improve consumers' recollections of the product and raise the possibility that they will make a buy. However, the power of the content to grab the audience's attention still determines how successful content frequency is (Sahaf & Nazir, 2024). The second hypothesis is developed as follows, drawing on the theories of exposure and message repetition:

H2: Purchase decisions are positively impacted by content frequency.

Additionally, the degree to which influencer material aligns with the audience's requirements, interests, and context is largely determined by content relevancy. Relevant content is often seen as more valuable, educational, and intimate, which boosts customer engagement and promotes more favorable behavioral reactions. Relevant content is thought to improve consumer-brand relationships and raise the likelihood of purchases in digital marketing (uniyal et al., 2025). Thus, the following is the formulation of the third hypothesis:

H3: Purchase decisions are positively impacted by content relevancy.

Overall, the formulation of the study's hypotheses is predicated on the idea that influencer marketing's efficacy is influenced by both the message's delivery method and its relevance. This study aims to provide an empirical understanding of the relative roles of influencer attributes and content in influencing customer purchasing decisions by exploring these three hypotheses.

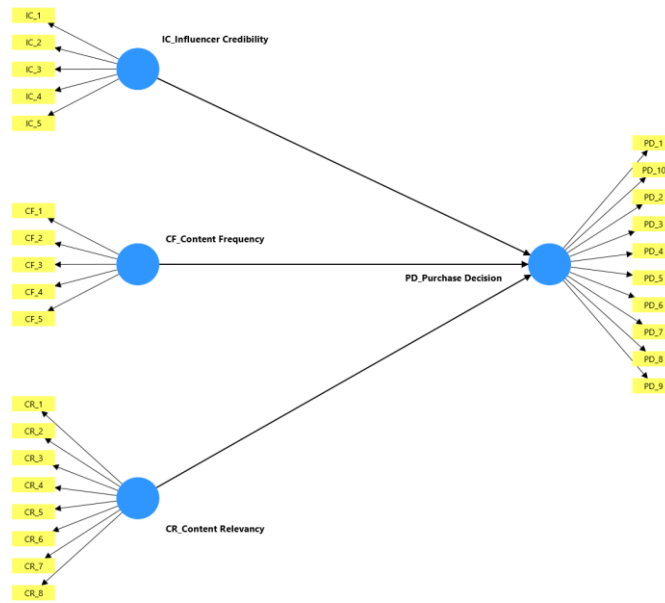


Figure 1. Conceptual Framework for Research

FINDINGS AND DISCUSSION

Findings

Respondent Characteristic

Because they offer a summary of the profiles of the research respondents and the sociodemographic context that shapes respondent behavior, respondent characteristics are a crucial component of quantitative research (Luo et al., 2024). To guarantee that the research sample and aims are appropriate, as well as to improve the external validity and representativeness of the study findings, information regarding the characteristics of the respondents is required. These features typically include demographic factors like age and gender, which are frequently linked to variations in consumer decision-making processes, information perceptions, and consumption behaviors.

Behavioral traits like social media usage intensity are important in addition to demographic traits, particularly in studies on influencer and digital marketing. Respondents' assessments of influencer legitimacy, content relevance, and its influence on purchasing decisions are influenced by their amount of social media usage, which is a reflection of their exposure to digital material and influencers. This study can reinforce the theoretical foundation for the ensuing research implications and offer a clear context for evaluating SEM-PLS analysis outcomes by methodically comprehending respondent characteristics.

Table 2. Respondents Demography

Characteristic	Category	Respondent	Percentage
Gender	Male	172	33,3
	Female	344	66,7
Age	< 18 years old	43	8,3
	18 - 20 years old	354	68,6
	21 - 23 years old	87	16,9
	> 23 years old	32	6,2
How often do you use social media each day?	Rarely	11	2,1
	Sometimes	78	15,1
	Often	427	82,8

Source: Processed Primary Data, 2025

According to gender characteristics, 344 respondents, or 66.7% of the total, were female, while 172 respondents, or 33.3% of the total, were male. This composition demonstrates that female participation in the study was more prevalent, suggesting that women are more involved in influencer content-related activities and social media use. In the context of digital marketing research, where women are frequently the main target in terms of content consumption and purchase decisions, the preponderance of female respondents is also pertinent.

The majority of respondents (354, or 68.6%) were between the ages of 18 and 20, suggesting that young individuals predominated in this survey. There were 87 respondents (16.9%) who were between the ages of 21 and 23, 43 respondents (8.3%) who were under the age of 18, and 32 respondents (6.2%) who were above the age of 23. According to this age distribution, the majority of respondents are young consumers or early adults, who are known to utilize social media extensively and be more receptive to influencer-based marketing.

Additionally, according to the intensity of social media use, 427 respondents, or 82.8%, said they use social media frequently. In contrast, 78 respondents, or 15.1%, reported using social media occasionally, while only 11 respondents, or 2.1%, reported using it infrequently. The majority of respondents are active social media users, according to these data, which is extremely pertinent to the study's goal of determining how influencers and content affect consumers' decisions to buy. The data collected is regarded as representative and sufficient for examining consumer behavior in the context of influencer-based digital marketing due to the high level of social media participation among respondents.

Convergent Validity Analysis

One of the key factors in assessing measurement models in Partial Least Squares-based Structural Equation Modeling (SEM-PLS) is convergent validity. The degree to which the indicators used to test a latent construct are actually connected with one another and represent the same construct is known as convergent validity. To put it another way, convergent validity guarantees that a set of indicators has a high degree of consistency in describing the latent variables being measured, allowing the research instrument to be considered empirically valid.

Three primary metrics are typically used in SEM-PLS to assess convergent validity: factor loading values, Average Variance Extracted (AVE), and Composite Reliability. Factor loading values show how strongly indicators and latent components are related; a value of ≥ 0.70 is advised. An indication with a high factor loading contributes significantly to the explanation of the construct. In the meantime, the AVE value—which has a minimum suggested value of 0.50—is used to calculate the percentage of indicator variance that may be explained by the latent construct. The construct can explain more than half of the variance of its indicators if the AVE value is higher than this cutoff (Hair, Jr. et al., 2022).

Furthermore, because Composite Reliability does not presume indicator weight equivalency, it is frequently regarded as more appropriate than Cronbach's Alpha in the context of SEM-PLS. It is used to evaluate the internal consistency of indicators in assessing latent constructs. An appropriate level of reliability is indicated by a Composite Reliability rating of > 0.70 . The measurement model is considered viable to move on to the step of discriminant validity assessment and structural model analysis if all of these requirements are satisfied, and the latent concept may be proclaimed to have strong convergent validity. Convergent validity analysis is therefore crucial to guaranteeing the accuracy of measurement and the interpretation of SEM-PLS-based research findings.

Table 3. Loading Factor

	CF_Content Frequency	CR_Content Relevancy	IC_Influencer Credibility	PD_Purchase Decision
CF_1	0,774			
CF_2	0,720			
CF_3	0,823			

CF_4	0,758	
CF_5	0,795	
CR_1	0,730	
CR_2	0,790	
CR_3	0,703	
CR_4	0,732	
CR_5	0,795	
CR_6	0,791	
CR_7	0,700	
CR_8	0,761	
IC_1		0,725
IC_2		0,766
IC_3		0,800
IC_4		0,766
IC_5		0,813
PD_1		0,763
PD_10		0,812
PD_2		0,820
PD_3		0,816
PD_4		0,811
PD_5		0,760
PD_6		0,832
PD_7		0,818
PD_8		0,816
PD_9		0,785

Source: Processed Primary Data, 2025

All of the indicators in this study have satisfied the convergent validity requirements, according to the measurement model evaluation results (outer model). Each indicator was able to accurately represent the latent construct being tested, according to the SEM-PLS version 4 analysis, since all factor loading values were above the 0.70 threshold. As a result, the research tool was deemed legitimate and appropriate for use in additional structural model study.

All indicators exhibit robust and consistent loading factors in the constructs of Influencer Credibility, Content Frequency, and Content Relevancy. Content Frequency and Content Relevancy have loading values between 0.720 and 0.823 and 0.700 and 0.795, respectively. With loading values ranging from 0.725 to 0.813, the Influencer Credibility construct likewise exhibits high values. These results show that the indicators have been successful in capturing the essence of each construct and that no indicators need to be eliminated.

Additionally, with values ranging from 0.760 to 0.832, the Purchase Decision construct demonstrated strong and consistent loading factors across all variables. Excellent measurement quality was demonstrated by the indicators' consistent representation of the respondents' purchasing decisions. Overall, the loading factor test findings show that all of the study's constructs have sufficient convergent validity, allowing the measurement model to move on to the structural model's reliability assessment, discriminant validity, and inter-construct relationship testing phases.

Validity and Reliability Analysis

A crucial stage in quantitative research is validity and reliability analysis, especially when evaluating measurement models in Partial Least Squares-based Structural Equation Modeling

(SEM-PLS). The purpose of this analysis is to make sure that research tools can measure latent constructs reliably and accurately. Results from structural model analyses could lead to biased, unreliable conclusions if they lack validity and reliability (Pereira et al., 2024).

The degree to which the indicators employed accurately reflect the latent concept being examined is referred to as validity. Convergent validity and discriminant validity are the two primary criteria used to assess validity in SEM-PLS. Average Variance Extracted (AVE) and factor loading values are typically used to verify convergent validity, which evaluates the degree of agreement among indicators within a concept. The indicator has a significant contribution to the latent construct if the factor loading value is ≥ 0.70 , and the construct can account for more than half of the indicator's variation if the AVE value is ≥ 0.50 . Conversely, discriminant validity, which is typically assessed using the Fornell–Larcker method or the Heterotrait–Monotrait Ratio (HTMT) criteria, seeks to guarantee that a construct is empirically distinct from other constructs (Bushashe, 2023).

The degree of internal consistency of indicators used to measure latent variables is related to reliability. Reliability in SEM-PLS is typically evaluated using Composite Reliability and Cronbach's Alpha. While Composite Reliability takes into account the weight of each indicator and is thought to be more suitable for SEM-PLS, Cronbach's Alpha assesses internal consistency based on the correlation between indicators. The indicators have sufficient reliability, as indicated by the recommended Cronbach's Alpha and Composite Reliability values of ≥ 0.70 . The measurement model might be deemed practicable to move on to the structural model evaluation stage if all validity and reliability requirements are satisfied. Therefore, validity and reliability analysis is crucial for guaranteeing the accuracy of measurement and the interpretation of SEM-PLS-based research findings (Demircioglu et al., 2021).

Table 5. Validity and Reliability

	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
CF_Content Frequency	0,833	0,882	0,600
CR_Content Relevancy	0,889	0,912	0,565
IC_Influencer Credibility	0,834	0,882	0,600
PD_Purchase Decision	0,939	0,948	0,646

Source: Processed Primary Data, 2025

All of the constructs in this study have satisfied the standards suggested by SEM-PLS analysis, according to the reliability and convergent validity testing results. Each construct's Cronbach's Alpha score is higher than the required minimum of 0.70, demonstrating the indicators' strong internal consistency. Furthermore, all constructs' Composite dependability values were greater than 0.70, indicating a high and consistent degree of dependability in measuring latent constructs. These results verify that each research variable is adequately represented by the indicators employed.

Additionally, all constructs have an AVE value above 0.50 according to the findings of the Average Variance Extracted (AVE) test, indicating that convergent validity is satisfied. While Content Frequency, Content Relevancy, and Influencer Credibility also shown good capacity to explain the variance of respective indicators, the Purchase Decision construct demonstrated the best reliability and validity values. Overall, these findings support the validity and reliability of the measuring model used in this investigation, allowing for the examination of discriminant validity and structural model testing.

Discriminant Validity Analysis

When evaluating measurement models in Partial Least Squares-based Structural Equation Modeling (SEM-PLS), discriminant validity is crucial. Making ensuring a latent construct is experimentally different and unique from other latent constructs in the study model is the goal

of discriminant validity. By ensuring that each construct measures a distinct concept and that there is no measurement overlap between constructs, discriminant validity can be satisfied, increasing the precision of understanding causal linkages in the structural model (Almaiah et al., 2022).

The Fornell–Larcker criteria, cross-loading, and the Heterotrait–Monotrait Ratio (HTMT) are some of the methods typically used in SEM-PLS to assess discriminant validity. By comparing the square root of each construct's Average Variance Extracted (AVE) value with the correlation between constructs, the Fornell–Larcker criteria evaluate discriminant validity. When a construct's square root of its AVE is higher than its correlation with other constructs, discriminant validity is satisfied. The cross-loading approach determines whether an indicator represents the proper construct if its loading value on the measured construct is higher than its loading on other constructs.

The Heterotrait–Monotrait Ratio (HTMT), which is thought to be more sensitive in identifying discriminant validity difficulties, is now the method most advised in SEM-PLS. The ratio of correlations between indicators from distinct constructs (heterotrait) to correlations between indicators within the same construct (monotrait) is measured by HTMT. Less than 0.85 (conservative criterion) or 0.90 (liberal criterion) is the suggested HTMT value. The model's constructs are deemed to have sufficient discriminant validity if the HTMT value is less than this cutoff. The measuring model can be deemed viable and the study can move on to the structural model evaluation step once discriminant validity is satisfied, allowing the research findings to be supported by science.

Table 4. Heterotrait-monotrait ratio (HTMT)

	CF_Content Frequency	CR_Content Relevancy	IC_Influencer Credibility	PD_Purchase Decision
CF_Content Frequency				
CR_Content Relevancy	0,859			
IC_Influencer Credibility	0,771	0,733		
PD_Purchase Decision	0,704	0,818	0,606	

Source: Processed Primary Data, 2025

All HTMT values between constructs are below the suggested threshold, according to the findings of discriminant validity testing using the Heterotrait–Monotrait Ratio (HTMT) criterion. For the constructs in the model to have sufficient discriminant validity, the HTMT value must be less than 0.85 (conservative criterion) or 0.90 (liberal criterion). These results show that none of the study's constructs measure the same idea and are empirically distinct from one another.

More precisely, while it is less than the maximum limit of 0.90, the HTMT value of 0.859 between Content Frequency and Content Relevancy is nevertheless appropriate in the setting of complicated consumer behavior research. Although there is a moderate degree of association, the HTMT values between Influencer Credibility and Content Frequency (0.771) and Content Relevancy (0.733) nevertheless show distinct concept differences. Additionally, the correlation between Purchase Decision and Influencer Credibility (0.606), Content Frequency (0.704), and Content Relevancy (0.818) is all within a reasonable range. All constructs are deemed unique and feasible to move on to the structural model testing stage since the HTMT results generally verify that the measurement model in this study has satisfied discriminant validity.

R² Analysis

One of the primary metrics for assessing structural models (inner models) in Partial Least Squares-based Structural Equation Modeling (SEM-PLS) is R² analysis (coefficient of determination). The degree to which endogenous variable variance can be explained by exogenous variables in the model is evaluated using R². To put it another way, the R² value is a

crucial foundation for evaluating the strength and quality of the established structural model since it shows the explanatory capacity of the research model.

The percentage of variance in the endogenous construct that can be accounted for by the exogenous constructs influencing it is known as the R^2 value in SEM-PLS. The model's capacity to explain the phenomenon under study increases with the R^2 number. Although this interpretation still depends on the context and complexity of the research, an R^2 score of 0.75 is considered strong (significant), 0.50 is considered moderate, and 0.25 is considered weak. As a result, the R^2 value is not evaluated in a vacuum; rather, it must be taken into account along with the features of the study field and the analysis's goal.

SEM-PLS offers modified R^2 in addition to R^2 , which accounts for the number of exogenous variables in the model. Because it accounts for possible R^2 value inflation brought on by the inclusion of predictors, adjusted R^2 is thought to be more cautious. A small difference between R^2 and adjusted R^2 suggests that the model is stable and does not overfit. As a result, the combined analysis of R^2 and modified R^2 offers a thorough picture of the explanatory power and quality of the structural model and serves as the foundation for the evaluation of effect size (f^2), predictive relevance (Q^2), and hypothesis testing in SEM-PLS.

Table 6. R^2 Estimates

	R-square	R-square adjusted
PD Purchase Decision	0,581	0,579

Source: Processed Primary Data, 2025

The Purchase Decision construct has an R^2 value of 0.581 and an adjusted R^2 of 0.579, according to the structural model evaluation results. The independent variables in the model—content frequency, content relevancy, and influencer credibility—account for 58.1% of the variance in purchase decisions, according to an R^2 value of 0.581. In the meantime, the model has a reasonable degree of stability and does not suffer from bias because of the amount of predictors used, according to the adjusted R^2 value, which is comparatively little different from the R-square.

A result of 0.581 can be classified as moderate to substantial explanatory power according to the SEM-PLS R^2 grading criteria. This suggests that respondents' purchasing decisions can be explained fairly well by the combination of influencer credibility and content strategy. In order to assess causal linkages between constructs, such as path coefficient analysis, effect size (f^2), and predictive relevance (Q^2), the structural model created in this study is deemed to have sufficient explanatory power.

Effect Size (f^2) Analysis

A crucial component of assessing structural models (inner models) in Partial Least Squares-based Structural Equation Modeling (SEM-PLS) is effect size analysis (f^2). Each exogenous variable's contribution to the variance of endogenous variables in the research model is evaluated using effect size. The understanding of research findings is enhanced by f^2 analysis, which offers information about the practical significance of each causal link examined, in contrast to statistical significance testing, which just indicates whether or not there is an effect.

The f^2 value in SEM-PLS is determined by examining how the endogenous construct's R^2 value changes when an exogenous construct is added or removed from the model. A given exogenous construct's contribution to the model's explanatory power increases with the degree to which its removal lowers the R^2 value. f^2 values of 0.02 for tiny effects, 0.15 for medium effects, and 0.35 for big effects. In the SEM-PLS model, this classification serves as a broad guideline for determining how strongly exogenous variables affect endogenous variables.

When determining which variables in structural models have a significant and dominant influence, effect size analysis (f^2) is crucial. Researchers can obtain a more thorough knowledge of the relative contribution of each variable in describing the phenomenon under study by combining f^2 data with path coefficient values and R^2 . As a result, f^2 analysis has significant

theoretical and practical implications for theory creation and strategy formulation based on SEM-PLS research findings in addition to supporting the assessment of structural model quality.

Table 7. Effect Size (f^2)

	PD_Purchase Decision
CF_Content Frequency	0,014
CR_Content Relevancy	0,370
IC_Influencer Credibility	0,008

Source: Processed Primary Data, 2025

To determine how much each independent variable contributed to the Purchase Decision dependent construct, effect size (f^2) testing was used. According to SEM-PLS, a small effect is defined as having a f^2 value of 0.02, a moderate effect as having a value of 0.15, and a big effect as having a value of 0.35. Exogenous variables play a larger role in explaining the variation of endogenous constructs when the f^2 value is higher.

The results of the analysis indicate that Content Relevancy has a significant impact on Purchase Decision, with a f^2 value of 0.370. This result shows that content relevance is the most important predictor of purchase decisions, contributing significantly to the model's increased explanatory power. To put it another way, the model's capacity to explain the variance in Purchase Decision will be greatly diminished if the Content Relevancy construct is eliminated.

On the other hand, Content Frequency is classified as a very minor or practically inconsequential effect with a f^2 value of 0.014, below the minimum threshold of 0.02. Similar results were obtained for Influencer Credibility, which had a f^2 value of 0.008, indicating a very low influence to Purchase Decision. These findings suggest that while there may be a statistical association between the two variables in the model, their actual contribution to enhancing Purchase Decision's explanatory power is rather small when compared to Content Relevancy.

Overall, the findings of the effect size test verify that, in this study model, Content Relevancy is the only variable that significantly influences Purchase Decision. This result highlights the significance of content quality and relevance in influencing purchasing decisions, rather than just content frequency or perceptions of influencer trustworthiness. As a result, these findings have significant theoretical and practical ramifications for the creation of influencer and content-based marketing tactics.

Predictive Relevance (Q^2 predict) Analysis

A crucial step in assessing structural models in Partial Least Squares-based Structural Equation Modeling (SEM-PLS) is predictive relevance analysis (Q^2 predict), which evaluates the model's capacity to forecast endogenous construct values. Q^2 predict highlights the accuracy of predictions made outside of the sample (out-of-sample prediction), in contrast to R^2 , which concentrates on explanatory power (in-sample explanatory power). As a result, Q^2 predict analysis shows that the research model is relevant and accurate in forecasting the phenomenon under study, in addition to being good at explaining the link between variables.

By comparing the model's predicted values with the actual observed values, the blindfolding or PLSpredict technique in SEM-PLS yields the Q^2 predict value. The primary criterion for understanding Q^2 predict is that the model must have predictive power if the Q^2 predict value is larger than zero. The model's predictive power increases with the Q^2 predict value. The predictive validity of the structural model is strengthened when endogenous constructions can be accurately predicted by exogenous constructs in the model, as indicated by a positive and suitably high Q^2 predict value.

When evaluating the practical utility of SEM-PLS models, Q^2 predict analysis is crucial, particularly in applied research areas like marketing, management, and consumer behavior. Researchers can obtain a thorough assessment of model quality in terms of explanation and prediction by combining Q^2 predict findings with R^2 and effect size (f^2). Consequently,

predictive relevance analysis offers a solid empirical foundation for theoretical implications and research-based decision making, making it a crucial addition to structural model evaluation.

Table 8. Predictive Relevance ($Q^2_{predict}$) of the Structural Model

	$Q^2_{predict}$
PD_Purchase Decision	0,570

Source: Processed Primary Data, 2025

The model's capacity to correctly forecast endogenous construct values outside of the research sample is assessed using predictive relevance testing ($Q^2_{predict}$). When it comes to SEM-PLS, a model's predictive capacity is indicated by a $Q^2_{predict}$ value greater than zero; a higher value denotes better prediction quality. As a result, $Q^2_{predict}$ is a crucial metric for evaluating the model's predictive significance as well as its explanatory capability.

The Purchase Decision construct has a $Q^2_{predict}$ value of 0.570, which is much higher than the minimum criterion of zero, according to the analysis results. The study model's strong predictive usefulness for purchase decisions is indicated by this value. This indicates that respondents' purchasing choice behavior may be properly and consistently predicted by combining the variables Content Frequency, Content Relevancy, and Influencer Credibility.

Overall, the $Q^2_{predict}$ results verify that the structural model created in this study has good predictive abilities in addition to sufficient explanatory power, as shown by the R-square value. These results corroborate the SEM-PLS model's validity and offer empirical evidence that it can serve as a foundation for future influencer and content-based marketing strategy development and decision-making.

Results of Hypothesis Testing

Because they are used to assess causal linkages that have been developed based on conceptual frameworks and theoretical underpinnings, hypothesis testing results are an essential component of structural model analysis in quantitative research. Path coefficient estimation is used in hypothesis testing to evaluate the impact of exogenous variables on endogenous variables in research based on Structural Equation Modeling with the Partial Least Squares technique (SEM-PLS). This step seeks to verify whether the research data experimentally supports the proposed correlations between constructs.

The bootstrapping process, which yields path coefficient (β) values, t-statistics, and p-values, is typically used in SEM-PLS hypothesis testing. Positive or negative numbers indicate the direction of the link, and path coefficients (β) show the strength and direction of effect between constructs. In the meantime, t-statistics and p-values are used to assess the relationship's statistical significance. At a 5% significance level, t-statistics must be larger than 1.96 and p-values must be less than 0.05. The proposed hypothesis is accepted if these conditions are satisfied; if not, it is rejected.

In addition to statistical significance, the magnitude of the path coefficients and the useful contribution of each causal relationship are taken into account when interpreting the findings of hypothesis testing. In order to give a more thorough knowledge of the relative roles of each variable in the structural model, hypothesis testing findings are frequently linked to effect size (f^2) and R^2 values. As a result, the results of hypothesis testing offer a solid empirical foundation for elucidating the phenomenon being studied, as well as a crucial ground for debating research findings and developing theoretical and practical implications.

Table 9. Results of Hypothesis Testing: Direct and Moderating Effects

	Path Coefficient (β)	T statistics ($ O/STDEV $)	P values
CF_Content Frequency -> PD_Purchase Decision	0,121	2,192	0,014
CR_Content Relevancy ->	0,613	11,058	0,000

PD_Purchase Decision			
IC_Influencer Credibility -> PD_Purchase Decision	0,080	1,410	0,079

Source: Processed Primary Data, 2025

The path coefficient (β) values, t-statistics, and p-values acquired by the bootstrapping technique in SEM-PLS version 4 were evaluated in order to test the hypothesis. At a 5% significance level, a relationship was deemed significant if the t-statistics value was greater than 1.96 and the p-value was less than 0.05. The direction and magnitude of the independent variable's influence on the dependent variable, purchase decision, are indicated by the path coefficient (β) value.

The test results indicate that Purchase Decision is positively and significantly impacted by Content Frequency ($\beta = 0.121$; $t = 2.192$; $p = 0.014$). This result suggests that consumers are more likely to make purchases when influencers publish material more frequently. The idea that Content Frequency affects Purchase Decision is supported empirically by these results, even though the route coefficient value is quite tiny.

Additionally, it was discovered that Purchase Decision was positively and significantly impacted by Content Relevancy ($\beta = 0.613$; $t = 11.058$; $p < 0.001$). The high path coefficient value suggests that the most important element influencing consumer purchasing decisions is content relevancy. This result demonstrates that the effectiveness of influencer-based marketing is significantly influenced by the content's appropriateness to the audience's requirements, interests, and context. As a result, there is substantial evidence to support the concept that content relevancy influences purchase decisions.

On the other hand, the test findings indicate that Purchase Decision is not significantly impacted by Influencer Credibility ($\beta = 0.080$; $t = 1.410$; $p = 0.079$). Even if the path coefficient shows a positive direction of influence, the influence is not statistically significant because the t-statistics value is below the crucial threshold and the p-value is greater than 0.05. As a result, the theory that claims influencer credibility affects purchase decisions is disproved.

Overall, the results of the hypothesis testing demonstrate that both Content Frequency and Content Relevancy have an impact on consumers' decisions to buy, with Content Relevancy being the most powerful predictor. In this research model, Influencer Credibility had no discernible effect. These results support the significance of pertinent content strategies in digital marketing and have theoretical implications that the quality and appropriateness of material are more important in determining consumer behavior than only the perception of influencer credibility.

Discussion

The study's findings offer a thorough summary of how influencer marketing and content attributes affect consumers' decisions to buy. With an R^2 value of 0.581, the structural model exhibits sufficient explanatory power overall, meaning that content frequency, content relevancy, and influencer credibility account for 58.1% of the variation in purchasing decisions. The model is relevant for explaining and forecasting consumer behavior in the context of influencer-based marketing, as seen by the Q^2 predict value of 0.570, which further demonstrates that it is both explanatory and has good predictive ability.

The primary conclusions of this study show that the most important element affecting purchasing decisions is content relevancy. The substantial significance level ($t = 11.058$; $p < 0.001$) and high route coefficient value ($\beta = 0.613$) demonstrate this. Furthermore, the effect size value ($f^2 = 0.370$) indicates that Purchase Decision is significantly impacted by Content Relevancy. Consumers are more receptive to content that is pertinent to their needs, interests, and personal context than to mere content exposure, according to earlier study, which is supported by this finding. For influencer marketing to be effective in influencing consumer decisions, the message's appropriateness and quality are crucial.

Additionally, purchasing decisions were found to be positively and significantly impacted by Content Frequency ($\beta = 0.121$; $t = 2.192$; $p = 0.014$), supporting the prediction pertaining to this variable. Nevertheless, the extremely modest effect size ($f^2 = 0.014$) suggests that while content frequency is statistically significant, its practical contribution is comparatively minor. These results imply that there won't be much of an effect on purchasing decisions if content intensity isn't balanced with substantive relevance. These findings support the theory found in the literature that when high frequency is not accompanied with pertinent informative value, consumers are more likely to suffer from content fatigue.

The hypothesis pertaining to Influencer Credibility was rejected because, in contrast to the other two factors, it was not shown to have a significant impact on Purchase Decision ($\beta = 0.080$; $t = 1.410$; $p = 0.079$). Furthermore, the extremely modest effect size ($f^2 = 0.008$) suggests that, in the context of this study, influencer reputation has very little bearing on purchase decisions. These results point to a change in consumer behavior, especially among younger age groups and active social media users, who are more critical and no longer only depend on their impression of the legitimacy of influencers. Customers appear to be more interested in the content's content than in the person giving it.

The findings of this study theoretically add significantly to the literature on influencer marketing by demonstrating that content, especially content relevance, is more important than the influencer's trustworthiness. These results broaden our knowledge of the mechanics underlying influencer impact, whereby the effectiveness of marketing is now determined by the message's relevance to the target audience rather than just who delivers it. Practically speaking, these findings imply that rather than concentrating only on choosing influencers who are well-known or credible, marketers and businesses should give top priority to methods for creating content that is pertinent, contextual, and helpful to consumers.

Despite the research model's impressive performance, this study includes limits that could open up new avenues for investigation. With an R^2 value of 0.581, variables outside the model, such brand trust, emotional engagement, or the entertainment value of content, account for 41.9% of the variance in purchasing decisions. Therefore, in order to have a more thorough understanding of the dynamics of purchase decisions in the context of influencer-based digital marketing, future study is advised to incorporate other variables or examine the function of mediating and moderating variables.

CONCLUSION

In the context of influencer-based marketing, this study attempts to investigate how customer purchase decisions are influenced by Influencer Credibility, Content Frequency, and Content Relevancy. This study anticipates that these three variables will be able to substantially explain purchase choice behavior based on the conceptual framework that was constructed. The study's findings indicate that this expectation is partially met, with content strategy—particularly content relevance—playing a far more significant role than the influencer's personal characteristics.

The study's primary conclusions support the idea that content relevance plays a significant role in influencing consumers' decisions to buy. It has been demonstrated that content relevance is not only statistically significant but also significantly enhances the model's explanatory and predictive capabilities. This indicates that customers are responding to digital marketing communications in a more logical and selective manner, prioritizing content benefits, value, and suitability. In the context of this study, Influencer Credibility has not been shown to be a significant influencer of purchasing decisions, while Content Frequency serves as a supporting factor that contributes to a limited extent.

From a conceptual standpoint, the study's findings support the idea that influencer marketing's efficacy now rests more on what and how the message is conveyed than on who delivers it. This result supports the idea that changes in customer behavior in the digital era necessitate a marketing strategy that is more focused on content quality than just credibility

symbols. Thus, by highlighting the significance of content as the primary mechanism influencing purchasing decisions, this study adds to the body of knowledge in the field of digital marketing.

There is still need for improvement even if this research model shows good explanatory and predictive abilities. In order to improve our comprehension of the connections between constructs, future studies should examine additional factors that might affect consumer choices, such as brand trust, emotional engagement, perceived authenticity, or entertainment value. They should also examine the function of mediating and moderating variables. Furthermore, it is anticipated that broadening the research environment to include various consumer demographics, social media platforms, and product categories will improve the generalization and applicability of subsequent findings.

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