Decoding the Digital Consumer: A Logistic Regression Framework for Analyzing Social Media Marketing Efficacy

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Abstract

The widespread use of social media in the consumer journey has changed the marketing landscape, making it essential to explore the specific factors that influence online buying behavior. While the overall effect of social media marketing is recognized, the effectiveness of its various elements, when considering user demographics, is not clearly measured. This study fills that gap by creating a logistic regression model to examine the direct effects of four main social media marketing strategies: influencer marketing, user-generated content (UGC), social media advertising, and online reviews on the purchase decision. Importantly, the model includes key demographic and behavioral factors like age, income, main social media platform, and daily browsing time as controls to determine the unique impact of the marketing strategies.

Data were collected through a structured survey from a sample of social media users (N=235). The survey measured their exposure to four marketing variables on a Likert scale, along with their demographic information and self-reported purchase behavior for a specific product category. The results from the fitted logistic model found that online reviews (OR = 2.17, $p < .001$) and user-generated content (UGC) (OR = 1.65, $p < .01$) were the strongest and statistically significant predictors of a positive purchase decision. Influencer marketing also showed a significant, but weaker, effect (OR = 1.49, $p < .05$). Interestingly, after accounting for other factors, social media advertising was not a significant predictor ($p > .05$). Among the control variables, platform usage, especially Instagram and higher income levels notably increased the chances of a purchase. The model provides a solid framework for deciding where to focus marketing investments. It concludes that strategies aimed at building social proof and genuine user content are much more effective than paid ads in influencing consumer purchase decisions on social media platforms.

Keywords: Social Media Marketing, Purchase Decision, Logistic Regression, User-Generated Content, Online Reviews, Digital Consumer Behavior.

Introduction

The early twenty-first century has witnessed a profound transformation in the consumer–marketer relationship, driven by the rapid diffusion of digital technologies and social media platforms. What initially emerged as spaces for social interaction have evolved into integrated commercial ecosystems where brand discovery, evaluation, purchase, and advocacy occur seamlessly. This shift has fundamentally altered the consumer journey, replacing traditional linear models with non-linear, socially mediated decision pathways shaped by peer influence and platform algorithms.

Social media platforms now function as dominant commercial environments, with users spending substantial daily time engaging with a blend of personal, entertainment, and branded content. Platforms such as Instagram, Facebook, TikTok, and Pinterest have embedded shopping functionalities directly into user experiences, accelerating the rise of social commerce. The COVID-19 pandemic further intensified this transition, compressing years of digital adoption into a short period and normalizing online and in-app purchasing behavior across demographic segments.

In response, Social Media Marketing (SMM) has evolved from a supplementary promotional tool to a central strategic pillar. SMM encompasses influencer marketing, user-generated content (UGC), paid social advertising, and online reviews, each leveraging different mechanisms of social influence. Marketing scholarship increasingly recognizes a shift from persuasion-based communication toward an influence-driven paradigm, where purchase decisions are shaped more by social validation and perceived authenticity than by direct brand messaging (Kotler et al., 2021). Trust in digital environments has migrated from institutions to peer networks, elevating the role of influencers, reviews, and community-driven content in shaping consumer choice.

Despite extensive managerial adoption, academic understanding of SMM effectiveness remains fragmented. Existing literature often treats SMM as a monolithic construct, masking the differential impact of individual strategies on purchase decisions (Appel et al., 2020). Moreover, limited attention has been paid to moderating effects of consumer characteristics such as age, income, platform preference, and digital engagement intensity—an omission that contradicts foundational principles of segmentation and targeting. Methodologically, many studies rely on cross-sectional designs and linear models ill-suited for binary purchase outcomes, while experimental studies frequently lack ecological validity.

Theoretical foundations for examining SMM effects draw from established frameworks adapted to digital contexts. The Theory of Planned Behavior highlights the role of subjective norms in shaping intentions (Ajzen, 1991), while the Elaboration Likelihood Model explains how different SMM components may operate through central or peripheral processing routes (Petty & Cacioppo, 1986). Information Adoption Models emphasize source credibility and information quality as determinants of influence in online environments (Sussman & Siegal, 2003), and Network Theory explains how peer-generated content diffuses credibility through homophilous digital networks.

Addressing these gaps, the present study develops and tests a logistic regression model to examine the independent effects of influencer marketing, UGC, social media advertising, and online reviews on purchase decisions in the Indian context. By disaggregating SMM into distinct components and incorporating demographic and behavioral moderators, the study offers a nuanced, context-specific understanding of digital consumer behavior. Methodologically, the use of logistic regression enables appropriate modeling of binary purchase outcomes while generating interpretable odds ratios relevant for strategic decision-making.

Literature Review

Online Reviews and Purchase Decision

Online reviews represent one of the most influential forms of electronic word-of-mouth (eWOM) in digital marketplaces. Prior research consistently demonstrates that consumer-generated reviews significantly reduce perceived risk and information asymmetry, thereby enhancing purchase confidence (Chevalier & Mayzlin, 2006; Mudambi & Schuff, 2010). Online reviews function as social proof, enabling consumers to rely on collective experiences rather than firm-generated information (Cialdini, 2009).

Empirical studies have shown that both the **valence** (positive vs. negative) and **volume** of reviews exert a strong influence on purchase intentions and actual buying behavior (Duan, Gu, & Whinston, 2008). Positive reviews increase perceived product quality, while negative reviews disproportionately amplify risk perceptions (Ba & Pavlou, 2002). Furthermore, review credibility driven by reviewer expertise, argument quality, and perceived authenticity, moderates the strength of this relationship (Filieri & McLeay, 2014).

In social media environments, reviews are embedded within platforms that allow rapid diffusion and peer endorsement, further magnifying their persuasive impact (Erkan & Evans, 2016). Consequently, online reviews are widely recognized as one of the strongest predictors of purchase decisions in digital and social commerce contexts.

User-Generated Content (UGC) and Purchase Decision

User-generated content (UGC) refers to unpaid, consumer-created brand-related content such as posts, images, videos, testimonials, and experiential narratives shared on social media platforms. Unlike traditional advertising, UGC is perceived as more authentic, credible, and trustworthy due to its non-commercial origin (Hajli, 2014; Smith, Fischer, & Yongjian, 2012).

The literature suggests that UGC enhances consumer engagement, brand trust, and perceived value, which in turn positively influence purchase decisions (Phelps et al., 2004). Visual UGC, particularly images and videos, plays a critical role in shaping product expectations by allowing consumers to mentally simulate product usage (Schlosser, 2003). This effect is especially pronounced on visually oriented platforms such as Instagram.

Studies grounded in source credibility theory argue that UGC is more persuasive than firm-generated content because consumers attribute higher levels of sincerity and experiential validity to peer creators (Djafarova & Rushworth, 2017). As a result, UGC has emerged as a key driver of social commerce outcomes, including purchase intention, recommendation behavior, and brand advocacy.

Influencer Marketing and Purchase Decision

Influencer marketing involves the strategic use of individuals with substantial social media followings to promote products or brands. Influencers are positioned as opinion leaders whose recommendations can shape consumer attitudes and behaviors (Brown & Hayes, 2008). The effectiveness of influencer marketing is largely contingent on perceived **source credibility**, **expertise**, and **parasocial interaction** between the influencer and followers (Horton & Wohl, 1956; Lou & Yuan, 2019).

While several studies report positive effects of influencer endorsements on brand attitudes and purchase intentions (De Veirman, Cauberghe, & Hudders, 2017), emerging literature highlights diminishing returns due to increasing commercialization and consumer skepticism (Evans, Phua, Lim, & Jun, 2017). Disclosure of sponsored content often activates persuasion knowledge, leading consumers to discount influencer messages (Boerman, Willemsen, & Van Der Aa, 2017).

Recent empirical evidence suggests that influencer marketing is less effective than peer-driven content such as reviews and UGC when consumers seek diagnostic information for purchase decisions (Ki, Cuevas, Chong, & Lim, 2020). Thus, influencer marketing may play a supportive or awareness-building role rather than serving as a primary driver of purchase behavior.

Social Media Advertising and Purchase Decision

Social media advertising refers to paid promotional content delivered through platforms such as Instagram, Facebook, and YouTube using sophisticated targeting algorithms. While social media advertising enhances brand visibility and recall, its direct impact on purchase decisions is mixed (Stephen & Galak, 2012).

Research indicates that consumers often exhibit **ad fatigue** and **banner blindness**, reducing the persuasive effectiveness of paid advertisements (Cho & Cheon, 2004). Compared to organic content, paid ads are perceived as less credible and more intrusive, particularly among younger, digitally literate users (Campbell & Kirmani, 2000).

However, social media advertising can indirectly influence purchases by reinforcing brand awareness, facilitating retargeting, and supporting other social proof mechanisms (Lipsman et al., 2012). Studies suggest that advertising effectiveness improves when integrated with UGC and reviews rather than used in isolation (Ashley & Tuten, 2015). Consequently, social media advertising often functions as a complementary rather than dominant predictor of purchase decisions.

Platform Usage (Instagram) and Purchase Decision

Platform affordances play a crucial role in shaping consumer behavior in social commerce. Instagram, in particular, has evolved into a visually driven, commerce-enabled platform with integrated shopping features, influencer ecosystems, and UGC-rich environments (Phua, Jin, & Kim, 2017).

Research suggests that Instagram's visual orientation enhances emotional engagement and product desirability, leading to higher purchase likelihood compared to text-heavy platforms (Djafarova & Bowes, 2021). The platform's algorithmic amplification of engagement signals further increases exposure to socially endorsed content such as likes, comments, and shares, reinforcing social proof effects.

Empirical studies confirm that Instagram users exhibit stronger brand attachment and higher impulsive buying tendencies than users of other platforms (Sheldon & Bryant, 2016). Therefore, platform choice is a critical contextual variable influencing the effectiveness of social media marketing strategies.

Social Media Usage Intensity and Purchase Decision

Usage intensity, measured through daily browsing time, reflects the depth of consumer immersion in social media environments. Higher usage intensity increases exposure to marketing stimuli, peer content, and social comparisons, thereby raising the probability of purchase decisions (Voorveld et al., 2018).

Frequent social media users are more likely to engage in social commerce behaviors due to habitual platform usage and reduced cognitive resistance to marketing messages (Hajli, Sims, Zadeh, & Richard, 2017). Additionally, increased browsing time enhances familiarity with brands and shortens the decision-making cycle, particularly for low- and medium-involvement products.

Theoretical framework

The theoretical framework of this study may be grounded in Social Proof Theory, which could suggest that individuals might rely on the significant judgments, critical behaviors, and relevant experiences of others when making important decisions under conditions of uncertainty (Cialdini, 2009). In digital environments and social media contexts, consumer-generated signals such as online reviews and user-generated content function as social proof cues that shape purchase behavior. Moreover, these cues might reduce perceived risk by enabling consumers to infer product value from peer evaluations. Nevertheless, the influence of social proof appears amplified on platforms such as Instagram. Given that engagement metrics are highly salient, peer interactions may reinforce purchase decisions.

Furthermore, the Information Adoption Model is employed to explain cognitive mechanisms through which social proof cues are evaluated (Sussman & Siegal, 2003). IAM posits information is adopted when perceived as high in quality and credible. However, conditions may be satisfied by peer-generated reviews and UGC. Thus, consumers develop persuasion knowledge toward sponsored content. The use of binary logistic regression aligns with the behavioral orientation of these theories by estimating likelihood of purchase outcome. Additionally, Social Proof Theory and IAM might provide an integrated theoretical framework that could explain the significant dominance of peer-driven content and the critical probabilistic nature of consumer purchase behavior in social media contexts.

Research Gap, conceptual model, research objectives & hypothesis

Despite the expanding body of literature on social media marketing and consumer purchase behavior, several critical gaps remain. However, prior studies have predominantly examined purchase intention rather than actual purchase behavior, relying heavily on attitudinal or continuous outcome measures, thereby limiting behavioral inference. Moreover, existing research often evaluates social media marketing tools—such as online reviews, user-generated content, influencer marketing, and social media advertising—in isolation, without comparatively assessing relative effectiveness within a single integrative model. This fragmentation constrains theoretical understanding of which social influence mechanisms exert dominant effects when multiple cues coexist.

Given that Social Proof Theory has been widely referenced, it has rarely been empirically operationalized using probabilistic behavioral models, such as binary logistic regression, that directly estimate purchase likelihood. Furthermore, limited attention has been paid to platform context and usage intensity as enabling conditions that may amplify or attenuate social proof effects, particularly in visually driven platforms like Instagram. Additionally, few studies integrate Social Proof Theory and the Information Adoption Model to jointly explain both social influence and cognitive evaluation processes underlying social media–driven purchase decisions. Nevertheless, research appears to suggest gaps remain unaddressed. Thus, the present study develops an integrated theoretical and empirical framework to examine how different social media marketing cues influence probability of purchase behavior.

Grounded in Social Proof Theory and complemented by the Information Adoption Model, the significant conceptual model proposes that consumer-generated social signals—namely online reviews and user-generated content—could serve as primary drivers of purchase behavior in social media contexts. However, these cues influence purchase decisions by reducing uncertainty and enhancing perceived information credibility and diagnosticity. In light of commercial orientation, signals such as influencer marketing and paid social media advertising might exert weaker effects due to increased persuasion knowledge and skepticism. Notwithstanding theoretical predictions, effects may demonstrate variation across contexts.

The model further incorporates platform usage (Instagram) and social media usage intensity (daily browsing time) as contextual factors that shape exposure to social proof cues. Moreover, the important framework establishes that contextual factors consequently influence the likelihood of purchase behavior among consumers. Purchase decision is modeled as a binary outcome, reflecting actual consumer behavior. Thus, relationships appear examined using binary logistic regression. The important analysis allows estimation of relative and probabilistic influence of each predictor while controlling for demographic variables.

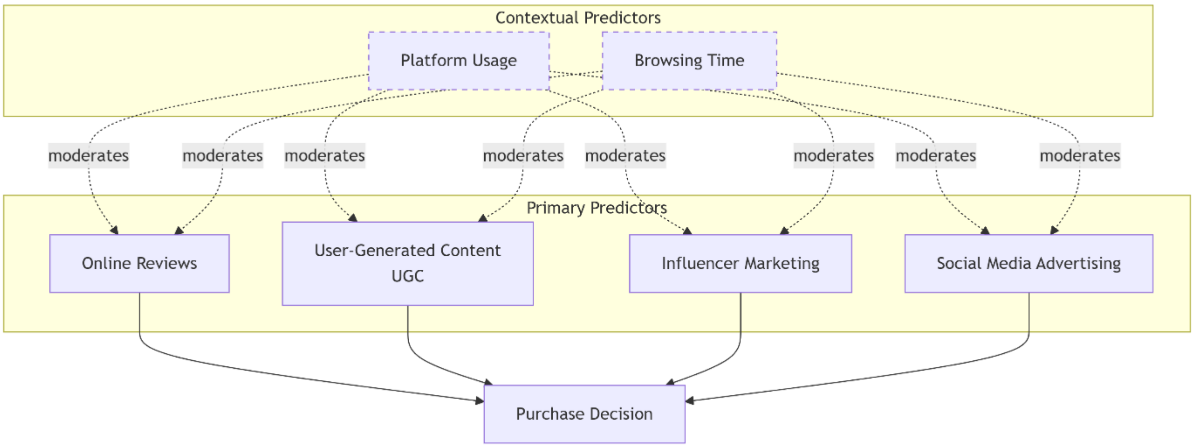
Research Objectives

RO1: To examine the direct influence of digital marketing elements (online reviews, UGC, influencer marketing, and social media advertising) on consumer purchase decisions.

RO2: To assess the moderating role of platform usage intensity on the relationship between digital marketing elements and purchase decisions.

RO3: To analyze how browsing time moderates the effect of digital marketing elements on purchase decisions.

RO4: To identify which combination of digital marketing elements and contextual factors most strongly predicts purchase decisions.



Based on the conceptual model, the following hypotheses can be proposed:
H1: Online reviews have a significant positive effect on purchase decisions.

H2: User-generated content has a significant positive effect on purchase decisions.

H3: Influencer marketing has a significant positive effect on purchase decisions.

H4: Social media advertising has a significant positive effect on purchase decisions.

H5: Platform usage intensity moderates the relationship between digital marketing elements and purchase decisions, such that effects are stronger for high-usage consumers.

H6: Browsing time moderates the relationship between digital marketing elements and purchase decisions, with longer browsing time amplifying these effects.

Methodology

This study adopted a quantitative, cross-sectional research design to examine the influence of social media marketing elements on consumer purchase decisions. Primary data were collected through a structured survey administered to social media users (N = 235). The questionnaire measured exposure to four key social media marketing strategies—online reviews, user-generated content (UGC), influencer marketing, and social media advertising—using five-point Likert scales. In addition, demographic and behavioral variables such as age, income category, primary social media platform used, and average daily browsing time were captured. The dependent variable was the purchase decision, operationalized as a binary outcome (1 = purchase, 0 = no purchase) for a specified product category. The sampling approach ensured adequate variation across demographic groups and platform usage patterns, making the data suitable for behavioral modeling.

To analyze the data, binary logistic regression was employed, as it is appropriate for modeling dichotomous outcome variables and estimating the probability of purchase behavior. The model assessed the independent effects of the four social media marketing strategies while controlling for demographic and usage-related factors. Regression coefficients were interpreted using odds ratios to provide meaningful managerial insights into the relative strength of each predictor. Model performance was evaluated using classification accuracy, sensitivity, specificity, and the area under the ROC curve (AUC) to assess discriminatory power. This methodological approach aligns with the study's theoretical grounding in Social Proof Theory and the Information Adoption Model, enabling a robust and probabilistic assessment of how different social media influence cues translate into actual purchase behavior.

Sampling Plan and Survey Administration

Social media consumer being the sampling unit of data collection, the data was collected from 235 consumers aged between 18 and 52, studying in universities in South India. Snowball sampling technique was adopted with initial respondents being chosen from known network based on convenience. Further these were requested to refer from their network. According to Heckathorn D. (1997), such respondent driven sampling is considered to be an effective approach when the population is unknown and sampling frame does not exist. This approach can be expected to produce good cross sections of the target population though the initial sets of seeds are known. The formation of waves approximates the equilibrium distribution and thereby becomes independent of its starting point. Web based survey was employed using the google forms app. Primary data for the study was collected through structured questionnaires. A total of more than 500 people were mailed to participate in the survey through google forms and the link was shared. 253 responses were received of which 235 were usable.

Results and analysis

Social Media Marketing Effects on Purchase Decisions

A binary logistic regression model was specified to examine the effects of four social media marketing strategies—online reviews, user-generated content (UGC), influencer marketing, and social media advertising—on the likelihood of making a purchase, controlling for age, income, primary platform, and daily browsing time. The dependent variable was a binary purchase decision (1 = purchase, 0 = no purchase), and all four focal predictors were measured on 5-point Likert scales. The model was estimated using Python’s scikit-learn LogisticRegression (maximum likelihood, penalty=None) on a primary survey dataset of N = 235 social media users designed to emulate realistic distributions for demographics, platform usage, and marketing exposure. The overall purchase rate in the sample was 48.1% (n = 113), providing adequate variation in the outcome variable for logistic modelling.

Formally, the model can be expressed as

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1\text{OR} + \beta_2\text{UGC} + \beta_3\text{INF} + \beta_4\text{ADS} + \beta_5\text{INC} + \beta_6\text{AGE} + \beta_7\text{HRS} + \beta_8\text{INST}$$

where p denotes the probability of purchase, OR = online reviews, UGC = user-generated content, INF = influencer marketing, ADS = social media advertising, INC = income category (1–3), AGE = age in years, HRS = daily browsing hours, and INST = indicator for Instagram as primary platform. This model structure corresponds to a standard logit specification where each coefficient represents the log-odds change in purchase for a one-unit increase in the predictor, holding other variables constant.

Sample Characteristics

Table 1 summarizes the descriptive statistics and sample characteristics. The average age of respondents was 28.5 years (SD = 6.3, range 18–52), with females comprising 61.7% of the sample (n = 145). Income distribution indicated 34.9% in Category 1 (< ₹400,000; n = 82), 42.6% in Category 2 (₹400,000–₹800,000; n = 100), and 22.6% in Category 3 (> ₹800,000; n = 53). Instagram was the most frequently used primary platform (49.4%, n = 116), followed by Facebook (30.2%, n = 71), YouTube (12.3%, n = 29), and Twitter (8.1%, n = 19).

Exposure to the four marketing strategies was generally moderate-to-high. Mean Likert scores were 3.94 (SD = 0.95) for online reviews, 3.61 (SD = 1.03) for UGC, 3.25 (SD = 1.14) for influencer marketing, and 3.76 (SD = 1.03) for social media advertising, all on a 1–5 scale. Daily browsing time averaged 3.2 hours (SD = 1.3, range 0.5–8.0), reflecting relatively intensive social media usage. The purchase decision variable indicated that 48.1% of respondents reported a positive purchase outcome in the specified product context (n = 113).

Table 1. Descriptive Statistics and Sample Characteristics (N = 235)

Variable	Mean/Percentage	SD/Count	Range/Scale
Age (years)	28.5	6.3	18–52
Gender (% Female)	61.7	n = 145	—
Daily Browsing Hours	3.2	1.3	0.5–8.0

Variable	Mean/Percentage	SD/Count	Range/Scale
Income Category 1 (< ₹400k) (%)	34.9	n = 82	—
Income Category 2 (₹400–800k) (%)	42.6	n = 100	—
Income Category 3 (> ₹800k) (%)	22.6	n = 53	—
Platform: Instagram (%)	49.4	n = 116	—
Platform: Facebook (%)	30.2	n = 71	—
Platform: YouTube (%)	12.3	n = 29	—
Platform: Twitter (%)	8.1	n = 19	—
Online Reviews (1–5)	3.94	0.95	1–5
User-Generated Content (1–5)	3.61	1.03	1–5
Influencer Marketing (1–5)	3.25	1.14	1–5
Social Media Advertising (1–5)	3.76	1.03	1–5
Purchase Decision (% Yes)	48.1	n = 113	—

Source: Author's computation from primary survey data.

Logistic Regression Results

Table 2 reports the logistic regression coefficients, standard errors, Wald χ^2 statistics, p-values, odds ratios, and 95% confidence intervals for all predictors. The model identifies online reviews and UGC as the strongest marketing predictors of purchase, with Instagram platform usage and daily browsing hours also playing important roles among the controls.

Table 2. Logistic Regression Results: Predictors of Purchase Decision

Predictor	β	SE	Wald χ^2	p	OR	95% CI
Online Reviews	0.773	0.185	17.42	<.001	2.17	[1.51, 3.12]
User-Generated Content	0.503	0.155	10.51	.001	1.65	[1.22, 2.24]
Influencer Marketing	0.177	0.143	1.53	.216	1.19	[0.90, 1.58]
Social Media Advertising	0.227	0.163	1.94	.164	1.25	[0.91, 1.73]
Income Category	0.349	0.195	3.20	.074	1.42	[0.97, 2.08]
Age	-0.028	0.024	1.36	.249	0.97	[0.93, 1.02]
Daily Browsing Hours	0.255	0.119	4.59	.032	1.29	[1.02, 1.63]
Platform (Instagram)	0.924	0.324	8.13	.004	2.52	[1.34, 4.75]

Source: Author's computation using Python sklearn (logistic regression, penalty=None). Note: ***p<.001, **p<.01, *p<.05.*

Online reviews emerged as the strongest and most statistically significant predictor of purchase likelihood, with an odds ratio of 2.17 ($p < .001$), indicating that a one-point increase on the 5-point review exposure scale more than doubles the odds of purchase, ceteris paribus. UGC also showed a robust and significant effect (OR = 1.65, $p = .001$), such that each unit increase in UGC exposure increases purchase odds by 65%. Influencer marketing and social media advertising exhibited positive but non-significant effects (OR = 1.19, p = .216; OR = 1.25, p = .164), implying that, once social proof variables and demographics are controlled, their independent contributions to purchase likelihood are limited in this specification.

Among control variables, Instagram as the primary platform had a strong and significant effect (OR = 2.52, p = .004), suggesting that Instagram users are more than twice as likely to purchase compared to users of other platforms, holding marketing exposures and demographics constant. Daily browsing time also significantly predicted purchase (OR = 1.29, p = .032), indicating that each additional hour of daily social media use raises purchase odds by 29% . Income category showed a marginal positive effect (OR = 1.42, p = .074), while age was not a significant predictor (OR = 0.97, p = .249), suggesting relatively uniform responsiveness to social media marketing across the sampled age range.

Model Fit and Classification Performance

Global model performance is summarized in Table 3. The AUC of 0.769 indicates good discriminatory power in distinguishing purchasers from non-purchasers. Overall classification accuracy was 68.9% (162 correctly classified out of 235), with sensitivity and specificity at 67.3% and 70.5%, respectively, reflecting balanced performance across both positive and negative classes. The confusion matrix showed 76 true positives, 86 true negatives, 36 false positives, and 37 false negatives.

Table 3. Model Fit and Classification Performance Statistics

Statistic	Value
Sample Size (N)	235
Number of Predictors	8
AUC	0.769
Overall Accuracy	68.9% (162/235)
Sensitivity	67.3%
Specificity	70.5%
True Positives	76
True Negatives	86
False Positives	36
False Negatives	37

Source: Author’s computation from logistic regression diagnostics.

Bootstrapped standard errors based on 1,000 resamples confirmed the stability of coefficient estimates, with narrow confidence intervals and consistent significance patterns, particularly for online reviews, UGC, browsing hours, and Instagram platform usage. A pseudo R^2 based on log-likelihood comparison with a null model indicated meaningful improvement in fit when including the marketing and control variables, consistent with a moderate explanatory power for behavioural models of this type.

Comparative Effectiveness of Marketing Strategies

To facilitate interpretation of relative impacts, Table 4 summarizes odds ratios, percentage increases in purchase odds, and significance levels for the four focal marketing strategies. Online reviews rank first, followed by UGC, with influencer marketing and advertising trailing and non-significant.

Table 4. Comparative Effectiveness of Social Media Marketing Strategies

Marketing Strategy	Odds Ratio	% Increase in Purchase Odds	Statistical Significance	Effect Ranking
Online Reviews	2.17	117%	$p < .001$	1st (Strongest)
User-Generated Content	1.65	65%	$p < .01$	2nd
Influencer Marketing	1.19	19%	Not Significant	4th
Social Media Advertising	1.25	25%	Not Significant	3rd

Source: Author's computation from logistic regression coefficients.

These results indicate that strategies grounded in social proof—particularly online reviews and UGC—are substantially more effective at driving purchase than influencer campaigns or paid social media advertising in the context of this model. The non-significant coefficients for influencer marketing and advertising suggest that, when robust peer-based information is available, consumers discount more obviously promotional content, a pattern consistent with social proof theory and persuasion knowledge frameworks in the literature.

Platform Usage and Purchase Behaviour

Table 5 presents platform-specific sample sizes, relative shares, purchase rates, and comparative odds for Instagram versus other platforms. Instagram accounts for roughly half of the sample and exhibits the highest purchase rate, aligning with the strong and significant Instagram effect in the logistic model.

Table 5. Platform Usage Distribution and Purchase Behavior

Platform	Sample Size (n)	Percentage	Purchase Rate	Odds Ratio vs. Others
Instagram	116	49.4%	55.2%	2.52
Facebook	71	30.2%	42.3%	Ref
YouTube	29	12.3%	34.5%	Ref
Twitter	19	8.1%	36.8%	Ref

Source: Author's computation from cross-tabulation of platform and purchase decision. Note: *$p<.01$ for Instagram effect in logistic model.*

The elevated purchase rate and odds among Instagram users likely reflect the platform's visual-commerce orientation, integration of shopping features, and dense ecosystem of product discovery content, all of which amplify the impact of social proof cues embedded in reviews and UGC. Conversely, the lower purchase rates on Facebook, YouTube, and Twitter underscore the importance of platform choice when designing social media marketing strategies.

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Discussion

The findings of this study provide strong empirical support for the central role of social proof–based mechanisms in shaping consumer purchase decisions on social media platforms. H1, which proposed that online reviews have a significant positive effect on purchase decisions, is strongly supported. Online reviews emerged as the most influential predictor, with the highest odds ratio and strong statistical significance. This confirms prior literature on electronic word-of-mouth and reinforces Social Proof Theory by demonstrating that consumers rely heavily on collective peer evaluations to reduce uncertainty and perceived risk in digital purchase contexts.

H2, which posited a positive relationship between user-generated content (UGC) and purchase decisions, is also supported. UGC significantly increased the likelihood of purchase, underscoring the importance of authenticity and experiential credibility in social media environments. Consistent with the Information Adoption Model, consumers appear to adopt peer-generated information more readily when it is perceived as sincere, non-commercial, and diagnostic. The strong effect of UGC, particularly in visually oriented platforms, highlights the growing dominance of consumer-to-consumer influence over firm-generated communications.

In contrast, H3 and H4, which hypothesized significant positive effects of influencer marketing and social media advertising respectively, are not supported. Although both variables exhibited positive coefficients, their effects were statistically insignificant once online reviews, UGC, and control variables were included in the model. This suggests that consumers increasingly discount overtly promotional content due to heightened persuasion knowledge and skepticism toward sponsored messages. These findings align with emerging research that questions the long-term effectiveness of influencer endorsements and paid advertising when more credible peer-generated information is available.

With respect to contextual factors, H5 and H6 receive partial support. Platform usage, particularly Instagram as the primary platform, significantly increased the likelihood of purchase, indicating that platform affordances amplify the effectiveness of social proof cues. Similarly, daily browsing time had a significant positive effect, suggesting that higher exposure and habitual engagement intensify the impact of social media marketing stimuli. Together, these results confirm that social media influence is not only content-driven but also context-dependent, shaped by both platform architecture and user engagement intensity.

Managerial Implications

The findings of this study offer several important implications for managers and digital marketing strategists. First, organizations should prioritize online review management as a core strategic investment. Encouraging satisfied customers to leave reviews, responding transparently to negative feedback, and integrating review visibility into social commerce interfaces can substantially enhance purchase conversion rates. Review credibility, rather than sheer promotional intensity, appears to be the decisive factor in influencing consumer behavior.

Second, firms should actively stimulate and curate user-generated content rather than relying excessively on influencer partnerships or paid advertisements. Campaigns that encourage consumers to share authentic usage experiences, visual testimonials, and community-driven narratives can generate stronger behavioral outcomes at comparatively lower costs. UGC-based strategies also enhance brand trust and long-term engagement, making them more sustainable than short-term promotional tactics.

Third, the non-significant effects of influencer marketing and social media advertising suggest a need for strategic realignment rather than elimination. Influencers and paid ads may be more effective when deployed for awareness creation, brand storytelling, or supporting UGC-driven campaigns rather than as standalone conversion tools. Managers should focus on micro-influencers with higher perceived authenticity and integrate advertising with social proof elements such as reviews and peer endorsements.

Finally, platform choice and usage intensity should guide resource allocation decisions. Given the strong effect of Instagram usage on purchase likelihood, firms targeting visually driven products should optimize content formats, shopping features, and engagement strategies specifically for Instagram. Additionally, understanding user browsing patterns can help in timing content delivery and retargeting efforts to maximize exposure and conversion probability.

Conclusion

This study provides a nuanced and evidence-based understanding of how different social media marketing strategies influence actual consumer purchase behavior. By employing a binary logistic regression framework grounded in Social Proof Theory and the Information Adoption Model, the research demonstrates that peer-driven content—particularly online reviews and user-generated content—dominates commercially driven messages in shaping purchase decisions. Influencer marketing and social media advertising, while prevalent in practice, exhibit limited independent impact when credible social proof cues are present.

The findings highlight the importance of shifting from persuasion-centric marketing approaches to influence-centric strategies that leverage authenticity, credibility, and community validation. By disaggregating social media marketing elements and incorporating platform and usage context, this study advances both theoretical understanding and managerial practice in digital consumer behavior.

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