



THE IMPACT OF SOCIAL MEDIA ON CONSUMER BUYING BEHAVIOUR: A SURVEY-BASED STUDY FROM KOLLAM DISTRICT IN KERALA

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ABSTRACT

Social media has become a central information and persuasion channel in consumers' purchase journeys. This study examines how social media relates to buying behaviour, including attention to advertisements, trust, and perceived influence on purchase decisions. A structured questionnaire was administered to 61 social media users. Descriptive statistics were used to summarise usage patterns and perceptions. To address the common requirement of correlation and regression in social science reporting, the study also reports identification bounds for the association between time spent on social media and the percentage of purchases influenced by social media, because the available dataset contains marginal distributions rather than respondent-level pairings. Results indicate high daily engagement (1 to 5 hours for most respondents), substantial trust in information on social media, and a majority reporting that social media influences their buying decisions. Instagram and YouTube are reported as key influencing platforms, while offers and discounts are the most frequently cited motivator for shopping through social media. Implications for marketers include optimising platform selection and leveraging credible, information-rich content.

KEYWORDS: buying behaviour; consumer decision making; discounts; regression; social media marketing

1. INTRODUCTION

Social media has moved from a space for interpersonal communication to an infrastructure for everyday consumption. Platforms that began as tools for sharing updates now combine discovery, recommendation, and shopping features that shape how consumers become aware of products, compare alternatives, and decide whether to buy. In these environments, persuasion is rarely isolated. Paid advertising appears alongside influencer posts, peer discussions, ratings, and demonstrations of products in real-world use. The constant flow of content can make brand messages feel more personal and more immediate than many traditional media channels.

From a consumer behaviour perspective, social media can influence multiple stages of the decision-making process. It can lower information search costs by providing immediate access to product details, comparisons, and experiential content such as reviews and tutorials. It can also intensify persuasive exposure through social proof, scarcity cues, and personalised targeting based on browsing and engagement. During evaluation, user-generated content and peer feedback can change perceived quality, trust, and risk, especially when consumers cannot physically inspect a product before purchase.

A further feature of social media influence is that it operates through both content and context. Content includes explicit marketing communications such as advertisements, sponsored posts, affiliate links, and influencer promotions. Context includes the surrounding social environment: who shares a product, how friends respond, how frequently similar items appear, and

whether the message comes from a trusted source. Because purchasing is socially embedded, these contextual cues can be as influential as product information itself, shaping attitudes, preferences, and intentions.

These dynamics have practical significance for firms and for consumer well-being. For businesses, identifying the most influential platforms and motivations supports better allocation of resources across advertising, influencer partnerships, and organic content. For consumers, the same mechanisms that support discovery can blur the boundary between genuine recommendations and sponsored persuasion, increasing vulnerability to manipulative tactics. Promotions and discounts are particularly important because they can shift attention from long-term value to short-term savings, thereby accelerating impulse buying and reducing deliberation.

Although research on digital marketing continues to expand, actionable evidence is still needed on how everyday usage patterns relate to perceived buying influence and platform preferences within specific consumer groups. Many studies describe general mechanisms, but practitioners often need direct answers: which platforms shape purchase decisions, how strongly consumers perceive social media to influence their buying, and what motivations drive social commerce, such as discounts, convenience, product variety, or perceived trust. Survey-based studies that document these patterns can complement experimental and platform-level research by showing how consumers interpret influence in real settings.



This paper addresses these issues using a structured survey of 61 respondents. The analysis first reports descriptive patterns of time spent on social media, perceived influence on buying decisions, platform preferences, and motivating factors. It then examines the association between time spent on social media and perceived buying influence using correlation and regression techniques. Because the available results are summarised as marginal distributions rather than respondent-level paired observations, the statistical section uses identification bounds to present a transparent range of plausible associations consistent with the observed data.

2. REVIEW OF LITERATURE

2.1 Social Media as an information and influence channel

Social media platforms have reshaped the consumer decision journey by merging interpersonal communication, mass-media reach, and algorithmic personalization. Consumers no longer encounter product information only through dedicated advertising exposures; instead, brand messages appear alongside peer conversations, creator demonstrations, ratings, and short-form entertainment. This blended media environment matters because it can influence multiple stages of decision making—need recognition, information search, evaluation of alternatives, and post-purchase sharing—through both informational content and socially embedded cues such as likes, shares, and comments.

Kaplan and Haenlein (2010) define social media as internet-based applications that enable the creation and exchange of user-generated content. Because users actively participate by producing and curating content, social media functions as a hybrid element of the promotion mix in which consumer-to-consumer communication interacts with firm-generated messages (Mangold & Faulds, 2009). In practical terms, this hybridity can increase perceived authenticity and immediacy, while also complicating consumers' ability to distinguish unbiased recommendations from sponsored persuasion. The marketing implication is that influence depends not only on message frequency but also on the perceived credibility of the surrounding social environment.

2.2 Social media marketing activities, engagement, and community effects

A large stream of research focuses on social media marketing activities (SMMAs), commonly including interactivity, informativeness, customization, and entertainment. Interactivity enables dialogue, which can reduce uncertainty and create feelings of responsiveness; informativeness provides decision-relevant arguments and comparisons; customization increases perceived relevance by matching consumer preferences; and entertainment enhances affect, attention, and recall. These activity dimensions can strengthen brand relationships and purchase intentions by increasing perceived value and fostering a sense of connection with the brand's identity and community.

Engagement is an important mediating process in this literature. Engagement behaviours—commenting, sharing, saving content,

joining brand communities, and participating in polls or live sessions—represent more than mere exposure. They often indicate deeper cognitive and emotional involvement, which can strengthen brand salience and accelerate movement from consideration to purchase. Community dynamics can also generate normative pressure and identity-based motivations: consumers may buy products that signal membership in a group or align with aspirational lifestyles promoted within the community. Because platform architectures differ (for example, visually oriented feeds versus search-driven video), platform choice can influence which engagement mechanisms are most prominent.

2.3 Electronic word of mouth, credibility, and perceived risk

Electronic word of mouth refers to consumer-generated evaluations, recommendations, and experiences shared online. It tends to be particularly influential when consumers face uncertainty about product quality or when products are difficult to evaluate prior to purchase. Cheung and Thadani (2012) describe electronic word of mouth effects through an integrative logic: information quality and source credibility shape perceived usefulness, which in turn drives information adoption and purchase intention. In social networking contexts, credibility perceptions are frequently decisive because consumers are exposed to both genuine reviews and strategically constructed promotional narratives.

Perceived risk and trust are central in social commerce. Credible user-generated content can reduce functional and financial risk by providing diagnostic cues about real-world performance, after-sales experiences, and hidden costs. At the same time, suspicion of fake reviews, undisclosed sponsorship, or comment manipulation can reduce trust and lead to avoidance or delayed purchase. Credibility is often shaped by source attributes (expertise and trustworthiness), message attributes (specificity and consistency), and contextual signals (consensus in comments and alignment across multiple sources). Therefore, measuring consumers' reliance on social media during purchase uncertainty provides insight into how social media functions as a risk-reduction mechanism.

2.4 Influencer marketing and persuasion dynamics

Influencer marketing has emerged as a major persuasive format in which brands collaborate with creators who have accumulated followers and perceived expertise within a niche. Persuasion in influencer settings is commonly explained using source credibility and identification mechanisms: followers may perceive influencers as more relatable than traditional celebrities, which can increase trust and reduce resistance to persuasion. Meta-analytic evidence indicates that influencer endorsements have, on average, a positive effect on consumer responses, while the size of the effect varies by influencer characteristics, message design, product type, and platform context.

However, influencer persuasion is conditional. When followers perceive content as overly commercial, inconsistent with an



influencer's typical style, or insufficiently transparent about sponsorship, persuasive impact can weaken and produce skepticism. Conversely, content that provides concrete demonstrations, balanced reviews, or personally meaningful narratives can increase diagnosticity and perceived authenticity. These findings suggest that social media influence is rarely a single mechanism; rather, it reflects the combined effects of paid advertising, influencer cues, and peer-generated signals operating together in the consumer's information environment.

2.5 Behavioural theories relevant to social-media-driven purchase behaviour

Behavioural theories provide structured explanations for how social media translates into purchase decisions. The Theory of Reasoned Action and the Theory of Planned Behavior argue that behavioural intentions are driven by attitudes, subjective norms, and perceived behavioural control (Fishbein & Ajzen, 1975; Ajzen, 1991). Social media can shape attitudes through persuasive arguments and repeated exposure, subjective norms through visible peer approval (likes, comments, and shares), and perceived control through low-friction shopping features and social commerce tools. From this perspective, the "influence" consumers report may partly represent perceived normative pressure and perceived ease of action, not merely persuasion.

The Technology Acceptance Model explains adoption of technology-enabled behaviours using perceived usefulness and perceived ease of use (Davis, 1989). Social commerce becomes more likely when consumers believe that social media is useful for discovering products, comparing options, and finding deals, and when the platform interface makes searching and purchasing effortless. Uses and Gratifications Theory complements this view by treating social media use as goal-directed: users seek gratifications such as entertainment, information, social interaction, and self-presentation. These motivations influence attention allocation and the likelihood of encountering persuasive messages; for example, entertainment-oriented use may increase receptivity to visually compelling content, whereas information-oriented use may increase engagement with reviews and tutorials.

Dual-process theories clarify when consumers process messages deeply versus heuristically. The Elaboration Likelihood Model proposes a central route, based on careful evaluation of arguments, and a peripheral route, based on cues such as attractiveness, popularity, and source familiarity (Petty & Cacioppo, 1986). Social platforms supply abundant peripheral cues—follower counts, engagement metrics, and aesthetic presentation—so heuristic processing may be common, especially under time pressure or low involvement. The Heuristic-Systematic Model similarly suggests that consumers may rely on simple decision rules unless motivation and ability support systematic processing (Chaiken, 1980). This helps explain why social proof cues and influencer popularity can shift preferences even without detailed product evaluation.

The Stimulus–Organism–Response framework conceptualizes social media stimuli (advertisements, reviews, demonstrations, discounts, and social proof cues) as shaping internal states such as arousal, trust, and perceived value, which then drive responses such as click-through, impulse purchase, or planned purchase (Mehrabian & Russell, 1974). Social influence principles (for example, social proof and scarcity) help interpret why engagement metrics and limited-time offers can trigger action (Cialdini, 2009). Prospect Theory further predicts that consumers may overweight short-term gains such as discounts relative to longer-term value considerations, which can increase impulse buying and reduce deliberation (Kahneman & Tversky, 1979). Together, these perspectives justify examining both promotional motivations (offers and discounts) and psychological evaluations (trust and informational reliance).

2.6 Conceptual framework, hypotheses, and research gap

Synthesizing prior work, the present study conceptualizes time spent on social media and exposure to platform-based marketing as antecedents to perceived buying influence. Greater time spent increases the probability of exposure to persuasive content (advertisements and influencer posts) and to social cues (peer approval and community discussions). Trust and information credibility reduce perceived risk and increase the likelihood that consumers adopt social media information during purchase decisions. Promotions—particularly offers and discounts—can increase perceived value and urgency, thereby accelerating conversion.

Accordingly, the study uses the following directional hypotheses as organising expectations: H1: time spent on social media is positively associated with the perceived percentage of purchases influenced by social media. H2: higher trust in social media information is associated with stronger perceived buying influence. H3: greater attention to advertisements on social media is associated with stronger perceived buying influence. Because the available results are summarised as marginal distributions rather than respondent-level paired observations, the statistical analysis reports correlation and regression using a transparent identification-bounds approach. This keeps the analysis aligned with journal expectations while clearly stating what can and cannot be inferred from aggregated data.

3. OBJECTIVES

- To examine the impact of social media on consumers' buying behaviour.
- To identify the factors that motivate consumers to shop through social media platforms.
- To identify the social media platforms most preferred and most influential for purchase decisions.

4. METHODOLOGY

A cross-sectional survey design was used. Primary data were collected using a questionnaire aligned with the study objectives. Secondary information was consulted from books, journal



articles, and credible web sources to develop the conceptual background. The sample consisted of 61 respondents who reported using social media. The study acknowledges typical survey limitations, including response bias and limited time for data collection.

4.1 Measures

Key measures included time spent on social media per day, attention to advertisements, trust in social media, self-reported influence of social media on buying decisions, and multiple items capturing perceived informational and promotional value of social media. Several perception items used a five-point Likert-type response format (strongly agree, agree, neutral, disagree, strongly disagree).

4.2 Data Analysis Plan

Descriptive statistics (frequencies and percentages) summarised responses. To incorporate correlation and regression techniques, the association between (a) time spent on social media and (b) the percentage of purchases influenced by social media was analysed using a partial-identification approach. Because only marginal distributions were available, the Pearson correlation coefficient (r) and a simple linear regression slope were bounded by constructing the maximum and minimum feasible covariance pairings consistent with the observed marginals. This yields an interpretable range for the possible association, while clearly separating what is identified from what would require respondent-level paired data.

4.3 Conceptual model and variable operationalisation

Guided by the behavioural theories reviewed earlier, the empirical model treats exposure and credibility as key predictors of perceived buying influence. Exposure is represented by time spent on social media per day and by attention to advertisements (self-reported). Credibility is represented by trust in information obtained from social media. The dependent construct—perceived buying influence—is measured in two complementary ways: a

categorical item capturing whether social media influences buying decisions (yes/no/maybe) and an ordinal item capturing the approximate percentage of purchases influenced by social media.

To support transparent reporting, all categorical variables are presented using counts and percentages. For correlation and regression, ordinal categories are converted into numeric scores using midpoints (for example, 1–5 hours coded as 3 hours). This midpoint coding is common in social survey analysis when interval-level measures are not available, but the paper interprets results cautiously and emphasises the descriptive nature of such approximations.

4.4 Statistical analysis using Python

All statistical computations for the correlation and regression section were implemented in Python to ensure reproducibility. The analysis used a partial-identification approach because the available survey results are aggregated into marginal distributions rather than respondent-level paired observations. Two extreme but feasible “pairings” between time-spent categories and purchase-influence categories were constructed: (a) a monotone positive pairing that matches higher time spent with higher purchase influence as much as possible, and (b) a monotone negative pairing that matches higher time spent with lower purchase influence as much as possible. These pairings provide identification bounds for the Pearson correlation and for the slope in a simple linear regression of purchase influence on time spent.

This approach has two advantages for small-scale social science projects. First, it communicates what can and cannot be inferred from aggregated data, preventing over-interpretation. Second, it still provides a quantitative range of plausible effect sizes that future work can test using respondent-level datasets. The Python code used to generate these bounds is provided in Appendix B.

5. RESULTS

Table 1. Time spent on social media per day (n = 61)

Category	n	Percent
0 hours	1	1.6
1–5 hours	42	68.9
5–10 hours	18	29.5
10+ hours	0	0.0

Table 2. Self-reported influence of social media on buying decisions (n = 61)

Category	n	Percent
Yes	31	50.8
No	13	21.3
Maybe	17	27.9

**Table 3. Percentage of purchases influenced by social media (n = 61)**

Category	n	Percent
<25%	14	23.0
25–50%	34	55.7
50–75%	13	21.3
75–100%	0	0.0

Table 4. Social media platform reported to influence purchase decisions (n = 61)

Category	n	Percent
Instagram	30	49.2
Facebook	4	6.6
YouTube	24	39.3
Twitter	0	0.0
Blog posts	3	4.9

Table 5. Factors motivating shopping through social media (n = 61)

Category	n	Percent
Low price	11	18.0
Saves time	12	19.7
Quality	11	18.0
Easy payment	5	8.2
Offers/discounts	22	36.1

5.1 Key Descriptive Findings

Most respondents reported spending 1 to 5 hours per day on social media (68.9%), while 29.5% reported 5 to 10 hours. A majority indicated that social media influences their buying decisions (50.8% answered 'yes', 27.9% 'maybe'). Regarding magnitude, 55.7% reported that 25% to 50% of their purchases are influenced by social media, and 21.3% reported 50% to 75%.

5.2 Correlation and regression results using identification bounds

Let X denote time spent on social media per day (coded using category midpoints: 0, 3, 7.5, and 12 hours) and Y denote the

percentage of purchases influenced by social media (coded using category midpoints: 12.5 percent, 37.5 percent, 62.5 percent, and 87.5 percent). Using only marginal distributions, the feasible Pearson correlation coefficient between X and Y ranges from -0.753 (most negative feasible pairing) to 0.730 (most positive feasible pairing). Under the same two extreme pairings, the simple linear regression of Y on X yields slopes from -5.91 to 5.73 percentage points of purchase influence per additional hour spent on social media.

Table 6 Summarises the Bounded Regression Results.

Scenario	Pearson r	Intercept	Slope	Coefficient of determination (R-squared)
Most Negative Feasible Pairing	-0.753	62.38	-5.91	0.567
Most Positive Feasible Pairing	0.730	12.56	5.73	0.534

Note: These bounds use only the observed marginal distributions; an exact estimate requires respondent-level paired measurements of time spent and purchase influence.

6. DISCUSSION

The results suggest that social media is meaningfully involved in consumers' purchase journeys, particularly as an informational channel and as a vehicle for promotions. Instagram and YouTube stand out as the most cited influencing platforms, consistent with the dominance of visual and video content in contemporary social media marketing. Offers and discounts are the leading motivator for shopping through social media, reinforcing the importance of price-related cues and time-limited promotions. The bounded correlation and regression analysis indicates that, based on the

marginals alone, the relationship between time spent on social media and the percentage of purchases influenced could be moderately strong in either direction; therefore, future data collection should preserve respondent-level pairing to identify the direction and magnitude reliably.

6.1 Interpretation through behavioural theories

Several behavioural mechanisms help interpret the descriptive patterns. The dominance of Instagram and YouTube as influencing platforms fits dual-process persuasion accounts:



visually rich demonstrations and tutorials can provide central-route arguments (features, comparisons, evidence of use) as well as peripheral cues (aesthetics, popularity metrics, and creator likeability). When attention is fragmented, these peripheral cues may operate as heuristics that accelerate choice without extensive deliberation.

The prominence of offers and discounts as the main motivator is consistent with behavioural economics. Prospect Theory suggests that consumers can overweight salient gains such as price reductions, especially when these gains are framed as limited-time opportunities. In a Stimulus-Organism-Response framing, promotions act as stimuli that raise perceived value and urgency, which can increase impulse-oriented responses when combined with scarcity cues.

Trust and credibility connect to Technology Acceptance Model logic. When users perceive social media as useful for lowering search costs and credible enough for evaluation, they are more willing to rely on it as a shopping-support channel. The Theory of Planned Behavior also implies a normative pathway: visible peer approval (likes, comments, shares) can strengthen subjective norms and raise purchase intention even when attitudes are only moderately positive.

6.2 Correlation and regression: what the bounds imply

The bounded correlation and regression results carry an important methodological message. With marginal distributions alone, the direction of association between time spent on social media and the share of purchases influenced by social media is not identified: one feasible pairing implies a positive association, while another implies a negative association. Reporting bounds is therefore more defensible than presenting a single point estimate because it communicates exactly what the aggregated data can support.

Substantively, the width of the bounds suggests that the association could be moderate in magnitude. Future surveys should preserve respondent-level pairing so that standard correlation, linear regression, or logistic regression can be estimated with standard errors and confidence intervals. Even small samples can support such modelling if variables are recorded consistently and missing data are limited.

6.3 Managerial implications

For practitioners, two implications follow. First, platform choice matters: focusing content and budgets on the platforms that respondents cite as most influential (here, Instagram and YouTube) is likely to improve efficiency. Second, promotions appear to be a strong trigger, so firms should design discount strategies that are transparent and paired with credibility-building information (clear specifications, demonstrations, and consistent reviews). Overly aggressive promotion or low-transparency influencer partnerships risk weakening trust, which behavioural theory suggests is central to information adoption.

6.4 Theoretical contribution and fit with prior research

Although the present study is descriptive and does not identify causal effects, it contributes by linking a survey snapshot of social commerce perceptions to behavioural theory. The results support the view that social media influence is multi-mechanistic: it arises from information value, social and heuristic cues, and behavioural triggers such as discounts and urgency. Methodologically, the paper also illustrates a transparent way to incorporate correlation and regression ideas when only aggregated results are available, which is common in student and small-scale studies.

7. CONCLUSION

This study provides survey evidence that social media use is widespread among the sampled respondents and that many perceive it as influencing their buying decisions. For practitioners, the findings highlight the relevance of platform choice (especially Instagram and YouTube) and the effectiveness of promotions and discounts. For researchers, the study demonstrates how correlation and regression can be incorporated transparently even when only marginal distributions are available, using identification bounds.

8. Limitations and Future Research

The study is limited by the sample size and the absence of respondent-level paired data for some variables, which restricts standard multivariable modelling. Future research should collect a respondent-level dataset enabling multivariable regression (for example, logistic regression for purchase influence) and should include demographic controls and scale reliability assessment.

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Appendix A. Selected Survey Items

The questionnaire included items on social media usage, time spent per day, attention to advertisements, trust in social media, platform influence on purchase decisions, and perception statements rated on a five-point Likert-type scale.

Appendix B. Python code for correlation and regression bounds

```
# Python 3.x
import numpy as np
import statsmodels.api as sm

# Marginal distributions (n = 61)
# Time spent on social media per day (hours): 0 (1), 1-5 (42), 5-10 (18), 10+ (0)
X = np.array([0]*1 + [3]*42 + [7.5]*18) # midpoint coding

# Percentage of purchases influenced by social media: <25 (14), 25-50 (34), 50-75 (13), 75-100 (0)
Y = np.array([12.5]*14 + [37.5]*34 + [62.5]*13) # midpoint coding

def corr(a, b):
    return np.corrcoef(a, b)[0, 1]

def ols_slope(a, b):
    Xmat = sm.add_constant(a)
    model = sm.OLS(b, Xmat).fit()
    return model.params[0], model.params[1], model.rsquared

Xp = np.sort(X)
Yp = np.sort(Y)
Yd = np.sort(Y)[::-1]

# Most positive feasible pairing
r_pos = corr(Xp, Yp)
b0_pos, b1_pos, r2_pos = ols_slope(Xp, Yp)

# Most negative feasible pairing
r_neg = corr(Xp, Yd)
b0_neg, b1_neg, r2_neg = ols_slope(Xp, Yd)

print("Positive pairing: r=%.3f, intercept=%.2f, slope=%.2f, R2=%.3f" % (r_pos, b0_pos, b1_pos, r2_pos))
print("Negative pairing: r=%.3f, intercept=%.2f, slope=%.2f, R2=%.3f" % (r_neg, b0_neg, b1_neg, r2_neg))
```