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Social Media Marketing and Smartphone Buying Behaviour during Festive E-Commerce Sales: Evidence from College Students in Bengaluru

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Abstract: ***Festive e-commerce sales have become important occasions for smartphone discovery, comparison and purchase. Social media marketing can connect consumers with product information, influencer endorsements, reviews, discounts and time-limited offers, but these cues may not contribute equally to buying decisions. This study examines the relationships between five social-media-related promotional constructs—social media advertising, influencer promotions, reviews and recommendations, discounts and promotional benefits, and urgency cues—and impulse buying behaviour among college students in Bengaluru in the context of Amazon's Great Indian Festival and Flipkart's Big Billion Days. We analysed primary questionnaire data from 153 respondents using descriptive statistics, scale reliability, Pearson correlation, multiple regression, and a reported structural equation model. All seven measured scales showed good-to-excellent internal consistency (Cronbach's alpha = .885–.933). Each promotional construct was positively correlated with impulse buying, with urgency cues showing the strongest bivariate association (r = .804), followed by influencer promotions (r = .708). The multiple regression model was statistically significant, F(5, 147) = 75.376, p < .001, and explained 71.9% of the observed variance in impulse buying. In the simultaneous model, urgency cues (β = .612, p < .001) and influencer promotions (β = .356, p < .001) were significant positive predictors. After controlling for the other predictors, social media advertising and discounts were not statistically significant, while reviews showed a negative conditional coefficient despite a positive bivariate correlation. The AMOS model's global fit was inadequate, and high latent correlations raised discriminant-validity concerns; therefore, the authors treat its findings as provisional. Because the available analyses pool respondents across the two sale events, they do not establish which platform or event is more effective. The article discusses implications for responsible festive-sale marketing, student decision-making and future platform-wise research.***

Keywords: Social Media Marketing; Smartphone Buying Behaviour; Impulse Buying; Influencer Promotions; Urgency Cues; Festive E-Commerce; College Students; Bengaluru

1. Introduction

Social media has altered how consumers discover products, evaluate alternatives and encounter promotional messages. Unlike traditional one-way advertising, social platforms let firms, influencers, and consumers participate in the circulation of product information. A promotional message may be encountered alongside a product demonstration, a creator's recommendation, customer comments or a friend's shared link. These touchpoints form part of a broader customer journey in which consumers move between awareness, evaluation and purchase rather than following a strictly linear path (Lemon & Verhoef, 2016).

Festive e-commerce sales provide a particularly visible setting for these interactions. Amazon's Great Indian Festival and Flipkart's Big Billion Days combine product promotions with price reductions, bank offers, exchange benefits, influencer content and time-bound deals. Such campaigns can make a product easier to notice and compare. At the same time, countdowns and scarcity messages can create pressure to act quickly, potentially shortening deliberation. These cues may matter most for smartphones, which many students view as high-involvement purchases: a phone involves a substantial expenditure and may be assessed in terms of camera quality, processor, battery life, brand reputation, warranty, after-sales service, and expected useful life.

College students are a useful population for studying these dynamics because many are active digital-media users but operate within constrained budgets. A social-media advertisement may prompt interest without resulting in a purchase; an influencer review may trigger further research; and a discount may be attractive only when the product fits the buyer's needs and spending capacity. Thus, exposure should not be treated as equivalent to persuasion, and a stated impulse-buying tendency should not be interpreted as proof that a promotional cue caused a transaction.

This study focuses on college students in Bengaluru and examines five promotional constructs related to impulse buying behaviour: social media advertising, influencer promotions, reviews and recommendations, discounts and promotional benefits, and urgency cues. Purchase intention is also considered in the broader analytical model. The setting is framed by two major festive sale events, but the analyses in this article pool data across the events. Accordingly, the article reports associations in the combined sample and does not claim that one platform outperformed the other.

2. Literature and Conceptual Background

2.1 Social Media as part of the promotion mix

Social media marketing extends promotional communication beyond the firm's own messages. Mangold and Faulds (2009) describe social media as a hybrid element of the

promotion mix because organisations communicate while consumers also create, circulate and evaluate content. This creates opportunities for engagement and peer-to-peer information exchange, but it reduces the firm's control over how messages are interpreted. Hutter et al. (2013) similarly illustrate the relevance of social-media engagement to consumer responses in a brand context. For smartphone marketing, this implies that advertising reach alone may not fully capture campaign value: the credibility, usefulness, and timing of information may also matter.

2.2 Influencer promotions and electronic word of mouth

Influencer promotions combine product exposure with a perceived relationship between the content creator and their audience. A creator may demonstrate a phone's camera, battery performance or user interface in a way that is more concrete than a conventional advertisement. However, an endorsement can be interpreted differently depending on the creator's perceived expertise, transparency and commercial relationship with the brand. Reviews and recommendations serve a related but distinct role. Consumer reviews can reduce uncertainty by providing information from other users, although their usefulness depends on credibility, relevance and the consumer's ability to distinguish detailed experience from promotional or unrepresentative content. Research on online reviews shows that consumer-generated evaluations can affect product demand, but the effect depends on context (Chevalier & Mayzlin, 2006).

2.3 Discounts, scarcity and urgency

Discounts and promotional benefits can improve perceived value by reducing a product's effective cost. In smartphone purchases, bank offers, exchange value, bundled accessories, and payment options can affect the final price. However, these offers can be difficult to compare, and a stated discount does not necessarily mean the consumer's preferred option is the best-value choice. Urgency cues operate through a different mechanism. Limited-time offers and scarcity messages may increase the perceived cost of delay. Aggarwal, Jun and Huh (2011) examine how scarcity messages can influence consumer responses, supporting the need to distinguish urgency from a straightforward price incentive. Urgency may encourage action, but it may also reduce time available for checking specifications, warranty conditions and alternatives.

2.4 Impulse buying and purchase intention

Impulse buying generally refers to a purchase made with limited prior planning and a strong immediate response to a stimulus. Rook's (1987) work helped establish impulse buying as a distinct consumer-behaviour phenomenon rather than simply an unplanned purchase. In online shopping, visual presentation, personalised recommendations, limited-time messages and ease of checkout can make the transition from interest to action faster. Nevertheless, impulse buying is not the same as purchase intention. A consumer can intend to purchase a phone after careful comparison, while an impulse response may occur without an established plan. In this study, impulse buying behaviour is treated as the principal outcome of the five promotional constructs, while purchase intention is examined as a related outcome in the reported structural model.

2.5 Conceptual framing and research gap

The study draws on established perspectives that help explain how marketing cues may be associated with behaviour. The stimulus–organism–response perspective distinguishes external cues from internal evaluation and behavioural responses. The Theory of Planned Behaviour highlights the role of attitudes, perceived social expectations and perceived behavioural control in shaping intention (Ajzen, 1991). The AIDA model offers a practical description of attention, interest, desire and action in promotional communication. These perspectives are complementary rather than interchangeable: they suggest that exposure, evaluation, intention and purchase should be measured separately.

The research context brings together three areas: social-media promotional cues, smartphone buying behaviour and large festive online-sale events in an Indian metropolitan student population. The project identifies a practical need to understand which promotional cues are associated with impulse buying and to compare two competing sale events. However, the present article's available statistical outputs do not contain completed platform-wise tests. Its empirical contribution is therefore narrower: it evaluates the pooled-sample relationships among the five promotional constructs and impulse buying, while identifying the additional analysis needed for a defensible comparison between Amazon and Flipkart.

3. Objectives and Hypotheses

The article addresses three focused objectives: (1) to describe respondents' social-media exposure and smartphone-sale behaviour; (2) to assess the reliability and bivariate associations of the five promotional constructs with impulse buying behaviour; and (3) to estimate the unique association of each promotional construct with impulse buying when the five are considered simultaneously. The broader project also aims to compare Amazon's Great Indian Festival with Flipkart's Big Billion Days, but that comparative objective cannot be resolved from the pooled results reported here.

The analytical expectation was that social media advertising, influencer promotions, reviews and recommendations, discounts and promotional benefits, and urgency cues would be associated with impulse buying behaviour. We assessed these relationships through correlations and multiple regression. The article does not label platform-specific hypotheses as supported or rejected because the supplied outputs do not include direct platform-wise statistical comparisons.

4. Methodology

4.1 Research design and participants

The study used a cross-sectional questionnaire-based design and collected primary responses from 153 college students

in Bengaluru. The project describes the design as descriptive and comparative because the broader research context concerns two festive sale events. The analyses used for this article, however, are pooled across respondents rather than based on a reported independent comparison between the two events. The sampling approach is described in the project as convenience sampling; therefore, the sample should not be assumed to represent all college students in Bengaluru or Indian consumers more generally.

4.2 Measures

The principal constructs were social media advertising (SMA), influencer promotions (INF), reviews and recommendations (REV), discounts and promotional benefits (DPR), urgency cues (URG), impulse buying behaviour (IBB), and purchase intention (PI). We analysed construct scores as mean scale scores. The questionnaire also captured demographic information, social-media platform use, exposure to promotional content, and purchase-related experiences during festive sales. The source report provides the construct-level reliability coefficients and descriptive statistics but does not establish that the measures are free from all forms of measurement error.

4.3 Analytical procedure

The reported analyses included descriptive statistics, Cronbach's alpha reliability analysis, Pearson correlations, multiple linear regression and structural equation modelling using AMOS. In the regression, impulse buying behaviour was the dependent variable and the five promotional constructs were entered simultaneously. This approach estimates each construct's conditional association with impulse buying while controlling statistically for the other included constructs. It does not establish causality. The AMOS model included paths from the five promotional constructs to impulse buying and from impulse buying to purchase intention.

4.4 Research integrity and interpretation

The findings reflect associations within the observed sample. The design is cross-sectional and based on self-reported responses, so temporal order and causal mechanisms cannot be established. The source report also notes limitations associated with recall, single-city coverage, a single product category, and the changing nature of platform promotions. The AMOS model is treated cautiously because its reported global fit was inadequate, some latent constructs were highly correlated, and multivariate non-normality was substantial.

5. Results

5.1 Respondent profile and promotional exposure

The sample was male-dominated: 60.1% of respondents identified as male and 33.3% as female, with the remainder selecting another description or preferring not to disclose. The largest age group was 21–23 years (45.1%), and postgraduate students represented 44.4% of the sample. Prior smartphone ownership was reported by 90.8% of respondents, indicating that most participants had experience with the product category. The monthly-budget question had 128 valid responses; among those valid responses, 25.0% reported a budget of ₹2,000–₹4,999 and another 25.0% reported ₹5,000–₹9,999.

YouTube (58.8%) and Instagram (57.5%) were the most frequently selected social-media platforms for smartphone-related promotional content. WhatsApp was selected by 19.6%, Facebook by 11.1%, other platforms by 9.8%, and X by 5.2%; multiple selections were permitted. Overall, 68.0% reported exposure to social-media smartphone promotions, 19.0% reported no exposure, and 13.1% were unsure. These figures indicate that promotional content was familiar to many respondents, but platform use does not itself demonstrate persuasive effectiveness.

During the sale period, 41.8% reported purchasing a smartphone, 20.9% had seriously considered but did not purchase, 20.3% had browsed without serious consideration, and 17.0% had neither browsed nor seriously considered a purchase. In addition, 51.6% said that they had planned to purchase before promotional exposure, 32.7% were considering or undecided, and 15.7% had not planned a purchase. The results therefore include both planned purchasing and behaviour closer to unplanned consideration; this distinction matters when interpreting impulse buying.

5.2 Descriptive statistics and reliability

Mean scores ranged from 3.106 for impulse buying behaviour to 3.680 for reviews and recommendations. The mean for urgency cues was 3.320, influencer promotions 3.369, social media advertising 3.474, discounts and promotional benefits 3.582, and purchase intention 3.395. The reported standard deviations ranged from approximately 1.05 to 1.23, indicating variation in respondents' evaluations.

Table 1: Descriptive statistics and internal consistency

Construct	Mean	SD	Cronbach's α
Social media advertising	3.474	1.086	.885
Influencer promotions	3.369	1.133	.897
Reviews and recommendations	3.680	1.059	.910
Discounts/promotional benefits	3.582	1.054	.892
Urgency cues	3.320	1.151	.930
Impulse buying behaviour	3.106	1.226	.933
Purchase intention	3.395	1.086	.912

Cronbach's alpha values ranged from .885 to .933, indicating good-to-excellent internal consistency for the seven scales in this sample. Reliability is a necessary measurement check, but it does not by itself establish construct validity, unidimensionality or discriminant validity. Those questions require additional evidence.

5.3 Correlations with impulse buying

All five promotional constructs were positively correlated with impulse buying behaviour. Urgency cues had the strongest bivariate association ($r = .804$, $p < .001$), followed by influencer promotions ($r = .708$, $p < .001$), social media advertising ($r = .674$, $p < .001$), discounts and promotional benefits ($r = .636$, $p < .001$), and reviews and

recommendations ($r = .492$, $p < .001$). Purchase intention was also positively correlated with impulse buying ($r = .743$, $p < .001$). These correlations indicate that higher scores on each promotional construct tended to co-occur with higher impulse-buying scores. Correlation does not establish that the promotional cue caused the behaviour.

5.4 Multiple regression

The simultaneous regression model was statistically significant, $F(5, 147) = 75.376$, $p < .001$. The model reported $R = .848$, $R^2 = .719$ and adjusted $R^2 = .710$, meaning that the five predictors jointly accounted for 71.9% of the observed variance in impulse buying scores in this sample. The result indicates substantial explanatory association, but it should not be interpreted as a causal percentage or assumed to generalise unchanged to other populations.

Table 2: Multiple regression predicting impulse buying behaviour

Predictor	Standardised β	p-value	Interpretation
Social media advertising	.074	.347	Not statistically significant
Influencer promotions	.356	< .001	Positive, statistically significant
Reviews and recommendations	−.317	< .001	Negative conditional coefficient
Discounts/ promotional benefits	.127	.158	Not statistically significant
Urgency cues	.612	< .001	Positive, statistically significant

Urgency cues had the largest positive standardised coefficient ($\beta = .612$, $p < .001$), followed by influencer promotions ($\beta = .356$, $p < .001$). Thus, after accounting for the other constructs in the model, stronger urgency-cue scores and influencer-promotion scores were associated with higher impulse-buying scores. Social media advertising ($\beta = .074$, $p = .347$) and discounts/promotional benefits ($\beta = .127$, $p = .158$) were not statistically significant unique predictors in this model.

Reviews and recommendations had a negative conditional coefficient ($\beta = -.317$, $p < .001$), although their bivariate correlation with impulse buying was positive. This change in direction should not be interpreted as evidence that reviews generally reduce impulse buying. The predictors share substantial variance—for example, the reported correlation between reviews and discounts was .815, and that between social media advertising and influencer promotions was .789. In a simultaneous regression, a coefficient reflects the association remaining after shared variance with the other predictors is accounted for. The negative coefficient may reflect this overlap or a suppression pattern and warrants further investigation. Reported variance inflation factors ranged from 2.494 to 4.169, which supports checking collinearity and coefficient stability rather than reading the estimates in isolation.

5.5 Structural equation model and measurement cautions

The reported AMOS model produced standardised paths of $\beta = .643$ from urgency cues to impulse buying, $\beta = .610$ from influencer promotions to impulse buying, $\beta = -.487$ from reviews to impulse buying, $\beta = -.116$ from social media advertising to impulse buying ($p = .445$), $\beta = .254$ from discounts to impulse buying ($p = .089$), and $\beta = .855$ from impulse buying to purchase intention. However, global model fit was not satisfactory: $\chi^2/df = 2.446$, GFI = .744, AGFI = .692, CFI = .881, TLI = .867 and RMSEA = .098 (90% CI .089–.106). Several latent correlations were high, raising concerns about discriminant validity, and the reported multivariate kurtosis indicated substantial non-normality.

For these reasons, the SEM results should be regarded as provisional rather than conclusive confirmation of the proposed measurement and structural model. Strong factor loadings or provisional composite reliability and average variance extracted values do not compensate for inadequate global fit or overlapping constructs. Model respecification, if undertaken, should be theoretically justified, transparently reported and tested on suitable data; correlated errors should not be added solely to improve fit indices.

6. Discussion

The most consistent result is the prominence of urgency cues. They showed the strongest bivariate correlation with impulse buying and the largest positive coefficient in the simultaneous regression. This pattern is consistent with the possibility that time pressure, countdowns, or limited-period messages are associated with more immediate buying responses during festive sales. The evidence remains correlational, however. Respondents who are already interested in buying a phone may pay more attention to urgency messages, and other factors- such as perceived need, budget, brand preference or prior purchase planning- may also explain the association.

Influencer promotions were also positively associated with impulse buying and remained significant in the regression. Product demonstrations and creator-led explanations may make smartphone features more accessible and can help consumers imagine the product in everyday use. Yet the result does not mean all influencer campaigns are effective or that influencer exposure alone produces purchases. Credibility, sponsorship disclosure, the relevance of the creator and the accuracy of product claims are important considerations for practice and future measurement.

The non-significant regression coefficients for social media advertising and discounts require careful interpretation. Both constructs were positively correlated with impulse buying, but their unique associations were not statistically significant when the other constructs were included. This does not mean advertisements or discounts are unimportant. Their influence may overlap with influencer content, urgency cues or product information, and their contribution may depend on consumer characteristics and the specific offer. Future

research could examine interactions and mediation, provided the sample size and research design support those analyses.

The negative conditional coefficient for reviews is an important methodological finding. In isolation, reviews and recommendations were positively related to impulse buying. When the shared variance with the other promotional constructs was controlled, the coefficient became negative. A plausible interpretation is that reviews may play multiple roles: they can stimulate interest, but detailed evaluation may also encourage comparison and deliberation. The current analysis cannot establish that mechanism. High correlations among the predictors mean that the coefficient should be interpreted as a conditional statistical result, not as a general claim that reviews deter purchases.

The respondent profile also cautions against broad generalisation. Most participants had previously owned a smartphone, and the sample included a substantial postgraduate share. The findings may be more applicable to digitally engaged students with prior smartphone experience than to first-time buyers, older consumers or consumers outside Bengaluru. Self-reported exposure and retrospective responses may also be affected by recall and social-desirability bias.

7. Implications

7.1 Implications for e-commerce platforms and marketers

The results suggest that urgency cues and influencer promotions deserve attention when evaluating festive-sale campaigns, but effectiveness should not be measured only by immediate conversions. Platforms and brands should assess whether campaign information is accurate, whether offer conditions are transparent and whether product claims can be substantiated. Countdown timers and limited-stock messages should reflect genuine constraints rather than create artificial pressure. Influencer content should clearly disclose commercial relationships and provide balanced, product-relevant information.

Marketers should also distinguish attention, engagement, purchase intention and completed purchases in campaign analytics. A platform may generate high video views or clicks without producing incremental purchases; conversely, reviews may support a more deliberate purchase process even if they do not immediately increase impulse-buying scores. Campaign evaluation should therefore include downstream outcomes, returns, cancellations, customer satisfaction and post-purchase regret where data are available.

7.2 Implications for students and consumers

For students, the findings underline the value of separating promotional urgency from genuine need. Before purchasing a smartphone during a festive sale, consumers can set a budget, identify essential specifications, compare the final payable price across offers, check warranty and return conditions, and consult multiple independent reviews. A countdown should not replace evaluation of whether the product meets requirements. The effective price should include assumptions about exchanges, bank-card eligibility, processing fees, and any conditions attached to the offer.

7.3 Implications for research and teaching

For researchers, the shift in the reviews coefficient between correlation and regression illustrates why bivariate findings and multivariable estimates should be reported together. The study is also a useful example for teaching the distinction between reliability and validity, association and causation, and measurement-model fit and structural-path significance. Future analyses should make the comparative question explicit in the data structure and statistical plan rather than infer platform differences from pooled relationships.

8. Limitations and Future Research

The study has several limitations. First, the sample comprises 153 students from one city and uses convenience sampling, limiting representativeness. Second, the cross-sectional design does not establish temporal sequence or causality. Third, the measures rely on self-report and retrospective recall. Fourth, the analysis concerns smartphones rather than multiple product categories. Fifth, the simultaneous regression shows substantial overlap among predictors, and the negative conditional coefficient for reviews requires further investigation. Sixth, the reported AMOS model fit is inadequate, and discriminant-validity concerns remain. These measurement and model limitations restrict the strength of conclusions drawn from SEM.

Most importantly for the broader project, the supplied results do not include a completed direct comparison between Amazon's Great Indian Festival and Flipkart's Big Billion Days. The pooled-sample analyses cannot determine which sale event is more effective. Future work should report the platform/event variable clearly and compare outcomes using appropriate tests, such as cross-tabulations and chi-square tests for categorical outcomes, independent-group tests for scale scores where assumptions are met, or regression models with platform indicators and relevant covariates. If respondents evaluated both events, paired methods may be appropriate; if different respondents evaluated each event, independent-group methods may be required. The choice depends on the actual survey design and data structure.

Further research should validate the measurement model in an independent sample, examine discriminant validity and use robust estimation or bootstrap confidence intervals if distributional assumptions remain problematic. Researchers should pre-specify theoretically defensible models, report missing data and outlier decisions transparently, and avoid modifying the model solely to obtain better fit indices. Longitudinal or behavioural data- such as actual click-throughs, cart additions, transaction records or post-purchase surveys—could help distinguish attention from purchase and reduce dependence on recall. Studies could also investigate whether budget, prior purchase planning, brand loyalty, perceived risk or digital literacy moderates the association between promotional cues and buying behaviour.

9. Conclusion

This study examined social-media-related promotional cues and smartphone impulse buying behaviour among 153 college students in Bengaluru in the context of Amazon's Great Indian Festival and Flipkart's Big Billion Days. The scales showed good-to-excellent internal consistency, and each promotional construct was positively correlated with impulse buying. Urgency cues had the strongest bivariate association. In the simultaneous regression, urgency cues and influencer promotions were significant positive predictors, while social media advertising and discounts were not significant unique predictors. Reviews displayed a negative conditional coefficient despite a positive bivariate correlation, underscoring the importance of shared variance and cautious interpretation.

The reported AMOS model requires further validation because global fit was inadequate, latent constructs were highly correlated, and multivariate non-normality was substantial. The findings should therefore be treated as evidence of associations in this sample, not proof of causal effects. Nor do the pooled results show that Amazon or Flipkart performed better. A direct platform-wise analysis is needed to answer that comparative question. Overall, the study highlights the relevance of urgency and influencer-related cues in festive smartphone marketing while reinforcing the need for transparent promotion, careful consumer decision-making and methodologically rigorous comparative research.

References

[1] Aggarwal, P., Jun, S. Y., & Huh, J. H. (2011). Scarcity messages: A consumer competition perspective. Journal of Advertising, 40(3), 19–30.
[2] Ajzen, I. (1991). The theory of planned behavior. Organizational Behavior and Human Decision Processes, 50(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T
[3] Belk, R. W., Wallendorf, M., & Sherry, J. F. (1989). The sacred and the profane in consumer behavior: Theodicy on the odyssey. Journal of Consumer Research, 16(1), 1–38.
[4] Chevalier, J. A., & Mayzlin, D. (2006). The effect of word of mouth on sales: Online book reviews. Journal of Marketing Research, 43(3), 345–354.
[5] Duffett, R. G. (2015). Facebook advertising's influence on intention-to-purchase and purchase amongst Millennials. Internet Research, 25(4), 498–526.
[6] Hutter, K., Hautz, J., Dennhardt, S., & Füller, J. (2013). The impact of user interactions in social media on brand awareness and purchase intention: The case of MINI on Facebook. Journal of Product & Brand Management, 22(5/6), 342–351.
[7] Kim, A. J., & Ko, E. (2012). Do social media marketing activities enhance customer equity? An empirical study of a luxury fashion brand. Journal of Business Research, 65(10), 1480–1486.
[8] Lemon, K. N., & Verhoef, P. C. (2016). Understanding customer experience throughout the customer journey. Journal of Marketing, 80(6), 69–96.
[9] Mangold, W. G., & Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. Business Horizons, 52(4), 357–365.
[10] Mehrabian, A., & Russell, J. A. (1974). An approach to environmental psychology. MIT Press.
[11] Chaudhuri, A., & Holbrook, M. B. (2001). The chain of effects from brand trust and brand affect to brand performance: The role of brand loyalty. Journal of Marketing, 65(2), 81–93.
[12] Voramontri, D., & Klieb, L. (2019). Impact of social media on consumer behaviour. International Journal of Information and Decision Sciences, 11(3), 209–233.