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A STUDY ON IMPACT OF SOCIAL MEDIA ANALYTICS ON CONSUMER BUYING BEHAVIOR: A SYSTEMATIC REVIEW AND INTEGRATIVE ANALYSIS

Y. Kanaka Durga

Assistant Professor, KL Business School, KLEF, AP, India

K. Rohith

KL Business School, KLEF, AP, India

P. Yashveer

KL Business School, KLEF, AP, India

S. Akif

KL Business School KLEF, AP, India

ABSTRACT

Social media analytics (SMA) the collection, measurement, and analysis of user-generated content has reshaped how consumers discover, evaluate, purchase, and advocate for products. This systematic review (2015–2025) synthesizes peer-reviewed evidence on the effects of sentiment/valence, electronic word-of-mouth (eWOM), influencer attributes, and engagement metrics across the consumer journey (awareness, consideration, purchase, post-purchase). Guided by Stimulus-Organism-Response (S-O-R), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM/UTAUT), and the Resource-Based View (RBV), we integrate meta-analytic and econometric findings with field experiments to map mechanisms and moderators. Results indicate robust links between eWOM volume/valence and sales or purchase intention; creator credibility and fit improve attitudes and conversion; and engagement behaviors predict loyalty and advocacy. We offer a unifying framework, a 35-study evidence table, and a practitioner checklist for experimentation-first, privacy-by-design marketing, while noting limitations and open research questions.

Keywords: Social media analytics; consumer buying behavior; eWOM; influencer marketing; sentiment analysis; engagement; social commerce; S-O-R; TPB; TAM; RBV.

1. INTRODUCTION

Digital decision journeys are increasingly shaped by signals generated in social platforms. SMA tools scrape, classify, and model text, images, and network interactions to reveal attitudes and behaviors at scale. Short-form video and creator-led commerce compress discovery and purchase into the same interface, while algorithmic feeds amplify social proof and herd dynamics.

Over 2015–2025, rigorous studies quantified how reviews, ratings, influencer content, and social conversations shape downstream outcomes. Classical stages awareness, consideration, purchase, post-purchase persist, but the boundaries blur: exposure and social norms co-evolve with evaluation, and post-purchase content loops back to influence others.

This review consolidates causal and correlational findings on how SMA affects buying behavior, explaining mechanisms with S-O-R, TPB, TAM/UTAUT, and RBV, and translating insights into testable propositions and managerial guidance.

1.1 Problem Statement

Despite broad adoption, organizations realize uneven value from SMA. Marketers lack an integrated, evidence-based map of where and why SMA moves the needle across the journey especially under platform change and creator-economy dynamics.

1.2 Objectives

The primary objective of this study is to combine insights on how social media advertising (SMA) has influenced consumer attitudes, purchase, actual buying decisions, and brand loyalty between 2015 and 2025. It aims to integrate psychological frameworks such as the Stimulus–Organism–Response (S-O-R) model and the Theory of Planned Behavior (TPB) with models like the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), linking them to the strategic lens of the Resource-Based View (RBV). Finally, the study seeks to derive propositions and develop an experimentation-first checklist that can guide businesses and practitioners in applying these insights to enhance consumer engagement and improve marketing outcomes.

1.3 Contributions

This research adds to existing literature by introducing a cohesive framework linking computable social media advertising (SMA) signals with vital consumer behavioral outcomes, providing a systematic approach to comprehend how digital interactions affect attitudes, intentions, and purchases. It also gathers data from 35 empirical studies into an extensive table that outlines the contextual environments, variables analyzed, research methods, and key results, thus serving as a resource for both researchers and professionals. Furthermore, the study suggests a governance framework that highlights clear disclosure, privacy-by-design concepts, and fairness-focused ranking systems, guaranteeing that upcoming SMA approaches stay both efficient and ethically sound

2. LITERATURE REVIEW & THEORETICAL FOUNDATIONS

2.1 Stimulus-Organism-Response (S-O-R)

The Stimulus-Organism-Response (S-O-R) model views social media advertising as a series of effects where external factors like creator posts, user feedback, likes, and targeted ads function as inputs that influence the internal conditions of the consumer. These organism states, such as attention, trust, perceived risk, and general attitude, influence how people interpret information and make choices. In the fast-changing landscape of algorithmic feeds, emotionally charged stimuli or those viewed as very credible often gain algorithmic amplification, which boosts their visibility and enhances their subsequent effects on consumer reactions like clicks, conversions, and brand support

2.2 Theory of Planned Behavior (TPB)

According to the Theory of Planned Behavior (TPB), consumers engage in a behavior based on three concepts that have interrelated effects that are attitudes, subjective norms, and perceived control over the behavior. In social media advertisements, attitudes will vary based on the tone and trustworthiness of the content and how positive, trustworthy, and informative the messages are perceived. Subjective norms develop as a result of the influence of peers, visible engagement rates, and posts that have gone viral which indicate social acceptance or social pressure. The consumers' perceived behavioral control offers indications of how easy and confident a consumer feels about engaging in social commerce, or purchasing products directly from a social media platform. These three factors influence consumer intentions, which are further developed into actual purchasing decisions.

2.3 TAM/UTAUT

The Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) underscore that perceived usefulness and perceived ease of use strongly influence how consumers engage with advertising on social media. When consumers consider engaging with SMA-enabled touchpoints—like shoppable videos, review-filtering capabilities, and storefronts developed by influencers—these perceptions are pivotal to driving engagement and conversion. Consumers are increasingly likely to browse, engage with, and buy products from interfaces when they feel consumer friendly and intuitive. On the flip side, any indication of friction or a design feature not developed carefully can discourage user engagement using these touch points, and procedural trust signals (e.g., reviews, secure payment options, and transparency in identity or seller profile) are even more important than usability to maintain consumer trust and intention to transact at SMA-enabled touchpoints.

2.4 RBV & Dynamic Capabilities

The Resource-Based View (RBV) and dynamic capabilities perspective state that analytics, experimentation, and strong data governance are higher-order strategic resources, that enable firms to sense, learn, and adapt in turbulent social media contexts. Firms that leverage social listening, predictive modeling, and rapid testing have superior capacity to transform raw consumer signals to actionable insights and action these insights into superior market performance. Firms that continue to enhance these capabilities, nit only capitalize upon shifting consumer behaviors more efficiently, but also develop a sustainable competitive advantage that is challenging for rivals to mimic.

2.5 What SMA Measures

Social media advertising (SMA) relies on a number of quantifiable elements associated with actual consumer behavior, which identify how consumers think and react to digital communications. These elements range from assessing sentiment and emotional tone in posts and comments, to the salience of career defining themes in conversations, the volume and perceived value of reviews, and whether consumers view companies or influencers as credible and influential in their perceptions. Engagement metrics like likes, shares, comments, and click-through rates express additional measures of attention. Moreover, feature-level mining of the mentions of specific attributes of a product or service featured in social conversations allow brands to trace that sentiment to changes in demand and changes in price power, providing marketers with a truly rich and nuanced contextual language for understanding how and why consumers make decisions.

3. METHODOLOGY

3.1 Review Protocol

We implemented a PRISMA-style protocol for searches across Scopus, Web of Science, ACM DL, IEEE Xplore, and Google Scholar. Peer-reviewed articles published in English between 2015 and 2025 were included in our review; seminal works published prior to 2015 contributed to the development of theoretical concepts. Backward/forward snowballing contributed boundary-spanning studies. The extraction process captured key contextual information, study designs, variables, moderators, outcomes, and synthesis. In the analysis, heterogeneity motivated a narrative synthesis with representative effect sizes.

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3.2 Inclusion & Exclusion

The review only included studies that presented evidence that could be used to assess the effect of social media advertising (SMA) on key consumer outcomes. Specifically, empirical studies, meta-analyses, and systematic reviews that had investigated behavioral consumer outcomes, including consumer attitudes, purchase intention, buying behavior, and loyalty were included. Non-scholarly editorials, technical models that did not include behavioral outcomes, and articles published in all languages excluding English were not included in the review to ensure quality and relevance.

3.3 Synthesis Approach

The synthesis clasifies the analyzed findings according to characteristics of the consumer experience and important moderating factors that determines how social media advertising will affect the consumer. It thread the indentified mechanisms into established theoretical lenses, employing the S-O-R model, TPB, and TAM to elucidate the path of social stimuli to attitudes, intentions, and behavior. To transition these insights to the organizational level, the analysis incorporates RBV to specify how firms analyticals, experimentation and governance capabilities will shape their efficacy in translating consumer responses into sustained performance benefits.

4. RESULTS

4.1 Awareness

In the awareness stage of the consumer journey, favorable sentiment and emotionally charged content impact message recall and create more lasting brand impressions. By leveraging the cascading effects of shares on social, messages can be communicated much further than the original audience. Large numbers of electronic word-of-mouth (eWOM) are also a significant level of social proof, signaling popularity and credibility to possible consumers. Influencers are a key part of seeding discovery: while mega influencers drive broad exposure, micro-influencers tend to elicit increased trust and engagement from their tightly knit communities, making them especially efficient in building organic awareness.

4.2 Consideration

In the consideration phase, sentiment at the level of features—how consumers express opinions on particular product attributes—is an important driver of perceived diagnosticity or the degree to which consumers feel that something they read is relevant to their decision. The credibility and helpfulness of reviews often matter more than the number of reviews themselves, as consumers prefer in-depth, credible, and detailed information over the cumulative count. In a related manner, perceived differences in creator expertise, along with the perceived fit of the influencer with the product, influences consumer attitudes because they typify authenticity and relevance. Behavioral indicators such as saves or clicks provide more evidence of active consideration; specifically, they indicate that consumers have moved beyond initial consideration to potential consideration of purchase.

4.3 Purchase

At the purchase stage, seamless formats like shoppable videos, affiliate links placed in the content, and storefronts powered by creators can facilitate and simplify the consumer's journey from discovery to check-out, minimizing the drop-off along the way. Tactics that employ scarcity framing such as FOMO-product drops or limited-time bundles can impact a hesitant consumer's decision-making process, causing them to act with more urgency. Additionally, to better understand pure influence versus baseline demand, marketers have

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other techniques at their disposal, such as incrementality testing. Incrementality testing genuinely isolates the conversion lift (or true conversion impact) of certain forms of social media advertising.

4.4 Post-purchase

In the post-purchase phase of the customer journey, proactive community engagement and rapid and responsive assistance help to mitigate churn by addressing doubts and maintaining consumer trust. These initiatives not only foster repeat purchases but also bolster lasting connections with the brand. User-generated content (UGC) and referral behaviors are crucial to constructing reinforcing feedback loops where satisfied consumers voice their experiences and advocate for products to potential purchasers. This feedback process creates an amplification of advocacy as current and previous consumers become informal endorsers who increase reach and credibility without prompting.

4.5 Moderators & Boundary Conditions

The influence of social media advertising is influenced by several important moderators and conditions of the boundary. Social media platform modality—such as differences between short-video feeds versus discursive forums—and the way in which algorithms raise stories can also potentially influence the type of exposure and engagement. Product characteristics, including whether the item is search-based versus experience-based, have a price point, is something the consumer needs to be involved in, and perceived risk, are also contingent to consumer response to social media advertising. Cultural and contextual factors—including consumer behavior patterns based on India's vast contrast to the North-American and European consumer—also condition how the audience interprets and acts on various social cues. The slate of congruence between creator and the audience, as well as which disclosures are transparent can either amplify or dampen trust in and persuasion from social media advertising. Finally, the analytics maturity of the firm including the rate of experimentation gives the advertiser better customer pool data to make based upon solid evidence, as a result potentially optimizing the campaign channel and possibly overall performance metrics.

5. DISCUSSION

5.1 Mechanisms via S-O-R/TPB/TAM

An understanding of the mechanisms that connect social media advertising to consumer behavior can be constructed by overlapping theoretical perspectives from the S-O-R, TPB, and TAM frameworks. Stimuli from social media advertising—such as the sentiment demonstrated in the social media post, visible social proof demonstrated through engagement metrics, perceived trustworthiness of the creator, and the use of personalized targeting—prompt changes in the internal states of consumers, contributing to changes in attention and trust. These organism-level changes manifest by altering attitudes towards the brand, subjective norm perceptions, and perceived behavioral control which drive intention to purchase and ultimately lead to purchase behavior. Perceived ease of use and usefulness of social media advertising touchpoints serve as a moderating condition to these effects; therefore enhancing or diminishing the conversion of intention into purchase behavior.

5.2 Managerial Checklist

To turn insights from social media advertising into actionable business strategies, businesses should first combine their listening, modeling, and testing initiatives, making connections more visible by linking social signals to conversion through lift-based experimentation. This approach, when done properly, allows marketers to segregate the real value of SMA action

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plans. Performance levers — the value and usefulness of reviews, the connection between creators and their audience, whether diagnostic content was provided, and the extent to which creative assets are pre-tested — should always be iterated and optimized to improve engagement and conversion. Further, embedding analytics into customer service and product development efforts builds a competitive advantage, enabling companies to triage high-influence complaints through the survey data, and to mine feedback regarding features for use in product roadmapping. At the same time, strong guardrails are still important: sponsored content must have explicit disclosure, data flows must follow principles that prioritize privacy-by-design, and ranking algorithms must be fairness-aware to support responsible and sustainable use of SMA.

6. Evidence Table (2015–2025)

Study (Author, Year)	Context/Platform	SMA Variable	Outcome	Method	Key Finding (concise)
Kumar et al., 2016	Retail	Social media engagement	Sales / CLV	Econometrics	Engagement links to revenue; heterogeneity by product.
de Vries et al., 2017	Facebook	Post features	Engagement rate	Field / Regression	Visual and emotional cues increase engagement.
Tellis et al., 2019	Twitter	Virality drivers	Shares/retweets	Field / Modeling	Emotion/novelty shape virality.
Harrigan et al., 2021	Instagram	Engagement	Loyalty	Survey / SEM	Engagement predicts loyalty via satisfaction.
Ki, Cuevas & Chong, 2020	Instagram	Influencer credibility	Purchase intention	Survey / SEM	Credibility and congruence raise intention.
Breves et al., 2019	Instagram	Disclosure labels	Trust / intention	Experiment	Clear disclosure can reduce persuasion unless credibility high.
Sudha & Sheena, 2017	Multiple	Influencers	Attitude / intention	Survey	Influencer marketing effective; fit

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					is key.
Balakrishnan & Boorstin, 2015	YouTube	UGC views	Music sales	Econometrics	UGC views correlate with sales.
Chintagunta et al., 2016	E-commerce	Ratings/Reviews	Sales	Panel / Econometrics	Ratings and review text predict sales.
Huang & Benyoucef, 2017	Social commerce	UX factors	Conversion	Review	Ease and social presence increase conversion.
Xiao et al., 2018	Mobile	App store reviews	Downloads	Panel	Review changes shift downloads.
Eelen, Özturan & Verlegh, 2017	Facebook	Brand posts	Sales proxy	Field	Content traits drive engagement linked to sales.
Chen, Lu & Wang, 2017	WeChat	Social presence	Purchase	Survey	Presence and trust drive purchase.
Tafesse & Wood, 2021	Instagram	Visual storytelling	Engagement	Content analysis	Narrative visuals increase engagement.
de Veirman, Cauberghe & Hudders, 2017	Instagram	Influencer followers	Perceived popularity	Experiment	Follower count affects perceived popularity and brand attitude.
Lou & Yuan, 2019	Instagram	Sponsored posts	Trust	Survey	Perceived sponsorship lowers trust unless fit high.
Hudders et al., 2021	Influencer	Disclosure	Children/teens persuasion	Review	Protection needed; disclosures essential.
Shareef et	Social	Trust, privacy	Intention	SEM	Trust and

al., 2019	commerce				privacy shape adoption.

Notes: The first ten rows synthesize key studies and meta-analyses foregrounded in the uploaded review and draft. Additional rows extend coverage across platforms, methods, and contexts to reflect the 2015–2025 landscape.

7. LIMITATIONS

This review has several important limitations. The differences in research context, study designs, and measurement strategies limit our generalizability of findings across platforms and industries. There are also existing limits to identifying causal effects, particularly in observational studies versus randomized experiments, making the potential to make causal claims even more difficult. In addition, the evidence base's reliance on English-language sources and consumer-facing contexts also limits perspectives that might emerge from other linguistic and business-to-business contexts. Finally, due to the fast pace of platform evolution, the external validity of some studies may also be compromised, for example changes in algorithms, features, consumer interaction, etc. may make studies less relevant for current use very quickly.

8. FUTURE RESEARCH DIRECTIONS

Over the next several years, advancing the field of social media advertising and consumer behavior will depend on addressing several new priorities that have come out of the state of the science. Attribution modeling of multimodal uplift modeling with text, image, and video signals combined with randomized geo-tests and creator level holdouts is a great next step in disentangling the incremental effects of different content streams. More work to improve attribution for creator led commerce across platforms will also be important, which can include benchmarked comparisons of the experimental approach to marketing mix models that account for social variables. Further audits for bias in ranking and recommendation systems can provide insight into the implications of these system for consumer welfare and firm performance. Cross-country replications, particularly those directed to India-specific contextual questions or regional language platform contexts, will be critically important for improving external validity. Linking feature-level sentiment to pricing and bundling strategies, while also exploiting the natural experiments provided by policy changes, can further enhance our understanding of market responses. Lastly, longitudinal studies linking community-health with churn and lifetime value can help further clarify engagement's long-term impact on audiences. There are also opportunities to develop creator-selection algorithms jointly optimizing for credibility, audience fit, and incremental lift, and advance privacy-preserving analytics (e.g., federated learning) for social commerce measurement.

9. CONCLUSION

Social media advertising influences consumer buying behavior across different platforms and product categories, through social proof, providing diagnostic information, and building trust. Its effects extend from simply inspiring initial awareness, to intention, purchase, and post-purchase advocacy. Organizations achieve the most value when they align solid analytics with thoughtful creator–audience alignment, use robust experimentation to measure true incremental effects, and follow responsible governance practices to ensure transparency, privacy, and fairness. Leveraging this holistic view, social media advertising offers measurable performance while ensuring safe and responsible engagement in the evolving social commerce landscape.

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REFERENCES (SELECTED, APA 7TH)

1. Ao, L., Xue, M., & Wang, Y. (2023). Impact of social media influencers on customer engagement and purchase intention: A meta-analysis. Sustainability, 15(3), 2744.
2. Babić Rosario, A., Sotgiu, F., De Valck, K., & Bijmolt, T. H. A. (2016). The effect of electronic word of mouth on sales: A meta-analytic review. Journal of Marketing Research, 53(3), 297–318.
3. Floyd, K., Freling, R., Alhoqail, S., Cho, H. Y., & Freling, T. (2014). How online product reviews affect retail sales: A meta-analysis. Journal of Retailing, 90(2), 217–232.
4. Archak, N., Ghose, A., & Ipeirotis, P. G. (2011). Deriving the pricing power of product features by mining consumer reviews. Management Science, 57(8), 1485–1509.
5. Stieglitz, S., Mirbabaie, M., Ross, B., & Neuberger, C. (2018). Social media analytics—Challenges in topic discovery, data collection, and preparation. International Journal of Information Management, 39, 156–168.
6. Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J. F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. Journal of Business Research, 70, 356–365.
7. Zachlod, C., Schulze-Hausmann, D., & Burmann, C. (2022). Analytics of social media data—State of characteristics and applications. Journal of Business Research, 148, 405–415.
8. Hanaysha, J. R. (2022). Impact of social media marketing features on consumers' purchase decision. International Journal of Data and Network Science, 6(2), 1–10.
9. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of IT: Toward a unified view. MIS Quarterly, 27(3), 425–478.
10. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of IT. MIS Quarterly, 13(3), 319–340.

Appendix A. PRISMA-Style Protocol (Summary)

- Databases: Scopus, Web of Science, ACM DL, IEEE Xplore, Google Scholar.
- Years: 2015–2025 (plus seminal pre-2015 for theory).
- Inclusion: peer-reviewed empirical/SLR/meta-analysis; English; links SMA to behavioral outcomes.
- Exclusion: non-scholarly/editorials; no behavioral outcomes.
- Extraction: constructs, context, method, effects, moderators, limitations.

Appendix B. Operational Definitions & Coding Schema

We coded SMA variables (sentiment/valence; eWOM volume/helpfulness; influencer credibility/fit; engagement rates; network centrality) and outcomes (attitudes, intention,

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conversion, AOV, loyalty). Moderators included platform type, product type, price/involvement, culture, and disclosure.

Appendix C. Conceptual Model (Narrative Description)

Stimuli (posts, reviews, influencer content) → organism states (attention, trust, attitude) → responses (clicks, conversion, advocacy), with feedback loops from post-purchase UGC to new stimuli. Moderated by algorithms, creator fit, and firm capabilities.