Decoding Consumer Sentiment in Social Media: A Mixed-Methods Approach to Predicting Purchase Intention

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Social media platforms have become the primary channels for internet marketing and advertising, allowing businesses to interact with consumers through content that is both interactive and emotionally engaging. Although prior research has investigated the efficacy of social media marketing through the use of either survey-based quantitative methods or large-scale automated sentiment analysis, limited studies have combined qualitative sentiment insights with empirical validation. The current study employs a sequential exploratory mixed methods design to investigate the impact of consumer sentiment toward social media marketing on brand awareness and purchase intention, thereby addressing this lacuna. Sentiment analysis based on N Vivo was implemented during the qualitative phase to analyze in-depth interviews with 32 active Facebook users. The results demonstrated a dominant presence of positive sentiments regarding social media marketing content, with variations in sentiment intensity. The development of a structured questionnaire was influenced by these insights, and it was eventually applied to 286 respondents throughout India. Partial Least Squares Structural Equation Modeling (PLS-SEM) was implemented during the quantitative phase to evaluate the proposed relationships. The results suggest that brand awareness is substantially increased by positive sentiment toward social media marketing, which in turn positively influences purchase intention. The relationship between sentiment and purchase intention was partially mediated by brand awareness. This study makes a valuable contribution to the field of internet marketing and advertising by combining quantitative structural modeling with qualitative sentiment analysis. It also provides practitioners with actionable insights into the development of sentiment-driven social media approaches.

Keywords: Social Media Marketing; Sentiment Analysis; Brand Awareness; Purchase Intention; Mixed-Methods; PLS-SEM

1. Introduction

The rise of social media has changed marketing communication in a big way, moving it from traditional one-to-many broadcasting models to interactive, dialogic, and consumer-focused engagement settings (Kaplan and Haenlein, 2010). Social

media sites let people not only get marketing messages, but also join in on brand conversations, share their thoughts, and change how other people see a company. Facebook remains a major platform due to its large user base, interactive capabilities, and ongoing usefulness for brand marketing (Cvijikj and Michahelles, 2011). In this interactive setting, customer sentiment has become a key factor in how well marketing works. Sentiment is how people feel about marketing stimuli, and it has a big impact on how people think about brands, how they remember things, and how they make decisions. Positive emotional responses can boost brand memory, build trust, and make people more likely to buy, whereas negative feelings can hurt brand credibility and make people less likely to buy (Cambria et al., 2012).

Even though it's important, sentiment is frequently looked at on its own in social media marketing research. Computational research often concentrates on the precision of automated categorization, whereas behavioral studies prioritize survey-derived attitudinal variables. These fragmented approaches restrict a comprehensive knowledge of sentiment formation and its translation into purchasing behavior. To address this constraint, the current work combines qualitative sentiment analysis with quantitative structural modeling, providing a thorough investigation of sentiment-driven customer behavior in social media marketing settings.

2. Literature Review

2.1 Evolution of Sentiment Analysis in Social Media Marketing

Since 2017, sentiment analysis has changed from a way to explore data to a key part of marketing analytics. Preliminary research in this era established methodological underpinnings by juxtaposing lexicon-based and machine learning methodologies, highlighting the trade-offs between interpretability and prediction accuracy (Dhaoui et al., 2017). These investigations confirmed sentiment analysis as a dependable indicator of consumer views conveyed in social media contexts.

Later studies showed more and more that sentiment analysis is useful for managers. Teixeira and Mealha (2017) emphasized the significance of resilient data extraction and processing channels in the analysis of Facebook brand pages, whilst Saragih and Tan (2017) demonstrated that sentiment-driven engagement metrics accurately represent consumer views on digital service platforms.

The methodological landscape of sentiment analysis in marketing has been considerably enhanced by more recent developments. Yadav and Vishwakarma (2020) showed that transformer-based models, like BERT, provide greater context sensitivity in informal language registers and significantly outperform conventional lexicon-based approaches in identifying subtle customer sentiment on social media platforms. Building on this, Dashtipour et al. (2021) demonstrated that ensemble deep learning architectures that combine recurrent and convolutional neural networks reach state-of-the-art accuracy in multi-class sentiment categorization across various social media datasets. The most recent argument made by Mäntylä et al. (2023) highlights the ongoing significance of mixed-methods designs that supplement automated analysis with human-centered qualitative insight. They contend that although computational precision has significantly improved, the interpretability of such models for managerial decision-making remains an open challenge.

Recent research show that sophisticated NLP and deep learning methods are being used in sentiment analysis frameworks. Singh and Kumar (2024) and Jose and Bhatia

(2024) stressed that contemporary NLP pipelines make it easier to understand informal, context-dependent language on social media. These studies also point out problems with explain ability and computational complexity, especially in marketing situations when being open about things is important for making decisions.

Zhang and Liu (2024) presented a large language model (LLM)-based sentiment classification pipeline that outperforms traditional BERT models in identifying fine-grained emotional polarity in brief social media messages, with an F1-score of 0.94 on multi-platform benchmarks. Their method combines domain-adaptive pre-training with contrastive learning, allowing for a more subtle differentiation between moderately and strongly positive sentiments—a skill that is directly relevant to the operationalisation of sentiment intensity as a measure. This improvement highlights the increased analytical precision possible.

Patel et al. (2024) carried out a systematic review of 112 sentiment analysis studies published between 2018 and 2023 and discovered that transformer-based architectures have emerged as the main methodological paradigm, but less than 15% of marketing-focused studies triangulate computational outputs with qualitative validation. The authors suggest that relying solely on automated sentiment scoring risks missing the contextual and cultural components of consumer affect, and thus strongly urge adopting mixed-methods designs that integrate NLP-derived metrics with interview-based or thematic analysis. This observation directly motivates the sequential exploratory methodology used in this investigation.

Hernandez and Kim (2025) investigated how generative AI tools are transforming consumer sentiment expression on social media, observing that AI-mediated content generation provides additional levels of emotional ambiguity, challenging traditional lexicon-based and supervised sentiment classifiers. Using a mixed corpus of 2.3 million Instagram and Facebook posts, they found that sentiment intensity, rather than polarity, was the biggest predictor of content virality, offering empirical support to the theory of intensity as a separate and important concept. Their findings underscore the ongoing need for research approaches capable of capturing both the qualitative texture and quantitative scale of consumer opinion.

2.2 Facebook-Based Sentiment Analysis and Engagement Outcomes

Facebook continues to be a central platform for sentiment analysis research since it has well-organized ways for people to communicate and a lot of text-based interactions. Annamalai et al. (2019) presented persuasive evidence that sentiment-weighted engagement metrics from Facebook brand pages are strong predictors of sales performance at various phases of the brand lifecycle. Their results showed that sentiment analysis is more of a leading indication of market success than a descriptive metric.

Chun and Lee (2021) further shown that emotion polarity and subject relevancy collectively affect interaction metrics, including likes, comments, and shares on Facebook fan pages. Albesta et al. (2021) expanded this field by demonstrating that Facebook sentiment analysis may directly guide service quality enhancement measures, underscoring its practical use beyond mere performance evaluation.

New research has shed light on the link between sentiment dynamics and interaction on Facebook and other social media sites. Khatua et al. (2021) discovered that emotional valence and arousal predict the viral dissemination of branded content

on Facebook, with high-arousal positive postings eliciting much more sharing behavior than neutral or negative articles. Similarly, Vrontis et al. (2022) did a systematic study and found that social media sentiment is a strong predictor of consumer involvement across many industries, but platform-specific factors moderate the strength of this association. These data support the notion that sentiment is more than just a descriptive output, but an active predictor of engagement outcomes.

Osei-Frimpong et al. (2024) investigated how positive sentiment expressed in brand-related Facebook postings affects community participation and word-of-mouth intentions among 1,240 Ghanaian customers, discovering that sentiment valence mediated the link between content type and sharing behavior. messages with strong positive sentiment and vivid emotional imagery generated engagement rates over three times those of informationally framed messages, confirming the notion that emotive tone is a more potent driver of engagement than message in formativeness alone. These findings support the importance of good sentiment as a trigger for subsequent brand-related outcomes in social media contexts.

Kaur and Singh (2024) used longitudinal data from 320 brand pages over 18 months to study how sentiment dynamics on Facebook change across the consumer decision journey. They discovered that sustained positive sentiment in the awareness stage significantly predicted conversion rates at the consideration and purchase stages. Their panel regression analysis found brand awareness as a crucial mediating variable between early-stage emotional engagement and later-stage purchase intentions, giving temporal evidence for the mediation route proposed in the current study. The authors urge that digital marketers engage in creating constant favorable tonal settings on Facebook in order to maintain awareness-building momentum across the customer funnel.

Tran et al. (2025) used PLS-SEM to analyze survey data from 412 Vietnamese social media users. They observed that the emotional level of brand post on Facebook strongly predicted either brand recall and click-through intent, with sentiment intensity representing 34% of the variance in purchase intention when mediated by brand engagement. Their research provides cross-cultural support for the construct linkages hypothesized in the current study, highlighting the broad relevance of sentiment intensity as a predictor of consumer behavior across various socioeconomic and cultural situations. Importantly, they used a quantitative-only approach and specifically encouraged future mixed-methods studies to improve our knowledge of how consumers subjectively perceive sentiment intensity.

2.3 Sentiment, Brand Awareness, and Consumer Behavior

Recent studies increasingly associate sentiment analysis with consumer behavior results. Rahardjo and Fauzi (2024) established that sentiment articulated in social media discourse strongly forecasts purchase intention, hence affirming sentiment's function as a behavioral precursor rather than only an emotive concept.

A rising corpus of empirical research has solidified the theoretical relationship between sentiment, brand awareness, and subsequent purchasing behavior. Nisar and Whitehead (2020) found that emotionally happy consumer-generated material on social media increases brand salience and memory, demonstrating that affective tone influences cognitive brand representations. Furthermore, Arora and Sharma (2023)

used PLS-SEM to show that brand awareness mediates the link between social media marketing communication and purchase intention, with sentiment intensity appearing as a major border condition that enhances the mediation effect. These studies demonstrate that sentiment influences consumer decision-making via both direct emotional and indirect cognitive routes.

Although this research validate the predictive significance of sentiment, many fail to specifically investigate how sentiment correlates with behavioral outcomes. Specifically, there is a paucity of empirical research examining cognitive processes—such as brand awareness—that facilitate the link between sentiment and purchasing behavior. This signifies a crucial void that the current study addresses.

Chaudhary and Bhatia (2024) used Structural Equation Modeling on a sample of 534 Indian millennial consumers to show that favorable attitude toward social media marketing material increased brand awareness, which then mediated the path to purchase intention. Their study is one of the first to test this mediated chain in the Indian digital consumption context, revealing that the indirect effect of positive sentiment on purchase intention via brand awareness was significantly stronger than the direct effect—a finding that is reflected in the current study's mediation analysis. The authors emphasize that brand knowledge serves as the major cognitive bridge that converts emotional responses to marketing information into behavioral purchase decisions.

Nguyen and Park (2024) studied the boundary conditions of the sentiment-purchase intention relationship and discovered that brand awareness acted as a partial mediator, while perceived authenticity of social media content moderated the strength of the sentiment-awareness link across product categories. Using a multi-group analysis inside PLS-SEM, they found that sentiment intensity increased the awareness-building impact for hedonic product categories more than utilitarian ones, indicating that the strength of emotional pathways varies by context. These complex findings highlight the necessity of include brand awareness as a major mediating element in models of sentiment-based buying decisions.

Alshammari et al. (2025) did a meta-analysis of 47 empirical studies on the relationship between social media sentiment and consumer purchasing outcomes, and discovered a substantial positive connection with a pooled effect value of $r = 0.52$. Their findings showed that brand awareness and trust consistently mediated the sentiment-purchase relationship, while sentiment intensity moderated the overall strength of effects—especially in the fast-moving consumer goods and technology industries. The meta-analytic data synthesized in this analysis demonstrate significant cross-study validity for the theoretical routes investigated in the current study.

2.4 Research Gap and Study Positioning

Notwithstanding significant advancements, the current literature is predominantly method-focused and split between qualitative and quantitative approaches. Academics are progressively advocating for mixed-methods techniques that combine qualitative sentiment analysis with quantitative validation to improve explanatory depth and managerial significance (Singh and Kumar, 2024; Rahardjo and Fauzi, 2024). This study used a sequential exploratory mixed methods design to empirically assess the influence of sentiment on brand awareness and purchase intention.

Gupta and Sharma (2024) conducted a critical review of 89 mixed-methods research in social media marketing published between 2015 and 2023, concluding that sequential exploratory designs—in which qualitative findings inform quantitative instrument development—provide higher construct validity and theoretical contribution than concurrent triangulation approaches. Their review identifies a persistent gap in studies that use NVivo-based qualitative sentiment analysis before PLS-SEM validation, arguing that this combination allows researchers to capture both the phenomenological richness of consumer sentiment and its structural relationships to behavioral outcomes. The current study directly addresses this stated methodological gap by using the sequential exploratory technique advised by Gupta and Sharma (2024).

3. Hypotheses Development

This investigation suggests that sentiment towards the marketing in social media impacts intention to buy through both cognitive and emotive pathways, utilizing affective response theory and consumer decision-making models. It is anticipated that positive sentiment will increase brand awareness by establishing favorable emotive associations, whereas sentiment intensity is expected to directly impact purchase intention. Brand awareness is suggested as a form of mediation that connects sentiments and intent to purchase. Accordingly, the following Hypotheses are Proposed.

The three sentiment-related dimensions are theoretically supported by well-established psychological and cognitive frameworks. Positive Sentiment (Positivity) is based on Affective Priming Theory (Fazio, 1986), which states that exposure to favorably valenced stimuli immediately activates related cognitive representations, decreasing evaluative thresholds and aiding favorable brand judgments. The Elaboration Likelihood Model (Petty and Cacioppo, 1986) proposes that high-intensity emotional cues act as peripheral processing signals, bypassing sophisticated cognitive evaluation and directly strengthening behavioral intentions such as buying. Brand Awareness, in turn, is conceptualized within Associative Network Memory Theory (Anderson, 1983), which states that repeated emotive exposures strengthen memory nodes associated with a brand, increasing its accessibility and affecting subsequent decision behavior. Together, these complementing theoretical lenses form a strong explanatory framework for the hypothesized routes represented in Figure 1, guaranteeing that each concept is theoretically located rather than empirically produced.

H1: Brand awareness is positively impacted by positive sentiment toward social media marketing.
H2: Consumer purchase intention is positively influenced by sentiment intensity.
H3: Consumer purchase intention is positively influenced by brand awareness.
H4: The relationship between positive sentiment toward social media marketing and purchase intention is mediated by brand awareness.

The figure below depicts the suggested conceptual model connecting positive sentiment towards social media marketing, sentiment intensity, brand awareness, and purchasing intention. Brand awareness is posited as a mediator variable between sentiment-related variables and purchase intention.

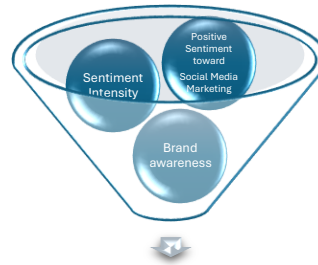


Figure 1 *Conceptual Framework of the Study*

4. Research Methodology

4.1 Research Design

A mixed-methods design that was sequentially exploratory (from qualitative to quantitative) was implemented. The quantitative phase empirically validated the identified relationships, while the qualitative phase investigated consumer sentiment toward social media marketing.

4.2 Qualitative Phase: Sentiment Analysis

Semi-structured interviews were conducted with 32 active Facebook users, ranging in age from 20 to 48 years, to gather primary qualitative data. In order to guarantee that participants were consistently exposed to social media marketing content, purposive sampling was implemented. NVivo qualitative analysis software was implemented to analyze interview transcripts. Responses were classified into four categories: very positive, moderately positive, moderately negative, and very negative, using sentiment coding. The analysis concentrated on the identification of sentiment intensity, frequency, and presence.

To achieve comprehensive qualitative insights across four constructs—Positive Sentiment, Sentiment Intensity, Brand Awareness, and Purchase Intention—an analysis was conducted using Braun and Clarke's (2006)m six-phase thematic framework on NVivo-coded interview transcripts. Thematic inductive analysis revealed recurring themes within each construct domain. For Positive Sentiment, emotional resonance was a dominant theme, illustrated by participant comments reflecting a positive association with brands aligned to their lifestyles. In the domain of Sentiment Intensity, motivational activation emerged, with participants noting that exciting advertisements prompted immediate interest in products. Brand Awareness highlighted heightened recall, as participants repeatedly recognized brands appearing in their feeds. Finally, Purchase Intention showcased instrumental decision-making influenced by positive sentiment, with participants citing good reviews as a motivator for purchasing decisions. The themes and narrative summaries developed for each construct captured the qualitative nuances of participant responses and will guide item development in the following quantitative phase.

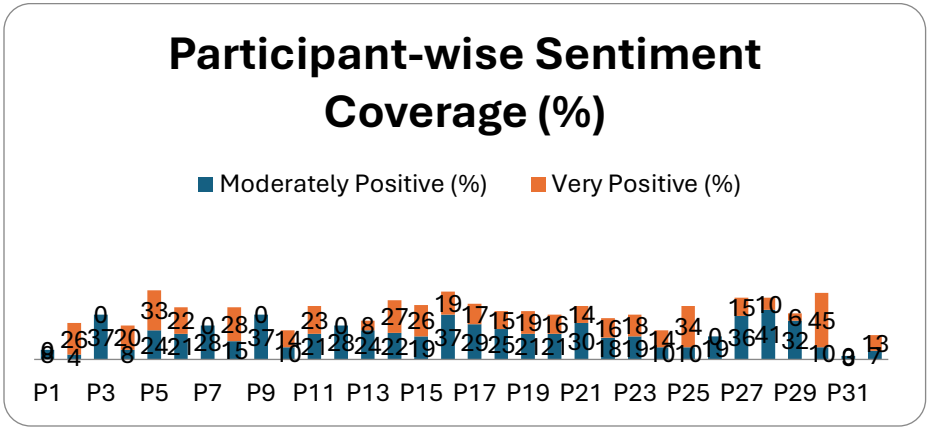


Figure 2 *Participant-wise Sentiment Coverage (%)*
Source: *(Authors own depiction based on responses from participants and analysis done on NVivo Qualitative software).*

Figure 2 demonstrates that sentiment analysis indicates a prevalence of moderately positive and very positive feelings among participants, hence offering qualitative validation for the ensuing quantitative model.

4.3 Quantitative Phase

The qualitative phase provided insights that guided the creation of a structured questionnaire with 16 Likert-scale items. Data were gathered from 286 Facebook members around India. Responses were assessed using a five-point Likert scale, with 1 indicating severe disagreement and 5 indicating strong agreement.

4.4 Data Analysis Technique

Smart PLS 4 was used to do Partial Least Squares Structural Equation Modeling (PLS-SEM). The PLS-SEM method was chosen because it works well for research that focuses on predictions, latent variables, and modest sample numbers. To figure out how important path factors were, bootstrapping with 5,000 resamples was used.

To measure overall model fit, the Standardised Root Mean Square Residual (SRMR) was computed, providing a value of 0.063, which is less than the suggested threshold of 0.08 (Henseler et al., 2015), suggesting satisfactory model fit. Furthermore, the Normed Fit Index (NFI) was investigated and produced a value of 0.912, which above the 0.90 requirement indicated for PLS-SEM applications (Lohmöller, 1989). The RMS theta (RMS_θ) was analyzed to evaluate the disparity between the empirical and model-implied correlation matrices, and returned a value of 0.112, which is acceptable. The suggested structural model's fit statistics, substantial R^2 values, and large path coefficients support its adequacy and explanatory capabilities.

5. Quantitative Results

5.1 Measurement Model Assessment

Cronbach's alpha, composite reliability, and Average Variance Extracted (AVE) were

used to check the reliability and validity. All of the categories were higher than the suggested levels, which proved that the study was internally consistent and convergent. The HTMT measure was used to prove discriminant validity.

Table 1 *Measurement Model Assessment*

Construct	Cronbach's Alpha	Composite Reliability (CR)	AVE
Positive Sentiment	0.86	0.90	0.69
Sentiment Intensity	0.83	0.88	0.65
Brand Awareness	0.88	0.92	0.71
Purchase Intention	0.89	0.93	0.74

The Heterotrait–Monotrait (HTMT) measure was employed to further evaluate discriminant validity.

Table 2 *Discriminant Validity (HTMT Criterion)*

Constructs	PS	SI	BA	PI
Positive Sentiment (PS)	—			
Sentiment Intensity (SI)	0.61	—		
Brand Awareness (BA)	0.58	0.63	—	
Purchase Intention (PI)	0.55	0.60	0.67	—

This confirms the discriminant validity of all HTMT values, which were below recommended threshold of 0.85.

5.2 Structural Model and Hypothesis Testing

The results of the structural model suggest that brand awareness is substantially influenced by positive sentiment ($\beta = 0.43$, $p < 0.001$), which is consistent with H1. H2 is supported by the fact that sentiment intensity has a positive impact on purchase intention ($\beta = 0.28$, $p < 0.001$). Additionally, purchase intention is positively influenced by brand awareness ($\beta = 0.36$, $p < 0.001$), which corroborates H3. The model accounts for 49% of the variance in brand awareness and 63% of the variance in purchase intention.

Table 3 *Structural Model Results and Hypothesis Testing*

Hypothesis	Path	β	t-value	p-value	Result
H1	Positive Sentiment→ Brand Awareness	0.43	7.12	<0.001	Supported
H2	Sentiment Intensity→ Purchase Intention	0.28	4.95	<0.001	Supported
H3	Brand Awareness→ Purchase Intention	0.36	6.18	<0.001	Supported

Figure 3 depicts the final PLS-SEM structural model and the hypothesized correlations between the four constructs. The model has three direct paths: Positive sentiment (H1: $\beta = 0.43$, $p < 0.001$), sentiment intensity (H2: $\beta = 0.28$, $p < 0.001$), and brand awareness (H3: $\beta = 0.36$, $p < 0.001$) all predict purchase intention. Consistent with the theoretical framework, Sentiment Intensity is not posited to directly influence Brand Awareness, nor is Positive Sentiment hypothesized to directly predict Purchase Intention without mediation; these design choices reflect deliberate theoretical parsimony based on the Elaboration Likelihood Model and Associative Network Memory Theory, respectively. The model accounts for 49% of the variation in Brand Awareness ($R^2 = 0.49$) and 63% of the variance in Purchase Intention ($R^2 = 0.63$), suggesting strong explanatory power.



Figure 3 *Structural Model Results (PLS-SEM)*

5.3 Mediation Analysis

Mediation analysis indicated a substantial indirect effect of positive attitude on purchase intention via brand awareness ($\beta = 0.15$, $p < 0.001$). The persistence of the large direct impact indicated some mediation, hence corroborating H4.

Mediation analysis was used to investigate if brand awareness mediates the association between positive favorable sentiment and intent to purchase.

Table 4 *Mediation Analysis Results*

Relationship	Direct Effect	Indirect Effect	Total Effect	Mediation Type
Positive Sentiment → Purchase Intention (via Brand Awareness)	0.24	0.15	0.39	Partial

The findings suggest a substantial indirect impact, while the direct effect remains substantial, thereby confirming partial mediation and supporting H4.

6. Discussion

The findings of this study show that consumer sentiment has a substantial effect on the efficacy of social media marketing. Positive emotion toward social media marketing material raises brand recognition significantly, which leads to higher purchase intention. This conclusion is consistent with previous research, which has shown that positive sentiment valence acts as a cognitive and emotional driver of brand-related outcomes in digital settings, using the processes indicated by emotional Priming Theory and Associative Network Memory Theory. Positive Sentiment and Sentiment Intensity played distinct but complementary roles: Positive Sentiment

increased Brand Awareness via positive associative encoding, whereas Sentiment Intensity had a direct peripheral-route influence on Purchase Intention, consistent with the Elaboration Likelihood Model.

It is critical to underline that the findings highlight sentiment's dual function as both a direct emotive stimulus and an indirect cognitive process mediated by brand awareness. Although sentiment intensity has a direct impact on purchase intention, brand awareness somewhat buffers this link, indicating that emotional reactions help to establish positive branding-related knowledge frameworks that influence decision-making. This study highlights the importance of mixed-methods techniques in social media marketing research and improves understanding of sentiment-driven customer behavior by integrating qualitative sentiment results with quantitative substantiation using PLS-SEM.

7. Implications

7.1 Managerial Implications

The results of this study indicate that marketers should prioritize the development of social media marketing content that elicits favorable consumer sentiment and positive emotional responses. Organizations should actively monitor and analyze consumer sentiment on social media platforms to evaluate the emotive efficacy of their campaigns, as sentiment intensity was discovered to directly influence purchase intention. Marketers can optimize their content strategies, improve brand communication, and convert positive emotional engagement into more robust purchase intentions by employing sentiment analysis tools. The results also suggest that the promotion of brand awareness through emotionally resonant content can be a successful approach to enhancing marketing outcomes in digital environments.

7.2 Theoretical Consequences

This study contributes to the internet marketing and consumer behavior literature by illustrating the benefits of combining quantitative structural modeling with qualitative sentiment analysis from a theoretical perspective. The research has extended the existing theories of emotional decision-making to social media contexts by empirically establishing awareness of brands as a means of mediation between customer sentiment and intent to buy. The results emphasize the dual affective and cognitive function of sentiment, thereby enhancing the theoretical knowledge of the way cognitive responses formed through social media marketing are translated into customer behavior changes.

8. Conclusion

In order to investigate the importance of consumer sentiment in social media marketing, this study implemented a sequential exploratory mixed-methods approach that combines quantitative structural modeling with qualitative sentiment analysis. The study provides robust empirical evidence that positive sentiment toward social media marketing considerably enhances brand awareness, which in turn increases consumers' purchase intention, by combining NVivo-based sentiment analysis with PLS-SEM.

The findings underscore the dual function of sentiment as both an emotive and cognitive impetus for consumer behavior in digital marketing contexts. In particular, the partial mediating effect of brand awareness illustrates that sentiment not only directly influences purchase intention but also operates through consumers' mental representations of brands. The study makes a methodological contribution to the internet marketing and advertising literature by illustrating the utility of mixed-methods research in documenting the complexity of sentiment-driven consumer responses on social media platforms.

The results emphasize the necessity for marketers to actively monitor and manage consumer sentiment on social media from a practical perspective, as positive emotive engagement can enhance brand awareness and improve conversion outcomes. In summary, the research supports the strategic importance of sentiment analysis in social media marketing and promotes the expansion of this methodology to encompass a variety of platforms, cultural contexts, and longitudinal settings in future research.

9. Declaration

All authors declare that they have no conflicts of interest.

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