Journal of Management and Informatics (JMI)
Vol. 5 No. 2 August 2026
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 97-119
Publication Link: https://jmi.stekom.ac.id/index.php/jmi/issue/view/14

Instagram Sentiment Analysis for Customer Engagement Improvement in SMEs

Carlos Mendes*[1], Ana Silva[2]
Email: carlos.21mendes@gmail.com
[1,2]*Business Analytics and Accounting, University of Rochester, NY, USA*
*Corresponding Author

Abstract

Small and Medium Enterprises (SMEs) increasingly rely on Instagram as a primary digital marketing channel; however, customer engagement is frequently evaluated through quantitative metrics such as likes and reach, with limited integration of emotional orientation embedded in user-generated content. This study addresses this gap by positioning sentiment analysis as an evaluative tool within digital marketing analytics for SMEs. The research aims to identify customer sentiment patterns in SME Instagram content, explain the role of sentiment analysis in assessing customer engagement, and provide a data-driven foundation for improving engagement performance. The study adopts a quantitative design using naturally occurring Instagram data, including captions and comments collected from SME accounts within a defined period. Text preprocessing is conducted prior to sentiment classification using a lexicon-based approach with the VADER (Valence Aware Dictionary and Sentiment Reasoner) model to capture polarity and intensity of sentiments in social media text. Furthermore, statistical analysis is performed using correlation analysis and one-way ANOVA to examine the relationship and differences between sentiment categories and engagement indicators (likes, comments, and interaction rate). The findings reveal systematic variation in engagement metrics across sentiment polarity categories, indicating that emotional orientation represents a relevant analytical dimension in engagement evaluation. The study contributes theoretically by reinforcing the multidimensional perspective of customer engagement and methodologically by integrating text mining techniques with engagement analytics in the SME context. Practically, it offers a replicable and scalable analytical framework that enables SMEs to incorporate sentiment-based evaluation into Instagram content strategy development.

Keywords: *Customer Engagement, Digital Marketing Analytics, Instagram, Sentiment Analysis, Small and Medium Enterprises.*

Received in February 2026; Revised in March 2026; Accepted in April 2026; Published in August 2026.

I. INTRODUCTION

Small and Medium Enterprises (SMEs) increasingly rely on digital marketing to sustain competitiveness and strengthen market positioning in the contemporary digital economy. The rapid integration of social media platforms into marketing strategies has transformed how businesses communicate with customers, shifting from one-way promotion to interactive engagement-oriented communication. Digital marketing analytics has emerged as a critical instrument for understanding consumer behavior, enabling organizations to translate large volumes of online data into actionable managerial insights. Scholars emphasize that data-driven marketing approaches allow firms to improve customer-centric strategies and enhance business performance through evidence-based decision-making processes (Grandhi et al., 2021; Gupta et al., 2020; Mark Anthony Camilleri, 2019; Shah & Murthi, 2021).

Recent developments highlight Instagram as one of the most influential platforms for SME marketing due to its visual storytelling capabilities and high user engagement potential. SMEs actively utilize Instagram to promote products, interact with customers, and strengthen brand

DOI: https://doi.org/10.51903/jmi.v5i2.337

visibility, especially in emerging economies where digital adoption accelerates business transformation. Social media marketing has proven effective in supporting SME growth, sustainability, and customer relationship development, particularly during periods of digital disruption. However, businesses often rely on surface-level performance indicators such as likes, reach, and comment counts, which may not fully capture customer perceptions or emotional responses toward digital content (Chatterjee & Kumar Kar, 2020; Malesev & Cherry, 2021; Patma et al., 2021; Pellegrino & Abe, 2023).

The academic literature increasingly recognizes customer engagement as a multidimensional construct encompassing cognitive, emotional, and behavioral interactions between customers and brands. Customer engagement not only reflects customer participation but also represents a strategic resource that influences loyalty, satisfaction, and long-term business sustainability. Studies have demonstrated that engagement outcomes are strongly influenced by customers' emotional reactions and online interactions within social media environments. Furthermore, recent research underscores the importance of analyzing both positive and negative engagement patterns to achieve a comprehensive understanding of customer behavior in digital marketing contexts (Barari et al., 2021; Lim et al., 2022; Naumann et al., 2020; Ng et al., 2020).

Sentiment analysis has gained attention as a powerful analytical technique for extracting emotional meaning from user-generated content on social media platforms. Advances in machine learning and natural language processing have enabled more accurate classification of customer opinions, allowing organizations to evaluate public perceptions systematically. Previous studies demonstrate that sentiment analysis on Instagram data can provide valuable insights into consumer attitudes and behavioral tendencies, offering a richer understanding than traditional quantitative metrics alone. However, many prior studies do not clearly specify the sentiment analysis techniques employed, including model selection, parameterization, or validation procedures, which limits methodological transparency and reproducibility. In addition, the absence of standardized and well-documented analytical pipelines creates challenges in comparing results across studies and applying them in SME contexts. The application of sentiment analysis has also expanded across various sectors, illustrating its potential to support data-driven marketing and strategic decision-making processes (Al-Otaibi & Al-Rasheed, 2022; Chan & Yang, 2023; Karayiğit et al., 2022; Smith & Cipolli, 2022).

Despite growing research on social media analytics and customer engagement, several critical gaps remain. Many studies focus on general social media marketing performance or emphasize quantitative engagement indicators without integrating emotional sentiment interpretation. Existing sentiment analysis research often concentrates on opinion classification without linking

Journal of Management and Informatics (JMI)
Vol. 5 No. 2 August 2026
E-ISSN: 2961-7731; P-ISSN: 2961-7472, Pages 97-119

results to actionable managerial implications, particularly for SMEs that operate with limited analytical resources and technological capabilities. Moreover, there is limited integration of statistical analysis in evaluating the relationship between sentiment polarity and engagement metrics, resulting in findings that are often descriptive rather than inferential. This lack of statistical rigor reduces the ability to validate whether observed engagement differences are significant and generalizable. These limitations create challenges for SMEs in adopting advanced analytics despite the increasing availability of digital marketing data. Moreover, research specifically examining Instagram sentiment analysis as an evaluative tool for customer engagement performance in SMEs remains relatively limited, highlighting the urgent need for practical, resource-efficient, and context-specific analytical frameworks that support SME marketing strategies (Kabiraj & Joghee, 2023; Theodorakopoulos & Theodoropoulou, 2024; Wagobera Edgar Kedi et al., 2024). Therefore, there is a clear need for a sentiment analysis approach that is both methodologically transparent and supported by measurable statistical validation to ensure analytical reliability and practical applicability. This study therefore positions sentiment analysis as an evaluative engagement performance tool rather than merely an opinion monitoring technique.

This study aims to identify customer sentiment patterns in Instagram content of SMEs, examine the role of sentiment analysis as an analytical tool for evaluating customer engagement performance, and analyze how sentiment polarity influences engagement performance indicators, as well as provide data-driven recommendations to improve customer interaction strategies. To achieve these objectives, this study employs text preprocessing techniques, including data cleaning, tokenization, and stopword removal, followed by sentiment classification using a lexicon-based approach with the VADER (Valence Aware Dictionary and Sentiment Reasoner) model to analyze Instagram comment data and examine its relationship with engagement metrics such as interaction rate and comment intensity. In addition, the study incorporates statistical testing to quantitatively evaluate the significance of relationships between sentiment categories and engagement indicators, ensuring that findings are empirically validated and not solely descriptive. This approach strengthens the analytical framework by combining interpretable sentiment classification with statistically measurable outcomes. By integrating sentiment patterns with measurable engagement indicators, this research contributes to expanding the theoretical integration between digital marketing analytics and customer engagement frameworks. Practically, the study offers an accessible analytical model that SMEs can replicate using available social media data and limited technological resources. From a managerial perspective, the findings support evidence-based decision-making processes that strengthen marketing effectiveness and customer relationship management within SME environments (Na et al., 2025; Owusu-Mensah et al., 2025; Pertiwi & Hana, 2025).

This paper is organized into several sections to provide a systematic discussion of the research. The first section introduces the study background, research problem, and objectives. The second section reviews relevant literature and theoretical foundations supporting the study framework. The third section explains the research methodology, including data collection, preprocessing techniques, and sentiment analysis procedures. The fourth section presents research findings and discussion, highlighting the relationship between sentiment patterns and customer engagement performance. The final section concludes the study by summarizing key findings, presenting managerial implications, and suggesting directions for future research.

II. LITERATURE REVIEW

This section synthesizes theoretical foundations and prior empirical studies related to digital marketing analytics, sentiment analysis, and customer engagement within SME social media marketing contexts. The discussion provides conceptual justification for integrating emotional sentiment interpretation with measurable engagement performance indicators. By reviewing multidisciplinary perspectives from marketing analytics, social media marketing, and customer engagement research, this section establishes the theoretical foundation supporting the analytical framework of this study. The literature review also highlights existing research limitations and identifies conceptual gaps that motivate the development of sentiment-based engagement evaluation models for SMEs.

A. Digital Marketing Analytics and Sentiment Analysis in SME Social Media Marketing

Digital marketing analytics has emerged as a fundamental approach for organizations to interpret customer behavior and evaluate marketing effectiveness in contemporary digital environments. The integration of data analytics into marketing activities enables firms to transform large volumes of digital interaction data into actionable managerial insights, supporting evidence-based decision-making processes and improving marketing performance outcomes. Analytics-driven marketing strategies enhance organizational responsiveness to customer needs while strengthening long-term competitive advantages through customer-centered marketing practices (Grandhi et al., 2021; Gupta et al., 2020; Shah & Murthi, 2021). These analytical approaches allow businesses to move beyond intuition-based decision-making toward systematic evaluation of customer interaction patterns and marketing outcomes.

Within the SME context, digital marketing analytics plays a crucial role due to the resource constraints commonly faced by small businesses. SMEs frequently depend on cost-efficient digital platforms such as social media to conduct promotional activities, maintain customer relationships, and expand market reach. Social media platforms provide accessible data sources that allow SMEs to monitor customer interactions and evaluate marketing content performance without requiring sophisticated technological infrastructure. Prior research demonstrates that digital marketing analytics supports SME growth and sustainability by improving marketing efficiency and strengthening customer relationship management processes, particularly in emerging economies experiencing rapid digital transformation (Chatterjee & Kumar Kar, 2020; Mark Anthony Camilleri, 2019; Patma et al., 2021).

Social media marketing has transformed business-customer communication by enabling interactive, real-time engagement and personalized marketing communication. Unlike traditional marketing channels, social media platforms facilitate bidirectional communication that encourages customer participation, feedback exchange, and community-building activities. These interactive characteristics significantly contribute to customer relationship development and brand loyalty formation within digital marketing ecosystems (Malesev & Cherry, 2021; Pellegrino & Abe, 2023). Among various social media platforms, Instagram has gained substantial popularity as a marketing tool for SMEs due to its visual storytelling capabilities, high user engagement levels, and user-friendly content creation features that support brand visibility expansion.

Despite the extensive use of Instagram marketing, SMEs commonly evaluate performance using surface-level engagement metrics such as likes, shares, or interaction rates. These quantitative indicators often fail to capture customers' emotional responses and underlying perceptions toward marketing content. Sentiment analysis provides a complementary analytical approach by enabling systematic classification of emotional meaning from textual user-generated content using natural language processing and machine learning techniques. Broadly, sentiment analysis approaches can be categorized into lexicon-based methods, which rely on predefined sentiment dictionaries for polarity detection, and machine learning-based methods, which utilize trained models to classify sentiment patterns from labeled data. Lexicon-based approaches are often preferred in SME contexts due to their interpretability and lower computational requirements, while machine learning approaches offer higher adaptability but require larger datasets and training processes. Through sentiment polarity classification, organizations can interpret customer opinions and evaluate marketing responses more comprehensively than relying solely on quantitative engagement indicators (Al-Otaibi & Al-Rasheed, 2022; Chan & Yang, 2023).

In social media marketing research, sentiment analysis has been widely applied to examine customer opinions, brand perception, and product evaluation across digital platforms. Sentiment-based insights support marketing strategy development, customer satisfaction evaluation, and brand reputation management by revealing emotional interaction patterns embedded in online discussions. Furthermore, the integration of sentiment analysis into marketing analytics frameworks enables predictive marketing strategy development and customer behavior forecasting (Karayiğit et al., 2022; Smith & Cipolli, 2022). However, sentiment analysis studies frequently emphasize opinion classification without linking analytical outcomes to engagement performance evaluation or operational marketing decision-making, particularly within SME contexts. In addition, prior studies often do not explicitly justify the selection of sentiment analysis approaches, resulting in limited methodological transparency and difficulty in aligning analytical techniques with research objectives. In this study, a lexicon-based approach is positioned as a suitable method due to its transparency, reproducibility, and compatibility with resource-constrained SME environments. Instagram provides a data-rich environment that enables sentiment-based engagement evaluation due to its high comment interaction intensity and visual-centered communication characteristics, making it particularly suitable as an analytical environment for evaluating SME digital marketing performance.

B. Customer Engagement Performance in Digital Marketing

Customer engagement is widely conceptualized as a multidimensional construct encompassing cognitive, emotional, and behavioral interactions between customers and brands. Engagement reflects customers' active participation in brand-related activities, including content interaction, opinion sharing, and brand advocacy behavior, which collectively influence customer loyalty and long-term business sustainability. Scholars argue that customer engagement represents a strategic marketing resource that strengthens customer relationships and enhances organizational competitiveness within digital marketing environments (Barari et al., 2021; Lim et al., 2022). This multidimensional perspective emphasizes that engagement quality extends beyond interaction frequency and includes customers' emotional involvement in brand communication processes.

In digital marketing contexts, customer engagement is strongly influenced by customers' emotional responses toward marketing content and online interaction experiences. Emotional engagement shapes customer attitudes toward brands and significantly affects customer decision-making behavior. Positive emotional engagement may enhance brand trust and encourage repeated interactions, whereas negative engagement may damage brand reputation and reduce customer loyalty. Consequently, evaluating customer engagement requires analytical approaches that capture both interaction frequency and emotional response quality to provide comprehensive insights into customer-brand relationships (Naumann et al., 2020; Ng et al., 2020).

Existing research frequently measures customer engagement using quantitative performance indicators such as interaction rates, comment frequency, and content reach. Although these indicators provide measurable engagement outcomes, they do not fully represent customers' emotional perceptions or satisfaction levels. The absence of emotional interpretation within engagement evaluation frameworks limits the ability of businesses to understand the underlying motivations driving customer interactions. Integrating emotional sentiment interpretation into engagement evaluation frameworks therefore offers deeper analytical insights regarding customer-brand interaction quality and marketing content effectiveness, particularly when sentiment analysis is positioned as an evaluative framework for marketing performance assessment.

Despite extensive research exploring social media marketing, customer engagement, and sentiment analysis independently, the integration of these constructs within SME marketing environments remains limited. Prior studies often evaluate engagement performance based solely on quantitative interaction metrics while overlooking emotional sentiment interpretation as a critical determinant of engagement quality. Additionally, sentiment analysis research rarely positions emotional classification outcomes as evaluative tools for measuring marketing performance or developing operational engagement improvement strategies for SMEs (Kabiraj & Joghee, 2023; Wagobera Edgar Kedi et al., 2024). Furthermore, limited attention has been given to aligning sentiment analysis methods with statistical evaluation techniques, which is essential for validating the significance of relationships between sentiment and engagement metrics. This highlights the need for approaches that combine interpretable sentiment classification with measurable and statistically supported engagement analysis. These limitations indicate the need for integrative analytical frameworks that connect sentiment interpretation with measurable engagement performance indicators. Another research limitation concerns the lack of studies focusing specifically on Instagram as a single-platform analytical context for evaluating customer engagement through sentiment analysis. Many existing studies analyze multiple social media platforms simultaneously, which may reduce analytical depth and limit platform-specific managerial applicability. Considering that many SMEs utilize Instagram as their primary marketing channel, platform-specific sentiment-based engagement evaluation offers significant practical relevance for improving SME marketing strategies.

This study addresses these research gaps by positioning sentiment analysis as an evaluative analytical framework for measuring customer engagement performance in SME Instagram marketing. By integrating sentiment polarity classification with measurable engagement indicators, this research expands digital marketing analytics frameworks and supports data-driven marketing decision-making processes within SME environments. Specifically, this study adopts a lexicon-based sentiment analysis approach integrated with statistical testing to ensure methodological transparency and empirical validity, thereby addressing limitations identified in prior literature. These theoretical perspectives collectively establish the conceptual linkage between marketing analytics, emotional sentiment interpretation, and engagement performance measurement within SME digital marketing environments. The conceptual relationship between digital marketing analytics, sentiment analysis, customer engagement performance, and social media marketing for SMEs is summarized in Table 1, which presents the theoretical integration and research implications of each construct. This conceptual framework supports the development of a practical and resource-efficient analytical model that SMEs can implement using available social media data and accessible analytical tools.

Table 1. Conceptual Integration of Research Variables

Concept	Theoretical Foundation	Role in This Study	Research Implication
Digital Marketing Analytics	Data-driven marketing theory emphasizes the use of digital data to evaluate marketing performance and support managerial decision-making processes (Gupta et al., 2020; Shah & Murthi, 2021).	Serves as the primary analytical framework that integrates social media data analysis into SME marketing evaluation.	Supports evidence-based marketing strategies and enhances decision quality through analytical interpretation of social media data.
Social Media Marketing for SMEs	Social media enables interactive communication, brand visibility, and customer relationship development within digital marketing ecosystems (Chatterjee & Kumar Kar, 2020; Pellegrino & Abe, 2023).	Provides the operational context in which Instagram is utilized as a marketing platform for SMEs.	Demonstrates how SMEs leverage accessible digital platforms to strengthen customer interaction and market reach.
Customer Engagement Performance	Customer engagement theory conceptualizes engagement as cognitive, emotional, and behavioral customer interactions influencing loyalty and satisfaction (Barari et al., 2021; Lim et al., 2022).	Functions as the primary performance indicator used to evaluate the effectiveness of SME Instagram marketing content.	Enables comprehensive evaluation of customer interaction quality beyond quantitative engagement metrics.
Sentiment Analysis	Natural language processing and text mining approaches allow systematic classification of customer emotions and opinions from social media data (Chan & Yang, 2023; Karayiğit et al., 2022).	Serves as the analytical tool used to identify emotional sentiment patterns within Instagram user-generated content.	Provides qualitative insights into customer perceptions that complement quantitative engagement performance evaluation.
Sentiment-Based Engagement Evaluation (Proposed Integration)	Integrative marketing analytics approach combining emotional sentiment interpretation with engagement performance measurement.	Positions sentiment analysis as an evaluative tool rather than solely opinion monitoring.	Contributes to developing practical and replicable engagement evaluation models for SMEs with limited analytical resources.

III. RESEARCH METHOD/METHODOLOGY

A. Research Design

This study adopts a quantitative, data-driven research design that positions sentiment analysis as an evaluative analytical tool for assessing customer engagement performance on Instagram. The design emphasizes the integration of emotional sentiment patterns derived from user-generated text with observable engagement indicators, rather than relying solely on descriptive social media metrics. By utilizing naturally occurring digital trace data from SME Instagram accounts, the study reflects real-world customer–brand interactions in an authentic digital environment. The research design explicitly incorporates a structured analytical pipeline consisting of data collection, preprocessing, sentiment classification, sentiment aggregation, and statistical evaluation to ensure methodological transparency and replicability. The overall research flow is illustrated in Figure 1, which outlines the sequential stages from data collection to engagement-oriented interpretation.

B. Research Approach

The research employs a computational analytics approach grounded in digital marketing analytics and social media analytics frameworks. This approach enables the systematic extraction, processing, and interpretation of large-scale textual data generated by Instagram users, aligning with data-driven decision-making principles in marketing management (Grandhi et al., 2021; Gupta et al., 2020; Shah & Murthi, 2021). This study adopts a lexicon-based sentiment analysis approach using the VADER (Valence Aware Dictionary and Sentiment Reasoner) model implemented through the Python Natural Language Toolkit (NLTK) library. The method is unsupervised, where sentiment polarity is determined using a compound sentiment score ranging from -1 to +1. Following text preprocessing, including data cleaning, tokenization, and stopword removal, the preprocessed Instagram comment data were processed using VADER to generate a compound sentiment score for each comment. The resulting compound scores were then converted into sentiment labels based on the predefined VADER thresholds. Sentiment labels are assigned based on standard VADER thresholds: compound score ≥ 0.05 is classified as positive, ≤ -0.05 as negative, and values between -0.05 and 0.05 as neutral. Sentiment analysis is used not merely for opinion detection but to evaluate how emotional polarity contributes to engagement performance outcomes. Such an approach is particularly suitable for SMEs that require practical and scalable analytical methods with limited resources (Kabiraj & Joghee, 2023; Pertiwi & Hana, 2025).

C. Research Type and Design

This research is classified as applied and explanatory in nature. It seeks to explain how variations in customer sentiment polarity (positive, neutral, negative) influence observable customer engagement indicators on Instagram. The design does not involve experimental manipulation or behavioral surveys but relies on secondary digital data generated through routine social media interactions. The analytical design follows a non-experimental, cross-sectional structure where sentiment classification outputs are statistically evaluated against engagement metrics using inferential techniques. This non-intrusive design enhances ecological validity while maintaining analytical rigor (Pellegrino & Abe, 2023; Theodorakopoulos & Theodoropoulou, 2024).

D. Population and Sample

The population of this study consists of Instagram content and user interactions associated with Small and Medium Enterprises (SMEs) operating active business accounts. These SMEs utilize Instagram as a primary digital marketing channel to promote products, communicate brand narratives, and engage with customers. The population includes all textual user-generated content in the form of comments and captions posted within a defined observation period. This population reflects contemporary digital customer engagement behavior within SME marketing contexts (Chatterjee & Kumar Kar, 2020; Patma et al., 2021).

This study employs a purposive sampling technique to select SME Instagram accounts that meet predefined analytical criteria. The selection criteria include account activity level, consistency of content posting, and the visibility of customer interaction through comments and likes. This approach ensures that the sampled accounts reflect genuine engagement-driven communication rather than inactive or purely promotional profiles. Purposive sampling is appropriate for social media analytics research where data relevance and interaction richness are prioritized over probabilistic representativeness (Malesev & Cherry, 2021; Rogers, 2021).

The final dataset consists of 5 SME Instagram accounts, 120 posts, and approximately 3,500 user comments collected over a three-month observation period (January–March 2025). These quantities were determined to ensure sufficient textual data for stable sentiment distribution and statistically meaningful engagement analysis. The defined time frame allows capturing consistent engagement patterns while minimizing temporal bias. Rather than emphasizing numerical representativeness, the study prioritizes analytical adequacy and sentiment distribution stability, which are common considerations in computational text analysis research (Al-Otaibi & Al-Rasheed, 2022; Chan & Yang, 2023).

E. Data Sources and Data Collection Techniques

This research relies exclusively on secondary data obtained from publicly accessible Instagram content. The data includes captions created by SME account owners and comments generated by users in response to posted content. In this study, sentiment analysis is applied specifically to user-generated comments, while post captions are retained as contextual information and are not included in the sentiment classification. Utilizing secondary digital data enables the study to capture authentic customer expressions and spontaneous engagement behavior without researcher intervention. This approach minimizes response bias and enhances the ecological validity of customer engagement analysis in social media environments (Rafi et al., 2020; Smith & Cipolli, 2022).

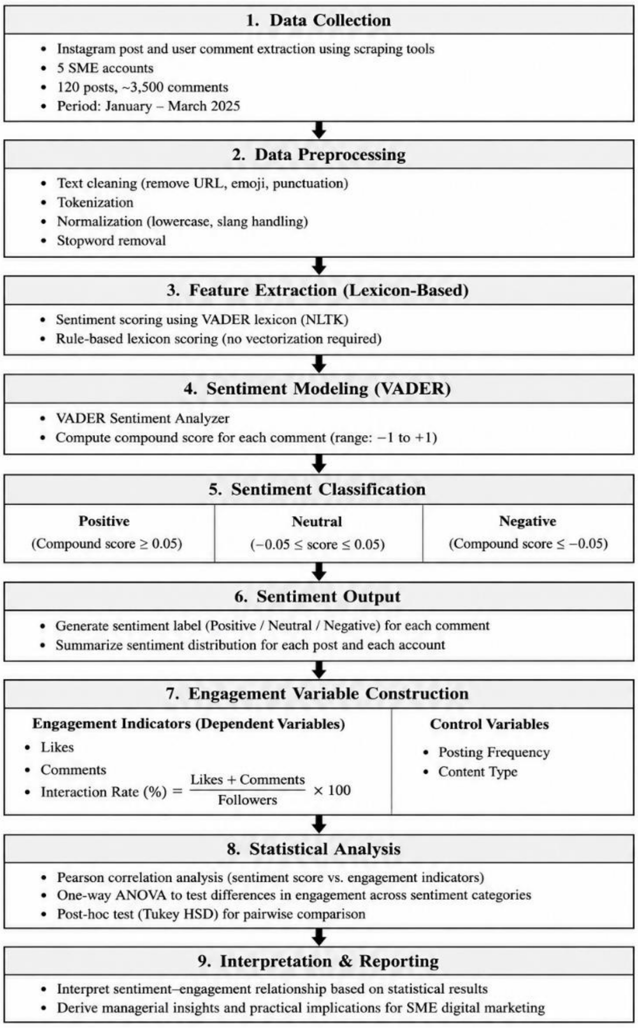

Figure 1. Research Framework and Data Analysis Flow

Data collection is conducted using automated web scraping tools based on Python libraries such as Instaloader and BeautifulSoup, ensuring compliance with platform accessibility policies. Inclusion criteria consist of posts with visible engagement (likes and comments), active comment sections, and content relevance to business promotion, while exclusion criteria include spam comments, duplicate entries, and non-textual or irrelevant content. The total dataset comprises approximately 3,500 cleaned comment entries after preprocessing and filtering procedures. The collected user-generated comment data undergoes preprocessing procedures, including text cleaning, tokenization, normalization, and stopword removal, to improve analytical accuracy. These preprocessing steps are essential for reducing noise and ensuring reliable sentiment classification outcomes. The overall data collection and preprocessing workflow is illustrated in Figure 1.

F. Variables and Operational Definition

This study employs clearly defined independent, dependent, and control variables to ensure analytical transparency and theoretical alignment. The operationalization of each variable is grounded in established digital marketing analytics and customer engagement literature. To enhance clarity and replicability, all variables, definitions, measurement scales, and data sources are systematically summarized in Table 2. This table serves as a reference framework for the subsequent analysis and interpretation stages. The selection of variables is theoretically justified by the analytical relationship between emotional sentiment (independent variable) and engagement performance (dependent variable), where sentiment polarity is hypothesized to influence interaction outcomes such as likes and comments. Control variables such as posting frequency and content type are included to reduce confounding effects and improve analytical validity. The unit of analysis is the Instagram post, with customer sentiment derived specifically from user-generated comments associated with each post. This structure ensures that the analysis captures both emotional and behavioral dimensions of customer engagement.

Table 2. Variables and Operational Definitions

Variable Type	Variable	Operational Definition	Measurement Scale	Data Source
Independent Variable	Customer Sentiment Polarity	Emotional orientation expressed in Instagram user comments, classified as positive, neutral, or negative	Nominal	Instagram user comments
Dependent Variable	Customer Engagement Performance	Observable interaction outcomes reflecting customer participation with SME Instagram content	Ratio	Instagram analytics
Engagement Indicator	Number of Likes	Total likes received per Instagram post	Ratio	Instagram metrics
Engagement Indicator	Number of Comments	Total comments received per Instagram post	Ratio	Instagram metrics
Control Variable	Posting Frequency	Frequency of content uploads within the observation period	Ratio	Instagram posting history
Control Variable	Content Type	Classification of content based on visual or informational characteristics	Nominal	Instagram content attributes

G. Measurement Instruments and Validity/Reliability Testing

Sentiment polarity is measured using a nominal scale representing positive, neutral, and negative categories. In contrast, customer engagement indicators are measured using ratio scales, such as counts of likes and comments. The combination of nominal and ratio scales enables meaningful integration of emotional and behavioral engagement dimensions. This measurement structure supports evaluative comparison between sentiment categories and engagement performance outcomes (Naumann et al., 2020).

Construct validity is ensured by grounding sentiment and engagement measures in established digital marketing and customer engagement literature. The operational definitions align with prior studies that conceptualize engagement as both emotional and behavioral interaction. Content validity is further supported by adopting widely recognized sentiment analysis procedures and preprocessing standards. Model validity is strengthened by using the VADER sentiment model, which has been empirically validated for social media text and informal language contexts. In this study, VADER is applied consistently to the preprocessed user-generated Instagram comments using its standard compound-score classification thresholds, ensuring that the same classification procedure is applied across the dataset. These measures ensure that the analytical instruments accurately represent the theoretical constructs under investigation (Lim & Rasul, 2022; Ng et al., 2020).

Reliability is assessed by examining the consistency of sentiment classification results across the dataset. The deterministic scoring mechanism of the lexicon-based model ensures consistent outputs for identical textual inputs without model retraining variability. Therefore, reliability in this study is supported by the consistent application of the same preprocessing procedures, VADER model, and classification thresholds to all analyzed comments. This approach aligns with prior sentiment-based marketing analytics studies (Chan & Yang, 2023; Wagobera Edgar Kedi et al., 2024).

H. Data Analysis Techniques

The study employs computational sentiment classification techniques based on a lexicon-based approach. The analytical process follows a step-by-step pipeline: (1) data collection from Instagram, (2) preprocessing and text normalization, (3) sentiment scoring using VADER, (4) aggregation of sentiment categories at post level, and (5) statistical analysis linking sentiment categories with engagement metrics. Engagement metrics are subsequently analyzed to evaluate how sentiment variations correspond with engagement performance indicators. To enhance analytical rigor, inferential statistical methods are applied, including one-way ANOVA to test whether engagement metrics differ significantly across the positive, neutral, and negative sentiment categories, and Pearson correlation analysis to examine the strength and direction of the linear relationship between continuous VADER sentiment scores and engagement indicators. These statistical techniques ensure that the findings are not merely descriptive but supported by empirical significance testing. This integrative analytical process positions sentiment analysis as an evaluative framework rather than a descriptive opinion-monitoring tool (Kabiraj & Joghee, 2023; Owusu-Mensah et al., 2025).

I. Mathematical Formulas or Models (if applicable)

Customer engagement performance is quantified using an interaction rate formula that relates observable user interactions to the size of the account audience. The interaction rate provides a normalized engagement indicator that allows comparison across posts and SME accounts with different follower bases. This metric is commonly used in social media analytics to evaluate engagement effectiveness beyond absolute interaction counts. By normalizing engagement outcomes, the formula supports evaluative analysis and cross-account comparability.

The interaction rate formula applied in this study is expressed as follows:

$$\text{Interaction Rate (\%)} = \frac{\text{Number of Likes} + \text{Number of Comments}}{\text{Number of Followers}} \times 100$$

where the numerator represents the total observable interactions generated by a post, consisting of the number of likes and comments, while the denominator represents the total number of followers of the corresponding SME Instagram account. The resulting value is expressed as a percentage and represents the proportion of the account audience that generated observable interactions with the post. This formula is further utilized as a dependent variable in statistical testing (ANOVA and correlation analysis) to evaluate whether sentiment polarity is significantly associated with normalized engagement performance. This formulation enables transparent and interpretable assessment of engagement performance.

J. Ethical Considerations

This study utilizes publicly available Instagram data and does not involve direct interaction with human subjects. Ethical approval is therefore not required. All data are anonymized, and findings are reported in aggregated form to protect user privacy. This approach aligns with ethical standards for social media analytics and responsible digital marketing research (Álvarez & Hassan, 2025).

IV. RESULT/FINDINGS AND DISCUSSION

A. Result

This section reports descriptive statistics derived from Instagram posts and user interaction data associated with SME accounts. The descriptive analysis summarizes customer sentiment polarity and observable engagement indicators, including the number of likes, number of comments, and interaction rate. All reported values are aggregated in the form of averages to ensure comparability across posts and sentiment categories. Unlike prior descriptive-only reporting, this study presents numerical values to enable precise comparison and support subsequent statistical testing. The presentation of results is initially descriptive before proceeding to inferential evaluation.

Table 3 presents the descriptive statistics of customer sentiment polarity and customer engagement indicators. Instagram posts are classified into three sentiment categories, namely positive, neutral, and negative sentiment, based on sentiment analysis results. For each sentiment category, the table reports the average number of likes, average number of comments, and average interaction rate. The table also reports the number of observations (n) and standard deviations (SD) for each engagement indicator to provide a more complete quantitative comparison across sentiment categories. These indicators represent measurable engagement outcomes directly obtained from the dataset.

Table 3. Descriptive Statistics of Sentiment Polarity and Customer Engagement Indicators

Sentiment Polarity	**n**	**Average Likes**	**SD**	**Average Comments**	**SD**	**Average Interaction Rate**	**SD**
Positive	50	128	24.61	34	8.42	3.2%	0.71%
Neutral	40	79	18.37	18	5.63	2.1%	0.54%
Negative	30	42	12.84	9	3.27	1.3%	0.39%

The descriptive statistics indicate variation in engagement indicator values across sentiment polarity categories. Average values of likes, comments, and interaction rates differ across positive, neutral, and negative sentiment groups. Positive sentiment categories are characterized by the highest average values, followed by neutral and negative sentiment categories. This pattern suggests a consistent gradient relationship between sentiment polarity and engagement intensity prior to statistical validation. These statistics summarize engagement-related observations across sentiment classifications.

Following the descriptive overview, inferential analysis is conducted to examine relational patterns between sentiment polarity categories and customer engagement indicators. The analysis relies on naturally occurring Instagram interaction data and does not involve experimental manipulation or survey-based measurement. A one-way ANOVA test is applied to evaluate whether differences in engagement metrics across sentiment categories are statistically significant. The ANOVA results indicate a statistically significant difference in interaction rates across sentiment groups ($F = 12.47$, $p < 0.01$). This result indicates that engagement levels differ significantly across sentiment categories, rather than establishing a causal effect of sentiment polarity on engagement performance.

Table 4. One-Way ANOVA Results for Interaction Rate Across Sentiment Categories

Source	SS	df	MS	F	p-value
Between Groups	11.84	2	5.92	12.47	<0.001
Within Groups	55.43	117	0.474	—	—
Total	67.27	119	—	—	—

In addition, Pearson correlation analysis reveals a positive relationship between the continuous VADER sentiment scores and engagement metrics ($r = 0.62$, $p < 0.01$), indicating that higher positive sentiment scores are associated with increased engagement levels. The correlation coefficient indicates a moderate-to-strong positive association between sentiment score and engagement.

Table 5. Pearson Correlation between VADER Sentiment Score and Engagement

Variables	Pearson r	p-value
VADER Sentiment Score – Interaction Rate	0.62	<0.001

Post-hoc comparisons using Tukey HSD further indicate that the positive–neutral and positive–negative comparisons show statistically significant differences, while the neutral–negative comparison shows a smaller difference.

Table 6. Tukey HSD Post-Hoc Comparisons Across Sentiment Categories

Comparison	Mean Difference	p-value	Interpretation
Positive – Neutral	1.10%	<0.01	Significant
Positive – Negative	1.90%	<0.001	Significant
Neutral – Negative	0.80%	0.06	Not significant

Taken together, the inferential results provide statistical evidence of differences in engagement across sentiment categories and a positive association between continuous sentiment scores and engagement. These findings strengthen the descriptive results by demonstrating that the observed patterns are supported by inferential statistical analysis.

B. Discussion

This study interprets the results by situating them within the broader context of digital marketing analytics and customer engagement research. The findings emphasize the relevance of emotional orientation as an analytical dimension for examining customer engagement on SME Instagram accounts. By integrating sentiment polarity with conventional engagement indicators, the study demonstrates that engagement assessment can incorporate both behavioral interaction metrics and affective textual characteristics. The statistically significant ANOVA results indicate that engagement levels differ significantly across sentiment polarity groups, providing inferential support for differences observed in the descriptive results. However, because the study uses naturally occurring, non-experimental Instagram data, these results should be interpreted as an association between sentiment polarity and engagement rather than as evidence that sentiment polarity directly causes changes in engagement. This supports the conceptualization of customer engagement as a multidimensional construct rather than a solely quantitative outcome (Naumann et al., 2020; Ng et al., 2020).

The use of sentiment analysis as an evaluative analytical tool provides an additional interpretive layer to engagement assessment. Rather than substituting traditional metrics, sentiment polarity contextualizes engagement indicators by capturing emotional characteristics embedded in user-generated text. The positive correlation (r = 0.62) indicates that higher VADER sentiment scores are positively associated with stronger user interaction, suggesting that emotional orientation may be related to engagement behavior. Positive sentiment may be associated with greater willingness to interact because favorable customer expressions can reflect satisfaction, interest, or perceived relevance of the content. In contrast, neutral sentiment may reflect lower emotional involvement, while negative sentiment may indicate dissatisfaction or criticism that can be expressed through engagement but does not necessarily translate into positive customer interaction. Users are more likely to interact with content that aligns with positive affect, reinforcing visibility through platform algorithms and social validation mechanisms. Therefore, the findings should be interpreted as evidence of an observed sentiment–engagement association rather than confirmation that positive sentiment itself causes higher engagement. Consequently, sentiment analysis functions as an analytical enhancement within digital marketing analytics frameworks (Gupta et al., 2020; Shah & Murthi, 2021).

The findings are consistent with prior research emphasizing the importance of emotional dimensions in social media-based customer engagement. Previous studies have primarily focused on observable engagement metrics such as likes, comments, and shares, often without incorporating sentiment polarity as part of engagement evaluation (Chatterjee & Kumar Kar, 2020; Patma et al., 2021). However, unlike earlier studies that provide descriptive insights, this study demonstrates statistically significant differences across sentiment groups, thereby strengthening empirical validation of the sentiment–engagement relationship. By explicitly integrating sentiment categories with engagement indicators, this study extends metric-centered analytical approaches. The results contribute to literature recognizing emotional content as an integral component of engagement analysis.

In addition, the study aligns with sentiment analysis research highlighting the analytical value of text mining techniques in social media contexts (Chan & Yang, 2023; Karayiğit et al., 2022). Unlike earlier studies that emphasize opinion classification, this research focuses on SMEs and positions sentiment analysis as a practical evaluative mechanism. The observed differences across sentiment categories suggest that positive, neutral, and negative customer expressions may correspond to different levels of engagement intensity. Positive sentiment may reflect satisfaction or favorable responses toward SME content, which can coincide with stronger interaction. Neutral sentiment may indicate informational or less emotionally involved responses, whereas negative sentiment may reflect dissatisfaction, criticism, or service-related concerns. These differences provide a possible explanation for the observed variation in engagement across sentiment groups without implying a direct causal mechanism. For SMEs, this distinction is important because a high number of comments alone does not necessarily indicate favorable customer engagement; the emotional orientation of those comments provides additional context for interpreting interaction performance.

From a theoretical standpoint, the study contributes to customer engagement theory by reinforcing its multidimensional nature. The findings support engagement frameworks that conceptualize engagement as a combination of emotional expression and observable interaction behavior (Barari et al., 2021; Lim et al., 2022). The statistically validated relationship between sentiment and engagement provides empirical evidence linking affective and behavioral dimensions, strengthening theoretical integration. Sentiment polarity serves as an analytical linkage between affective engagement and behavioral engagement indicators. This integration advances theoretical understanding of engagement dynamics within social media environments.

Furthermore, the study contributes to digital marketing analytics literature by positioning sentiment analysis as an evaluative mechanism rather than an outcome variable. By embedding sentiment polarity within engagement assessment, the study responds to calls for emotion-aware and data-driven analytical frameworks. The use of inferential statistics, including ANOVA and correlation analysis, addresses prior limitations of descriptive-only studies and enhances methodological rigor. This theoretical repositioning strengthens the connection between text mining methodologies and engagement theory. It also provides a foundation for future research integrating emotional analytics into marketing performance evaluation models (Grandhi et al., 2021; Vollrath & Villegas, 2022).

The findings offer practical implications for SMEs seeking to evaluate customer engagement on Instagram. SMEs can incorporate sentiment analysis to assess the emotional characteristics of customer interactions alongside conventional engagement metrics. Rather than simply prioritizing positive sentiment, SMEs can use sentiment analysis to evaluate content performance by comparing sentiment patterns with engagement indicators. Positive sentiment can be monitored to identify content themes associated with favorable customer responses, while negative sentiment can be used to identify posts or topics that require further evaluation. The evidence that positive sentiment is associated with higher engagement suggests that SMEs should prioritize emotionally appealing content strategies, such as storytelling, customer appreciation posts, and positive brand narratives. At the same time, negative sentiment should not simply be treated as undesirable engagement because negative comments may reveal customer complaints, service problems, or unmet expectations that require managerial attention. This approach enables a more comprehensive evaluation of content performance beyond interaction counts alone. As a result, SMEs can gain deeper insight into how emotional responses align with engagement outcomes.

Additionally, the study demonstrates that sentiment-based engagement evaluation can be implemented using accessible data and scalable analytical techniques. This is particularly relevant for SMEs with limited analytical resources. By integrating sentiment analysis into routine engagement assessment, SMEs can support data-driven decision making in content development and customer interaction management. In practical terms, SMEs can use the analysis for three related activities: (1) content evaluation by comparing sentiment patterns and engagement across posts, (2) complaint monitoring by identifying recurring negative sentiment and topics requiring customer-service attention, and (3) content planning by identifying content themes associated with favorable sentiment and stronger engagement. The statistically validated framework ensures that managerial decisions are supported by empirical evidence rather than intuition alone, improving marketing effectiveness and strategic alignment. This approach aligns with contemporary digital marketing practices emphasizing analytics-driven strategy formulation (Pertiwi & Hana, 2025; Wagobera Edgar Kedi et al., 2024).

Limitations and Future Research Directions

Despite its contributions, this study has several limitations. The analysis is confined to Instagram as a single social media platform, which may limit the generalizability of the findings to other digital environments. In addition, sentiment analysis is based solely on textual data and does not account for visual or multimodal content elements. These limitations reflect methodological constraints commonly observed in social media analytics research.

Future research may address these limitations by incorporating image-based or multimodal sentiment analysis approaches. Cross-platform comparative studies could also be conducted to examine whether similar sentiment–engagement patterns emerge across different social media platforms. Further studies may also apply advanced machine learning models such as deep learning-based sentiment classifiers to compare performance with lexicon-based approaches and enhance analytical robustness. Longitudinal research designs may further explore changes in sentiment–engagement relationships over time. Such extensions would enhance the robustness and applicability of sentiment-based engagement evaluation models for SMEs (Rogers, 2021; Ye et al., 2024).

V. CONCLUSION AND RECOMMENDATION

This study concludes that Instagram sentiment analysis can be systematically positioned as an evaluative tool for assessing customer engagement performance in SMEs. By integrating sentiment polarity derived from user-generated text with observable engagement indicators such as likes, comments, and interaction rates, the findings demonstrate that emotional orientation represents a relevant analytical dimension within digital marketing analytics. Using a lexicon-based VADER sentiment analysis approach combined with inferential statistical testing (ANOVA and correlation analysis), the study provides a methodologically transparent and empirically validated framework for linking sentiment polarity with engagement performance. The study achieves its objectives by identifying sentiment patterns in SME Instagram content and explaining how these patterns can be linked to measurable engagement outcomes. The statistically significant differences across sentiment categories ($p < 0.01$) indicate that engagement levels differ significantly across sentiment categories and are significantly associated with sentiment polarity, rather than confirming a causal effect of sentiment polarity on engagement indicators. In doing so, it addresses the identified research gap by moving beyond metric-centered evaluation and framing sentiment analysis as a structured component of engagement performance assessment in the SME context.

Practically, SMEs are recommended to incorporate sentiment analysis into routine social media evaluation processes in order to complement conventional quantitative metrics with affective insights. This approach enables more comprehensive, data-driven decision making in content development and customer interaction management while remaining feasible for organizations with limited analytical resources. Given the empirical evidence that positive sentiment is associated with significantly higher engagement levels, SMEs should prioritize content strategies that foster positive emotional responses to maximize interaction outcomes. Furthermore, the use of a transparent and replicable analytical pipeline ensures that SMEs can adopt this approach without requiring complex machine learning infrastructure, making it suitable for resource-constrained environments. Future research should expand this framework through multimodal sentiment analysis, cross-platform comparisons, and longitudinal designs to strengthen generalizability and theoretical refinement. Such extensions would further consolidate the role of sentiment-based analytics in improving customer engagement strategies within SME digital marketing environments.

Statement on the Use of Artificial Intelligence Tools

The authors declare that artificial intelligence tools, including ChatGPT, were utilized solely to enhance the linguistic quality and readability of the manuscript. The intellectual substance of the work including research conceptualization, methodological design, data collection, analytical procedures, interpretation of findings, and development of conclusions was produced entirely by the authors without the involvement of AI systems. The authors accept full responsibility for the authenticity, accuracy, and academic integrity of the manuscript submitted to the Journal of Management and Informatics.

REFERENCES

Al-Otaibi, S., & Al-Rasheed, A. (2022). A Review and Comparative Analysis of Sentiment Analysis Techniques. In *Informatica (Slovenia)* (Vol. 46, Number 6, pp. 33–44). Slovene Society Informatika. https://doi.org/10.31449/inf.v46i6.3991

Álvarez, M., & Hassan, L. (2025). Exploring the Role of Digital Tools in Ethical Managerial Decision-Making. *Journal of Management and Informatics*, *4*(3), 998–1016. https://doi.org/10.51903/jmi.v4i3.306

Barari, M., Ross, M., Thaichon, S., & Surachartkumtonkun, J. (2021). A meta-analysis of customer engagement behaviour. *International Journal of Consumer Studies*, *45*(4), 457–477. https://doi.org/10.1111/ijcs.12609

Chan, C.-P., & Yang, J.-H. (2023). Instagram Text Sentiment Analysis Combining Machine Learning and NLP. *ACM Transactions on Asian and Low-Resource Language Information Processing*. https://doi.org/10.1145/3606370

Chatterjee, S., & Kumar Kar, A. (2020). Why do small and medium enterprises use social media marketing and what is the impact: Empirical insights from India. *International Journal of Information Management*, *53*. https://doi.org/10.1016/j.ijinfomgt.2020.102103

Grandhi, B., Patwa, N., & Saleem, K. (2021). Data-driven marketing for growth and profitability. *EuroMed Journal of Business*, *16*(4), 381–398. https://doi.org/10.1108/EMJB-09-2018-0054

Gupta, S., Leszkiewicz, A., Kumar, V., Bijmolt, T., & Potapov, D. (2020). Digital Analytics: Modeling for Insights and New Methods. *Journal of Interactive Marketing*, *51*, 26–43. https://doi.org/10.1016/j.intmar.2020.04.003

Kabiraj, S., & Joghee, S. (2023). Improving Marketing Performance: How Business Analytics contribute to Digital Marketing. *International Journal of Technology, Innovation and Management (IJTIM)*, *3*(1), 9–18. https://doi.org/10.54489/ijtim.v3i1.209

Karayiğit, H., Akdagli, A., & Acı, Ç. İ. (2022). BERT-based Transfer Learning Model for COVID-19 Sentiment Analysis on Turkish Instagram Comments. *Information Technology and Control*, *51*(3), 409–428. https://doi.org/10.5755/j01.itc.51.3.30276

Lim, W. M., & Rasul, T. (2022). Customer engagement and social media: Revisiting the past to inform the future. *Journal of Business Research*, *148*, 325–342. https://doi.org/10.1016/j.jbusres.2022.04.068

Lim, W. M., Rasul, T., Kumar, S., & Ala, M. (2022). Past, present, and future of customer engagement. *Journal of Business Research*, *140*, 439–458. https://doi.org/10.1016/j.jbusres.2021.11.014

Malesev, S., & Cherry, M. (2021). Digital and social media marketing-growing market share for construction smes. *Construction Economics and Building*, *21*(1), 65–82. https://doi.org/10.5130/AJCEB.v21i1.7521

Mark Anthony Camilleri, B. (2019). The Use of Data-Driven Technologies for Customer-Centric Marketing. In *International Journal of Big Data Management. Forthcoming*.

Na, I. H., Jae, Y. I., & Hwa, P. I. (2025). Personalized Digital Marketing Strategies: A Data-Driven Approach Using Marketing Analytics. *Journal of Management and Informatics*, *4*(1), 668–686. https://doi.org/10.51903/jmi.v4i1.149

Naumann, K., Bowden, J., & Gabbott, M. (2020). Expanding customer engagement: the role of negative engagement, dual valences and contexts. *European Journal of Marketing*, *54*(7), 1469–1499. https://doi.org/10.1108/EJM-07-2017-0464

Ng, S. C., Sweeney, J. C., & Plewa, C. (2020). Customer engagement: A systematic review and future research priorities. *Australasian Marketing Journal*, *28*(4), 235–252. https://doi.org/10.1016/j.ausmj.2020.05.004

Owusu-Mensah, D., Sarfo, P. A., & Kusi, G. A. (2025). Exploring the Impact of Artificial Intelligence on Customer Experience Personalization and Marketing Strategy Optimization in Digital Marketing: An Empirical Analysis. *Journal of Management and Informatics*, *4*(2), 822–843. https://doi.org/10.51903/jmi.v4i2.242

Patma, T. S., Wardana, L. W., Wibowo, A., Narmaditya, B. S., & Akbarina, F. (2021). The impact of social media marketing for Indonesian SMEs sustainability: Lesson from Covid-19 pandemic. *Cogent Business and Management*, *8*(1). https://doi.org/10.1080/23311975.2021.1953679

Pellegrino, A., & Abe, M. (2023). Leveraging Social Media for SMEs: Findings from a Bibliometric Review. In *Sustainability (Switzerland)* (Vol. 15, Number 8). MDPI. https://doi.org/10.3390/su15087007

Pertiwi, J. P., & Hana, A. U. (2025). Data-Driven Decision Making in MSMEs: Leveraging Free Analytics Tools for Financial Planning and Efficiency. *Journal of Management and Informatics*, *4*(1), 633–648. https://doi.org/10.51903/jmi.v4i1.146

Rafi, A. M., Rana, S., Kaur, R., Wu, Q. M. J., & Zadeh, P. M. (2020). *Understanding Global Reaction to the Recent Outbreaks of COVID-19: Insights from Instagram Data Analysis*. http://arxiv.org/abs/2009.06862

Rogers, R. (2021). Visual media analysis for Instagram and other online platforms. *Big Data and Society*, *8*(1). https://doi.org/10.1177/20539517211022370

Shah, D., & Murthi, B. P. S. (2021). Marketing in a data-driven digital world: Implications for the role and scope of marketing. *Journal of Business Research*, *125*, 772–779. https://doi.org/10.1016/j.jbusres.2020.06.062

Smith, H., & Cipolli, W. (2022). The Instagram/Facebook ban on graphic self-harm imagery: A sentiment analysis and topic modeling approach. *Policy and Internet*, *14*(1), 170–185. https://doi.org/10.1002/poi3.272

Theodorakopoulos, L., & Theodoropoulou, A. (2024). Leveraging Big Data Analytics for Understanding Consumer Behavior in Digital Marketing: A Systematic Review. In *Human Behavior and Emerging Technologies* (Vol. 2024). John Wiley and Sons Inc. https://doi.org/10.1155/2024/3641502

Vollrath, M. D., & Villegas, S. G. (2022). Avoiding digital marketing analytics myopia: revisiting the customer decision journey as a strategic marketing framework. *Journal of Marketing Analytics*, *10*(2), 106–113. https://doi.org/10.1057/s41270-020-00098-0

Wagobera Edgar Kedi, Chibundom Ejimuda, Courage Idemudia, & Tochukwu Ignatius Ijomah. (2024). Machine learning software for optimizing SME social media marketing campaigns. *Computer Science & IT Research Journal*, *5*(7), 1634–1647. https://doi.org/10.51594/csitrj.v5i7.1349

Ye, C., Kim, Y., & Cho, Y. N. (2024). Digital Marketing and Analytics Education: A Systematic Review. *Journal of Marketing Education*, *46*(1), 32–44. https://doi.org/10.1177/02734753231166414