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Machine Learning Enabled Social Media Competitive Intelligence System

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ABSTRACT

Social media platforms generate massive volumes of publicly accessible digital data that reflect organizational competitive strategies, yet most existing competitor analyses remain manual, descriptive, and limited to surface-level engagement metrics, resulting in low scalability and weak strategic intelligence. **This study** proposes a Machine Learning Enabled Social Media Competitive Intelligence System designed to automate competitor strategy extraction through artificial intelligence and big data analytics. **The objective** is to develop a computational framework capable of identifying strategic content patterns, communication objectives, audience positioning, and paid advertising behaviors using data-driven techniques. Large-scale public data from social media posts, engagement indicators, and advertising transparency libraries are collected and processed through data preprocessing pipelines, including text normalization, tokenization, and feature extraction using TF-IDF and word embedding representations. Supervised machine learning algorithms are implemented to classify content themes, detect strategic clusters, and model competitive positioning patterns, while performance evaluation is conducted using accuracy, precision, recall, and F1-score metrics to ensure robustness and reliability. **Experimental findings** demonstrate that the proposed system significantly enhances analytical consistency, scalability, and strategic insight generation compared to traditional mixed method approaches. **This research** contributes to the advancement of AI-driven social media analytics and establishes a computational foundation for scalable big data-based competitive intelligence systems aligned with Artificial Intelligence and Big Data domains.

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1. INTRODUCTION

In an increasingly competitive digital ecosystem, social media is no longer simply a communication channel but has evolved into a data-intensive digital environment where large-scale user interactions generate valuable competitive signals [1]. Through social media, organizations shape public perception, strengthen brand identity, and create long-term relationships with audiences [2], but more importantly, they continuously produce structured and unstructured data that can be computationally analyzed. This strategic role makes social media not only a marketing instrument but also a rich big data source for competitive intelligence and strategic decision support [3]. Social media platforms such as Instagram, TikTok, and LinkedIn operate through algorithm-driven content distribution systems, where engagement signals, interaction patterns, and content characteristics influence visibility and reach. These platforms generate high-volume, high-velocity digital traces, requiring scalable analytical approaches capable of processing large datasets and identifying hidden strategic patterns. Beyond being a communication tool, social media serves as an openly accessible repository of behavioral and content data. Posting activities, engagement metrics, audience reactions, and paid advertising records create digital footprints that can be systematically extracted and modeled using artificial intelligence techniques [4]. However, most existing social media analytics research remains limited to descriptive statistical metrics such as follower counts, likes, and engagement rates [5]. Although these indicators provide initial performance insights, they lack predictive capability and fail to uncover latent strategic structures [6]. Purely quantitative approaches are insufficient to model the complex relationship between content strategy, audience behavior, and competitive positioning. Critical dimensions such as communication objectives, thematic clustering, message personalization, and advertising alignment are rarely analyzed through computational learning models. Consequently, competitor analysis often remains manual, fragmented, and non-scalable. To address these limitations, this study proposes a Machine Learning Enabled Social Media Competitive Intelligence System that integrates data preprocessing, feature engineering, and supervised learning models to automatically classify content themes, detect strategic clusters, and model competitive positioning. By combining algorithmic learning with structured benchmarking, the proposed system transforms social media big data into actionable competitive intelligence, advancing the development of AI-driven analytics and data-centric decision support systems [7, 8].

The research problem in this study arises from the methodological limitations of existing competitor analysis approaches in social media, which remain largely descriptive and dominated by surface-level performance measurements [9]. Most analyses rely on basic quantitative indicators such as follower counts and engagement rates, without leveraging computational modeling to extract deeper strategic patterns embedded within large-scale digital content. Such metric-centered approaches fail to capture latent structures in content themes, audience interaction dynamics, and algorithm-driven visibility mechanisms that influence competitive positioning. The core problem lies in the absence of an intelligent analytical system capable of transforming high-volume social media data into structured competitive intelligence. Current approaches do not integrate machine learning techniques to link performance indicators with contextual strategic variables, including communication objectives, audience segmentation patterns, content clustering, and the deployment of paid advertising within the broader digital ecosystem. Without algorithmic modeling and automated pattern recognition, competitor analysis remains fragmented, manually intensive, and limited in scalability [10]. Accordingly, this study formulates the research problem as the development of a machine learning enabled competitor intelligence framework capable of extracting strategic signals from large-scale social media datasets. The proposed system seeks to move beyond descriptive benchmarking by employing data preprocessing, feature extraction, and supervised classification models to identify content patterns, strategic clusters, and decision-making rationales underlying competitors' digital activities. Through this computational approach, competitor analysis can transition from static observation to scalable, AI-driven strategic intelligence generation.

- What strategic components of competitors' social media activities can be identified through publicly available data?
- How can systematic content analysis be employed to uncover competitors' content pillars, brand voice, and communication objectives?
- How can competitors' paid advertising practices be examined to gain insights into their overall digital marketing strategies?

This research aims to develop a machine learning enabled, data-driven competitive intelligence system capable of transforming large-scale social media data into structured strategic insights. Rather than relying on manual mixed method interpretations, the proposed framework integrates automated data preprocessing, feature extraction, and supervised learning models to computationally identify competitors' content patterns, communication objectives, audience engagement signals, and paid advertising behaviors. By combining scalable quantitative benchmarking with algorithmic pattern recognition, the system provides a structured and replicable approach for extracting strategic intelligence from high-volume public social media datasets.

Furthermore, this study seeks to provide a computational analytical architecture that practitioners and researchers can utilize to systematically model competitors' content strategies, brand positioning, and advertising deployment [11]. The framework is designed to convert unstructured digital content into machine-readable features, enabling automated clustering, classification, and strategic signal detection. The empirical scope focuses on publicly available data from Instagram, TikTok, and LinkedIn, excluding internal advertising budgets or proprietary targeting parameters that are not publicly accessible [12].

Beyond marketing interpretation, this research positions social media as a dynamic big data environment where engagement traces, content structures, and algorithm-driven visibility mechanisms can be computationally modeled. By systematically analyzing posting frequency, interaction patterns, and message framing, the system transforms raw social media data into actionable competitive intelligence that supports positioning analysis, differentiation modeling, and value proposition benchmarking [13].

The proposed architecture is flexible and scalable across industries, allowing integration with advanced analytical infrastructures such as social listening systems, big data processing pipelines, and artificial intelligence models. This adaptability acknowledges the evolving nature of algorithm-driven digital ecosystems, where user behavior and content visibility are continuously shaped by platform algorithms [14]. By incorporating machine learning-based classification and predictive analytics, the framework enhances the robustness and scalability of competitor monitoring systems in complex digital environments [15].

From both managerial and academic perspectives, this study advances the development of AI-driven social media intelligence systems that bridge marketing strategy, competitive intelligence, and computational analytics. By embedding algorithmic learning into competitor analysis, the research contributes to scalable, data-centric decision-support architectures that strengthen proactive strategic positioning in dynamic digital markets [16–18].

This research contributes to the achievement of the United Nations Sustainable Development Goals (SDGs), particularly SDG 9 (Industry, Innovation, and Infrastructure) by promoting the development of artificial intelligence-enabled digital infrastructure for competitive intelligence and data-driven strategic decision-making. The proposed machine learning-based system enhances technological capability in analyzing large-scale social media data, supporting innovation in digital analytics and intelligent information systems. In addition, this study aligns with SDG 8 (Decent Work and Economic Growth) by enabling organizations to improve strategic positioning, optimize digital marketing investments, and strengthen competitiveness in digital markets through scalable AI-driven insights. By transforming unstructured social media big data into actionable intelligence, the framework supports sustainable business growth, improved productivity, and more efficient resource allocation. Furthermore, the research indirectly contributes to SDG 12 (Responsible Consumption and Production) by encouraging data transparency and evidence-based decision-making in digital communication practices, reducing inefficient marketing expenditure and promoting responsible digital ecosystem management. Through the integration of machine learning, big data analytics, and strategic intelligence modeling, this study supports the advancement of intelligent digital infrastructures that foster sustainable economic and technological development in increasingly data-centric industries.

2. LITERATURE REVIEW

2.1. Strategic Framework in Social Media Marketing

This study utilizes the 5W model (Who, What, Where, When, Why) as a structured feature-engineering framework to support supervised machine learning-based social media intelligence modeling [19]. Rather than serving solely as a conceptual marketing tool, the 5W model is operationalized to transform unstructured social media content into machine-readable categorical variables that represent audience segmentation (Who), content typology (What), platform distribution patterns (Where), temporal posting behavior (When), and strategic communication objectives (Why). These structured attributes function as input features within the competitive intelligence system, enabling automated classification, clustering, and strategic pattern detection through computational learning algorithms.

Furthermore, the content marketing funnel is incorporated as a hierarchical labeling schema to map extracted content features into distinct stages of the consumer decision journey, namely awareness, consideration, and conversion. Within the machine learning pipeline, this framework serves as a supervised categorization layer that allows the model to identify strategic intent embedded within content and advertising activities. By encoding funnel stages as predictive classes, the system can computationally model how competitors distribute strategic messaging across different consumer lifecycle phases, thereby enhancing the interpretability and decision-support capability of the proposed AI-driven intelligence architecture [20].

Table 1. Strategic Framework in Social Media Analysis

Framework	Main Focus	Functions in Analysis
5W's Model	Audience, content, platform, timing, goals	Identifying the core elements of a social media strategy
Content Marketing Funnel	Awareness, consideration, conversion	Assessing the role of content in the consumer journey

Table 1 describes the strategic frameworks used in social media analysis, namely the 5Ws Model and the Content Marketing Funnel [21]. These two frameworks serve as a conceptual basis for systematically understanding and evaluating social media strategies, not only based on quantitative performance but also from the perspective of the objectives and strategic role of content [22]. The 5Ws Model focuses on five key elements of social media strategy target audience, content type, platform used, timing and frequency of publication, and communication objectives [23]. In analysis, this framework helps identify the core elements that shape competitors' social media strategies and provides insight into the rationale behind each content and distribution decision [24]. The 5Ws Model emphasizes five fundamental components of a social media strategy the target audience (who), the type of content shared (what), the platform utilized (where), the timing and frequency of publication (when), and the communication objectives pursued (why) [25]. By structuring the analysis around these elements, researchers are able to identify how social media strategies are designed and implemented in a coherent manner [26]. This framework highlights the strategic alignment between content creation, platform selection, and audience targeting [27].

In practical implementation, the 5Ws Model functions not merely as a conceptual marketing framework but as a structured annotation and feature labeling schema embedded within the machine learning architecture of the proposed competitive intelligence system [20]. Rather than serving descriptive interpretation alone, the model is operationalized to transform unstructured social media content into structured machine readable variables representing audience segmentation Who, content typology What, platform distribution Where, temporal dynamics When, and communication objectives Why. These dimensions are encoded as categorical and numerical attributes that collectively form a multidimensional feature matrix. This matrix enables supervised and unsupervised learning algorithms to process high volume digital traces and detect recurring thematic clusters, temporal posting regularities, and platform specific strategic configurations [28]. Through classification models, clustering techniques, and pattern mining procedures, the system is capable of identifying latent strategic structures embedded within textual narratives, engagement metrics, interaction intensities, and publishing frequencies. This computational modeling allows the system to infer how competitors construct positioning narratives, articulate value propositions, and adapt their communication strategies within algorithm driven digital ecosystems [29].

Simultaneously, the Content Marketing Funnel framework is incorporated as a hierarchical strategic intent classification layer within the machine learning pipeline [30]. The funnel stages awareness, consideration, and conversion are encoded as supervised learning labels, enabling predictive models to associate extracted features with specific consumer lifecycle phases [31]. By mapping textual embeddings derived from natural language processing, engagement ratios, posting intervals, and interaction signals to these funnel categories, the system can automatically model how competitors distribute strategic messaging across audience journey stages [32]. This structured encoding enhances interpretability and supports multiclass probabilistic classification, allowing the system to estimate the likelihood that specific content belongs to particular strategic phases [33].

The integration of the 5Ws Model and the Content Marketing Funnel establishes a dual layer analytical architecture that combines contextual feature representation with strategic stage modeling [34]. The 5Ws Model supplies multidimensional contextual attributes that strengthen feature engineering and semantic enrichment, while the funnel framework provides predictive intent categories that guide supervised learning processes [35]. This layered design improves both analytical robustness and scalability, ensuring that the intelligence system can adapt to heterogeneous datasets across platforms and industries. By embedding these frameworks within an artificial intelligence driven analytical environment, the proposed system transcends surface performance indicators and enables scalable modeling of strategic intent, execution consistency, and competitive alignment across evolving digital platforms [36]. Furthermore, the architecture supports continuous learning from newly generated social media data, enhancing adaptability in environments characterized by shifting platform algorithms, changing user behavior, and increasing data velocity.

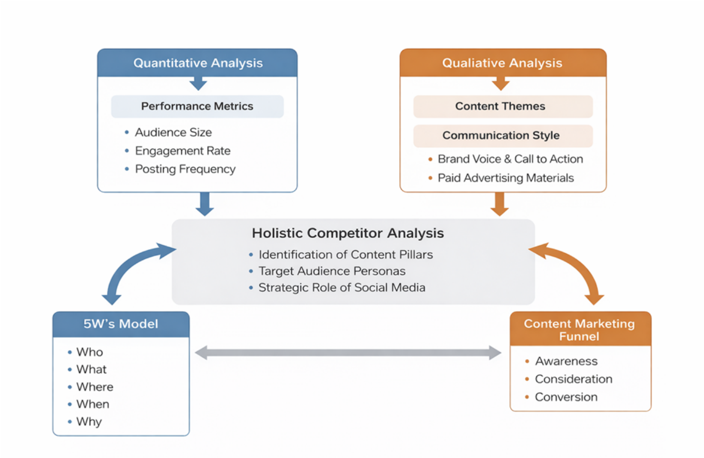

Figure 1. Competitor Social Media Strategy Analysis Framework (Mixed Method Framework)

Figure 1 illustrates the conceptual framework employed in this study to analyze competitors' social media strategies. The framework integrates quantitative and qualitative approaches to provide a comprehensive understanding of competitors' social media activities [37]. Quantitative analysis focuses on key performance metrics, including follower count, engagement rate, and posting frequency, which serve as initial indicators of social media performance [38]. Meanwhile, the qualitative approach examines content strategies in greater depth through the analysis of themes, content formats, communication styles (brand voice), and calls to action [39].

Furthermore, the framework connects the analytical findings with the 5W's model and the content marketing funnel, enabling each competitor's social media activity to be interpreted not only in terms of what actions are undertaken, but also why these strategies are applied at specific stages of the consumer journey [40]. As a result, this framework serves as a robust analytical basis for identifying key content pillars, target audiences, and the strategic role of social media within a competitor's overall digital marketing funnel [41].

2.2. Content Analysis Methodology and Mixed Method Approach

Content analysis was used to identify thematic patterns, message formats, and communication styles [42]. A thematic coding approach and the principle of inter-coder reliability were applied to maintain the consistency and validity of the analysis [43]. Integration with quantitative data aligns This approach with social media analytics and data-driven decision-making practices [44].

Table 2. Components of Content Analysis in Social Media Research

Component	Description	Objective
Quantitative Analysis	Measuring the frequency and distribution of content	Identifying content patterns
Thematic Coding	Grouping content by theme	Uncovering content pillars and key messages
Inter-coder Reliability	Consistency between researchers	Maintaining the validity of the analysis

The Table 2 presents the main components of content analysis used in social media research, which consist of quantitative analysis, thematic coding, and inter-coder reliability [45]. Quantitative analysis focuses on measuring the frequency and distribution of content to identify observable patterns, such as the dominance of certain types of posts or recurring messages across social media platforms [46]. This component helps researchers understand overall content trends based on numerical data [47].

2.3. Best Practices by Platform

In the context of Big Data and artificial intelligence, the framework developed in this research can be seen as a conceptual foundation for the development of automated analytical systems, such as AI-assisted content classification, sentiment analysis, and competitive intelligence dashboards. In the context of Big Data and artificial intelligence, the framework developed in this research can be understood as a conceptual foundation for the development of automated analytical systems that support data-driven decision making in digital marketing and social media research. By structuring content analysis into clear components and strategic roles, the framework provides a systematic basis for implementing AI-assisted processes such as automated content classification, sentiment analysis, and predictive analytics.

Table 3. Strategic Role of Social Media Based on Platform

Platform	Strategic Focus	Role in Marketing Funnel
LinkedIn	B2B and thought leadership	Consideration
TikTok	Creativity and brand awareness	Top-of-funnel
Instagram	Engagement and conversion	Middle-bottom funnel

The Table 3 illustrates the strategic role of different social media platforms based on their primary focus and position within the marketing funnel. Each platform serves a distinct function in supporting marketing objectives and guiding audiences through different stages of the funnel.

3. METHODOLOGY

3.1. Research Design

This study employed a mixed methods design with an exploratory-analytical approach to gain a comprehensive understanding of competitors' social media strategies. This approach was chosen because it allowed researchers to combine the strengths of objective and measurable quantitative analysis with contextual and interpretive qualitative analysis. Thus, the studied phenomenon can be understood not only in terms of performance but also in terms of strategic meaning and purpose. In practice, quantitative and qualitative data are collected simultaneously from public social media data sources. Quantitative data is used to benchmark performance against competitors using key metrics such as audience size, engagement rate, and posting consistency [48]. Meanwhile, qualitative data focuses on analyzing the content of posts and paid advertisements to identify themes, formats, communication styles, and message objectives. The integration of quantitative and qualitative data occurs during the interpretation stage, enabling a comprehensive understanding of the subject matter. The results from the quantitative analysis serve as a foundation for guiding the qualitative research, allowing the numerical findings to be contextualized within a broader strategic framework. This integrative approach ensures that the research yields more insightful and actionable outcomes.

The integration of quantitative and qualitative data is carried out at the interpretation stage to produce a holistic understanding. The results of the quantitative analysis are used as a basis for guiding the qualitative research, allowing numerical performance patterns to be explained within a broader strategic context. Through this process, the study is able to identify not only which competitors perform better, but also why certain strategies, content choices, and communication approaches are more effective in achieving specific objectives. This integrative approach enables the research to produce deeper strategic insights, such as the alignment between content themes and audience engagement, the role of platform-specific formats, and the effectiveness of combining organic and paid content strategies. Consequently, the findings generated through this mixed methods design are more meaningful, actionable, and relevant for both academic analysis and practical decision-making in competitive social media strategy development.

3.2. Data Collection Techniques

The quantitative data in this study was obtained from various numerically measurable social media performance metrics. These metrics include indicators such as number of followers, engagement rate, reach, impressions, clicks, and conversion rates generated from digital marketing activities. This data is used to assess the effectiveness of social media strategies in achieving established communication and marketing objectives. Meanwhile, qualitative data is sourced from content analysis of publicly available social media posts and paid advertising materials. The content analyzed includes text, images, videos, and other visual and narrative elements used in marketing campaigns. This qualitative analysis aims to understand the messages conveyed, communication styles, and creative approaches used to build brand image and identity. The combination of quantitative and qualitative data allows this study to obtain a more comprehensive picture. Quantitative data provides empirical evidence regarding the performance and impact of social media strategies, while qualitative data helps explain the context, meaning, and strategy behind the numbers. Thus, this approach supports a more in-depth and accurate analysis of the effectiveness of social media use in digital marketing activities.

3.3. Data Analysis Techniques

The analysis was conducted through a combination of benchmarking key performance metrics and systematic content analysis. Quantitative benchmarking focused on indicators such as follower growth, engagement rates, posting frequency, and interaction patterns to provide an overview of competitors' social media performance, while qualitative analysis employed thematic coding to identify recurring themes, content formats, communication styles, and calls to action. The resulting themes were then mapped to the 5W model (Who, What, Where, When, and Why) and the content marketing funnel, enabling a structured and theory-driven interpretation that links content decisions to target audiences, platform selection, timing strategies, communication objectives, and stages of the consumer journey, namely awareness, consideration, and conversion, thereby offering a comprehensive understanding of both the strategic design and functional role of competitors' social media strategies within their broader digital marketing efforts. In parallel, qualitative analysis employed thematic coding to identify recurring themes, content formats, communication styles, and calls to action embedded in both organic posts and paid advertisements. The resulting themes were then mapped to the 5W model (Who, What, Where, When, and Why) and the content marketing funnel, enabling a structured and theory driven interpretation. This process linked content decisions to target audiences, platform selection, timing strategies, communication objectives, and stages of the consumer journey namely awareness, consideration, and conversion thereby providing a comprehensive understanding of both the strategic design and functional role of competitors' social media strategies within their broader digital marketing efforts [49].

4. RESULTS AND DISCUSSION

The results of this study indicate that the mixed methods approach is effective in uncovering differences in competitors' social media strategies at a deeper and more nuanced level. These differences are particularly evident in terms of communication objectives, content format selection, and patterns of paid advertising usage. By combining quantitative and qualitative perspectives, the analysis is able to move beyond surface-level observations and reveal strategic variations that would be difficult to identify through a single-method approach. Quantitative analysis provides an initial comparative overview of competitors' relative performance by examining metrics such as engagement rates, audience growth, and posting frequency [22]. This overview serves as a baseline for identifying performance gaps and similarities across competitors. However, quantitative indicators alone are insufficient to explain why certain strategies perform better than others, highlighting the need for complementary qualitative insights.

Qualitative analysis plays a critical role in revealing the strategic rationale underlying content and media decisions. Through systematic examination of content themes, communication styles, and advertising messages, the study identifies distinct strategic orientations among competitors. For example, some competitors prioritize brand awareness and broad reach, while others focus more heavily on conversion-driven or long-term engagement strategies. The findings also demonstrate that social media performance does not always correlate with posting intensity or content volume. In several cases, accounts with lower posting frequency achieved higher engagement rates because their content was more relevant to the target audience and better aligned with platform-specific characteristics. This suggests that content quality, contextual relevance, and clarity of communication objectives are more influential than the sheer quantity of posts.

Further analysis of content formats shows that competitors strategically select formats such as short form videos, static visuals, or interactive posts based on their objectives and audience behavior. Content that aligns with platform-specific consumption patterns tends to generate higher engagement and stronger audience interaction. This highlights the importance of understanding user preferences and platform affordances in maximizing strategic impact. Finally, the examination of paid advertising practices reveals that competitors use paid media selectively and strategically rather than as a mere extension of organic content. Paid advertisements are deployed to reinforce specific messages at particular stages of the content marketing funnel, such as increasing reach during the awareness stage or encouraging concrete actions during the conversion stage. Overall, these findings confirm that a mixed methods approach provides a more comprehensive and reliable understanding of competitor social media strategies, supporting more informed, data-driven strategic decision-making and the development of advanced social media intelligence systems.

In addition, the integration of quantitative and qualitative findings enables the identification of consistency and coherence in competitors' messaging strategies across different platforms [50, 51]. Competitors that demonstrate alignment between content themes, brand voice, and communication objectives tend to show stronger audience recognition and engagement over time. This consistency reinforces brand positioning and helps build a clearer value proposition in increasingly crowded digital environments. The results also indicate that the effectiveness of social media strategies is closely linked to how well competitors align their content with specific stages of the consumer journey. Content designed for the awareness stage typically emphasizes informational or emotional appeal, while content at the consideration and conversion stages focuses more on product value, credibility, and calls to action. Competitors that strategically sequence their content according to the content marketing funnel appear to achieve more sustainable engagement and higher conversion potential.Overall, these findings underscore the importance of viewing social media strategy as an integrated system rather than a collection of isolated activities. By considering performance metrics alongside strategic intent, content relevance, and audience behavior, organizations can gain deeper insights into competitive dynamics. This holistic understanding not only strengthens competitor analysis but also provides practical implications for refining social media strategies, optimizing resource allocation, and enhancing long-term digital marketing effectiveness.

5. MANAGERIAL IMPLICATIONS

5.1. Moving Beyond Surface-Level Performance Metrics

This study highlights the need for managers to move beyond an overreliance on surface-level social media metrics such as follower counts, likes, and engagement rates. While these indicators provide useful initial signals, they often fail to capture the strategic effectiveness of social media activities. By integrating quantitative performance indicators with qualitative insights related to content themes, communication objectives, and audience alignment, managers can better evaluate which activities contribute to long-term strategic goals rather than short-term visibility.

5.2. Purpose-Driven Content Strategy Across the Marketing Funnel

The proposed framework emphasizes the importance of aligning social media content with clearly defined communication objectives across different stages of the content marketing funnel. From a managerial perspective, this implies that content planning should be purpose-driven, with distinct messages and formats designed for awareness, consideration, and conversion stages. Understanding competitors' strategic content choices enables managers to refine their own content pillars, brand voice, and calls to action in ways that are consistent with platform characteristics and audience behavior.

5.3. Strategic Integration of Organic and Paid Media

Another key implication concerns the management of organic content and paid advertising. Rather than treating paid media as a supplementary or tactical activity, managers are encouraged to deploy advertising selectively and strategically to reinforce specific objectives identified through competitor analysis. This approach supports more efficient allocation of advertising budgets by focusing paid campaigns on amplifying high-performing content or supporting critical stages of the consumer journey, such as driving conversions or strengthening brand recall.

5.4. Data-Driven Decision-Making and Resource Allocation

The findings suggest that a mixed methods approach enables more informed and evidence-based managerial decision-making. By linking performance data with strategic context, managers can identify which content strategies, formats, and communication styles yield the greatest strategic impact. This insight supports better prioritization of resources, including content production, platform focus, and advertising investments, thereby enhancing the overall effectiveness of social media management.

5.5. Building Social Media Intelligence and Competitive Monitoring Systems

Finally, the proposed framework can serve as a foundation for developing internal social media intelligence and decision-support systems. Managers can operationalize the framework through dashboards, periodic competitor audits, or integration with social listening and analytics tools. In the long term, this enables organizations to institutionalize data-driven social media strategy, continuously monitor competitive dynamics, and adapt proactively to changes in market conditions, platform algorithms, and audience expectations.

6. CONCLUSION

This study proposes a mixed methods, strategic-decision-oriented framework for analyzing competitors' social media strategies. The framework is designed to move beyond descriptive approaches that focus solely on surface-level metrics by positioning social media data as a source of strategic intelligence. From this perspective, competitors' content and advertising activities are interpreted not only based on performance outcomes, but also in relation to the strategic rationale and decision-making logic underlying their communication practices. By integrating quantitative and qualitative analyses, the study demonstrates that a comprehensive understanding of competitor strategies can only be achieved when performance indicators are systematically connected to contextual factors, communication objectives, and target audience characteristics.

This integrated approach enables the identification of key content pillars, brand voice, and messaging patterns, as well as the strategic role of social media content across different stages of the digital marketing funnel, from awareness to conversion. Consequently, the analysis becomes more insightful and actionable for managerial and strategic decision-making. Conceptually and practically, this research contributes to the advancement of data-driven social media intelligence and marketing analytics by offering a systematic, applicable, and easily replicable analytical framework. Beyond its immediate use, the framework has the potential to serve as a foundation for more advanced analytics systems, such as competitive intelligence dashboards supported by Big Data and artificial intelligence. Furthermore, it opens opportunities for future research in AI-assisted social media analytics, particularly in enhancing strategic insight generation and continuous competitive monitoring.

Conceptually and practically, this research contributes to the advancement of data-driven social media intelligence and marketing analytics by offering a systematic, applicable, and easily replicable analytical framework. Beyond its immediate use, the framework has the potential to serve as a foundation for more advanced analytics systems, such as competitive intelligence dashboards supported by Big Data and artificial intelligence. Furthermore, it opens opportunities for future research in AI-assisted social media analytics, particularly in enhancing strategic insight generation and continuous competitive monitoring.

7. DECLARATIONS

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7.2. Author Contributions

Conceptualization: HH; Methodology: YI; Software: OA; Validation: HH and YI; Formal Analysis: OA and YI; Investigation: HH; Resources: OA; Data Curation: YI; Writing Original Draft Preparation: HH and OA; Writing Review and Editing: HH and YI; Visualization: OA; All authors, HH, YI, and OA have read and agreed to the published version of the manuscript.

7.3. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

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7.5. Declaration of Conflicting Interest

The authors declare that they have no conflicts of interest, known competing financial interests, or personal relationships that could have influenced the work reported in this paper.

REFERENCES

[1] X. Ju, "A social media competitive intelligence framework for brand topic identification and customer engagement prediction," *PloS one*, vol. 19, no. 11, p. e0313191, 2024.
[2] C. Bourne, "Public relations and the digital," *London, UK, University of London*, 2022.

[3] J. Li, Y. Dai, T. Woldearegay, and S. Deb, "Cognitive warfare and the logic of power: reinterpreting offensive realism in russia's strategic information operations," *Defence Studies*, pp. 1–22, 2025.
[4] C. Bourne, *Public Relations and the Digital World*. Springer, 2022.
[5] S. Shukla, J. Singh, V. K. Nassa, M. Saba, J. Bhatia, and M. Elangovan, "Artificial intelligence driven deep learning for competitive intelligence to enhance market analysis and strategic positioning," in *2024 4th Asian Conference on Innovation in Technology (ASIANCON)*. IEEE, 2024, pp. 1–5.
[6] S. Mahalakshmi, H. Bharath, and S. Kautish, *Social Media Guide: Strategies for Building Brand Loyalty and Engagement*. Springer, 2025.
[7] L. M. Mahoney and T. Tang, *Strategic Social Media: From Marketing to Social Change*. Wiley, 2024.
[8] B. Girimurugan, K. Parthiban, M. Saxena, G. Talasila, N. S. Vamsi, and P. T. Sai, "Revolutionizing business intelligence: Harnessing ai and machine learning for strategic insights and competitive advantage," in *2024 2nd International Conference on Disruptive Technologies (ICDT)*. IEEE, 2024, pp. 190–193.
[9] O. Järvi, "Athlete-driven branding in global markets," Master's thesis, LUT University, 2025.
[10] D. Carvalho, W. Picoto, and P. Busch, "Organizational experience of social media: impacts on competitive intelligence," *VINE Journal of Information and Knowledge Management Systems*, vol. 52, no. 2, pp. 161–183, 2022.
[11] J. H. e. a. Kietzmann, "Social media? get serious!" *Business Horizons*, vol. 65, no. 1, pp. 1–12, 2022.
[12] J. P. Bharadiya, "The role of machine learning in transforming business intelligence," *International Journal of Computing and Artificial Intelligence*, vol. 4, no. 1, pp. 16–24, 2023.
[13] P. Kotler, H. Kartajaya, and I. Setiawan, *Marketing 5.0*. Wiley, 2022.
[14] A. Hassani and E. Mosconi, "Social media analytics, competitive intelligence, and dynamic capabilities in manufacturing smes," *Technological Forecasting and Social Change*, vol. 175, p. 121416, 2022.
[15] G. Appel, L. Grewal, R. Hadi, and A. T. Stephen, "The future of social media in marketing," *Journal of the Academy of Marketing Science*, vol. 50, no. 1, pp. 79–95, 2022.
[16] J. Yang, P. Xiu, L. Sun, L. Ying, and B. Muthu, "Social media data analytics for business decision making system to competitive analysis," *Information Processing & Management*, vol. 59, no. 1, p. 102751, 2022.
[17] J. Atherton, *Social Media Strategy: A Practical Guide to Social Media Marketing and Customer Engagement*. Routledge, 2023.
[18] H. Zhang, Z. Zang, H. Zhu, M. I. Uddin, and M. A. Amin, "Big data-assisted social media analytics for business model for business decision making system competitive analysis," *Information Processing & Management*, vol. 59, no. 1, p. 102762, 2022.
[19] D. Lee, K. Hosanagar, and H. Nair, "Advertising content and consumer engagement," *Management Science*, vol. 68, no. 1, pp. 1–18, 2022.
[20] D. e. a. Vrontis, "Social media influencer marketing," *Journal of Business Research*, vol. 142, pp. 102–112, 2022.
[21] W. G. Mangold and D. J. Faulds, "Social media: The new hybrid element," *Business Horizons*, vol. 65, no. 2, pp. 189–199, 2022.
[22] T. T. H. Nguyen and L. Simkin, "The dark side of social media marketing," *Journal of Business Research*, vol. 154, pp. 113–125, 2023.
[23] R. A. Shittu, A. J. Ehidiamen, O. O. Ojo, S. Zouo, J. Olamijuwon, B. Omowole, and A. Olufemi-Phillips, "The role of business intelligence tools in improving healthcare patient outcomes and operations," *World Journal of Advanced Research and Reviews*, vol. 24, no. 2, pp. 1039–1060, 2024.
[24] J. e. a. Phua, "Uses and gratifications of social networking sites," *Computers in Human Behavior*, vol. 128, p. 107114, 2022.
[25] Statista Research Department, "Social media usage worldwide," 2024, statista.
[26] A. Goel, A. K. Goel, and A. Kumar, "The role of artificial neural network and machine learning in utilizing spatial information," *Spatial Information Research*, vol. 31, no. 3, pp. 275–285, 2023.
[27] T. L. Tuten and M. R. Solomon, *Social Media Marketing*. SAGE, 2023.
[28] Q. Wu, D. Yan, and M. Umair, "Assessing the role of competitive intelligence and practices of dynamic capabilities in business accommodation of smes," *Economic Analysis and Policy*, vol. 77, pp. 1103–1114, 2023.
[29] M. e. a. Xiao, "Factors affecting youtube influencer credibility," *Journal of Media Business Studies*, vol. 19, no. 1, pp. 1–22, 2022.
[30] K. Z. K. e. a. Zhang, "Consumer participation in social commerce," *Information & Management*, vol. 59,

no. 3, p. 103115, 2022.
[31] M. S. Hosen, R. Islam, Z. Naeem, E. Folorunso, T. S. Chu, M. Al Mamun, and N. Orunbon, "Data-driven decision making: Advanced database systems for business intelligence," *Nanotechnology Perceptions*, vol. 20, no. 3, pp. 687–704, 2024.
[32] C. Ashley and T. Tuten, "Creative strategies in social media marketing," *Psychology & Marketing*, vol. 39, no. 4, pp. 735–747, 2022.
[33] X. J. e. a. Lim, "Social media influencer marketing," *Journal of Business Research*, vol. 150, pp. 92–105, 2022.
[34] D. Chaffey and F. Ellis-Chadwick, *Digital Marketing*, 8th ed. Pearson, 2022.
[35] E. Constantinides, "Foundations of social media marketing strategy," *Online Journal of Applied Knowledge Management*, vol. 10, no. 1, pp. 1–15, 2022.
[36] A. O. Adewusi, U. I. Okoli, E. Adaga, T. Olorunsogo, O. F. Asuzu, and D. O. Daraojimba, "Business intelligence in the era of big data: A review of analytical tools and competitive advantage," *Computer Science & IT Research Journal*, vol. 5, no. 2, pp. 415–431, 2024.
[37] E. Fürsich and J. L. Qiu, "Media power in digital platforms," *New Media & Society*, vol. 24, no. 9, pp. 2035–2053, 2022.
[38] J. F. Gräve, "What kpis matter in social media strategy?" *Social Media + Society*, vol. 8, no. 1, 2022.
[39] R. e. a. Hanna, "We're all connected," *Business Horizons*, vol. 65, no. 4, pp. 405–415, 2022.
[40] L. e. a. Hudders, "Advertising literacy in influencer marketing," *Journal of Advertising*, vol. 51, no. 3, pp. 387–404, 2022.
[41] A. M. Kaplan and M. Haenlein, "Social media strategy and performance," *Business Horizons*, vol. 65, no. 1, pp. 25–36, 2022.
[42] A. J. Kim and E. Ko, "Impacts of luxury fashion brand social media marketing," *Journal of Business Research*, vol. 141, pp. 376–389, 2022.
[43] F. e. a. Li, "Social media marketing strategy," *Journal of International Marketing*, vol. 30, no. 2, pp. 1–30, 2022.
[44] E. C. e. a. Malthouse, "Managing customer relationships in the social media era," *Journal of Interactive Marketing*, vol. 57, pp. 20–36, 2022.
[45] J. McCarthy and J. Rowley, "Social media brand communities," *Journal of Marketing Management*, vol. 39, no. 5-6, pp. 467–493, 2023.
[46] V. Mahalakshmi, N. Kulkarni, K. P. Kumar, K. S. Kumar, D. N. Sree, and S. Durga, "The role of implementing artificial intelligence and machine learning technologies in the financial services industry for creating competitive intelligence," *Materials Today: Proceedings*, vol. 56, pp. 2252–2255, 2022.
[47] T. M. Nisar and C. Whitehead, "Brand interactions on social media," *Journal of Strategic Marketing*, vol. 30, no. 2, pp. 130–146, 2022.
[48] M. Paramesha, N. Rane, and J. Rane, "Big data analytics, artificial intelligence, machine learning, internet of things, and blockchain for enhanced business intelligence," *Artificial Intelligence, Machine Learning, Internet of Things, and Blockchain for Enhanced Business Intelligence (June 6, 2024)*, 2024.
[49] D. Martinez and L. Magdalena, "Integrasi ai dan blockchain: Meningkatkan keamanan dan transparansi dalam transaksi keuangan," *Transactions on Artificial Intelligence*, 2024.
[50] L. Zheng, *DEI Deconstructed*. Berrett-Koehler, 2022.
[51] Ministry of Communication and Informatics of the Republic of Indonesia, "Machine learning enabled social media competitive intelligence system: Enhancing digital transformation in government services," Ministry of Communication and Informatics, Jakarta, Indonesia, Tech. Rep., 2023. [Online]. Available: https://www.kominfo.go.id