A Systematic Review of Graph Neural Networks and Social Network Analysis Techniques for Public Sentiment Uncovering

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Abstract*—The rapid growth of social media has produced large-scale, highly interconnected user-generated data, creating the need for analytical approaches that can capture both textual meaning and relational structure. This systematic literature review examines the integration of Graph Neural Networks (GNNs) and Social Network Analysis (SNA) for public sentiment uncovering in social media. Following a PRISMA-based review process, 75 studies were selected from ScienceDirect and IEEE Xplore. The synthesis shows that recent research has expanded beyond direct sentiment classification to include closely related tasks that improve sentiment reliability, including misinformation detection, rumor analysis, bot detection, anomaly detection, and recommendation personalization. Within the reviewed sentiment-oriented studies, the thematic distribution indicates that 32% focus on direct sentiment or emotion analysis, 29% on misinformation or rumor detection, 24% on malicious-user, bot, or anomaly detection, and 15% on community detection or link prediction. Hybrid models consistently reported strong empirical gains, including 95.25% accuracy for GNN–LSTM sentiment classification, improvements of more than 5% over baseline in heterogeneous neural network and language-model integration, and up to 98.4% accuracy/F1 in bot detection settings. The review also identifies key limitations related to scalability, noisy and incomplete data, interpretability, class imbalance, and cross-platform generalization. In response, it proposes future research directions centered on real-time graph learning, multilingual adaptation, emotion-aware graph representations, fairness-aware evaluation, and human-in-the-loop explainability. These findings provide a clearer methodological foundation for researchers and practitioners seeking to build more robust, explainable, and socially aware sentiment analysis systems.

Keywords*—Graph Neural Networks (GNNs); Social Network Analysis (SNA); public sentiment analysis; hybrid models; Systematic Literature Review (SLR)

I. INTRODUCTION

In recent years, the rapid development of social media platforms has resulted in an unprecedented volume of publicly available user-generated content. This explosion of data has prompted researchers to explore advanced techniques for analyzing and extracting meaningful information from social networks, particularly in understanding public sentiment. Public sentiment analysis, or opinion mining, involves the process of identifying, extracting, and analyzing subjective information from various forms of text, including social media posts, reviews, and comments. The ability to effectively capture the pulse of public sentiment is invaluable for numerous applications, including market research, political analysis, and social trend prediction [1], [2].

Graph Neural Networks (GNNs) have emerged as a powerful tool for analyzing data in the form of graphs, where entities (nodes) and their relationships (edges) are inherently interconnected. Social networks, by their very nature, represent complex graphs where individuals (nodes) are connected through interactions, friendships, or shared interests (edges). GNNs have demonstrated significant promise in capturing the complex dependencies and non-linear relationships within such data, making them ideal for social network analysis [3], [4]. By leveraging GNNs, researchers have been able to enhance the accuracy and efficiency of sentiment analysis models, enabling them to detect patterns, trends, and influences within social media conversations [5], [6].

The integration of Social Network Analysis (SNA) techniques with GNNs allows for a deeper understanding of how information flows across social networks, how communities are formed, and how sentiment propagates across interconnected nodes. SNA focuses on the structural aspects of social networks, such as identifying influential nodes, community detection, and examining the dynamics of relationships [7], [8]. These techniques have proven to be highly beneficial in the analysis of sentiment, as they offer insights into how individual opinions are shaped by the network structure and interactions [9], [10].

Despite the considerable progress made in these fields, the application of GNNs and SNA for public sentiment uncovering still faces challenges. These include the difficulty of handling dynamic networks, heterogeneous data, and noisy or biased inputs [11], [7]. Additionally, the interpretability of models, particularly in the context of sentiment analysis, remains a critical issue for practical deployment [10], [11].

Although prior studies have demonstrated the usefulness of Graph Neural Networks (GNNs) for relational learning and the value of Social Network Analysis (SNA) for understanding community structure and information diffusion, the literature remains fragmented in three important ways. First, many studies examine sentiment classification, misinformation detection, bot

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identification, anomaly detection, and recommendation as separate tasks, even though these tasks are structurally connected in real social media ecosystems. Second, existing discussions often emphasize either textual content or network structure, but fewer studies systematically explain how the integration of GNNs and SNA improves the uncovering of public sentiment at the community and interaction level. Third, recent advances in hybrid GNN models, multimodal learning, and temporal graph analysis have grown rapidly, yet the field still lacks a focused review that synthesizes their methodological contributions, empirical gains, and unresolved limitations in a single analytical framework. Therefore, a clear research gap exists in the form of a systematic synthesis that not only maps recent developments at the intersection of GNNs and SNA but also explains how these techniques jointly support robust, interpretable, and scalable public sentiment analysis on social media.

This systematic literature review (SLR) addresses that gap by synthesizing recent studies on the integration of GNNs and SNA for public sentiment uncovering in social media environments. The review focuses not only on direct sentiment and emotion analysis, but also on closely related tasks such as rumor detection, misinformation identification, malicious account detection, anomaly discovery, user behavior prediction, and recommendation personalization, because these tasks shape the quality and reliability of sentiment inference [15]. By organizing the literature around five research questions, this review aims to clarify the methodological landscape, identify empirical trends and performance patterns, highlight current challenges, and formulate more concrete directions for future research.

II. Methodology

This systematic review was conducted following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to ensure a rigorous and transparent process in the selection, evaluation, and synthesis of studies [12], [13]. The goal of the review was to examine the application of Graph Neural Networks (GNNs) and Social Network Analysis (SNA) techniques for public sentiment analysis, particularly in the context of social media platforms. The methodology was structured to ensure that the review process was reproducible and comprehensive, addressing key research questions through systematic data collection and synthesis [14].

A. Literature Search Strategy

A thorough and systematic search was carried out in two widely recognized academic databases, namely ScienceDirect and IEEE Xplore, to identify relevant research articles. The primary search was designed to capture the most recent developments in the use of Graph Neural Networks (GNNs) and Social Network Analysis (SNA) for public sentiment uncovering, with the core review corpus limited to studies published between 2023 and 2026. The search terms used were “Graph Neural Networks” and “Social Network Analysis,” reflecting the two central methodological dimensions of this review. Because the review also considers adjacent tasks that affect sentiment reliability, such as misinformation detection, bot detection, anomaly detection, and recommendation, broad search terms were used and followed by manual relevance screening at the title, abstract, and full-text stages.

In ScienceDirect, the initial search yielded 1,763 records, of which 1,511 were classified as research articles. After filtering by subject area and publication period, 312 articles remained for screening, and 45 studies were finally retained. In IEEE Xplore, the search returned 561 records, of which 550 belonged to IEEE-published content. After restricting the results to the target publication period and screening for relevance, 30 studies were retained. In total, 75 studies constituted the core PRISMA-based review corpus [15], [16], [17].

To avoid excluding influential earlier work, the review also cites a limited number of pre-2023 foundational studies when they introduced methods, architectures, or analytical ideas that were directly extended by the 2023–2026 literature. These earlier studies were used only to contextualize the evolution of the field and were not counted as part of the 75 studies reported in the PRISMA flow diagram. This two-layer design preserves the recency of the review while still acknowledging foundational developments relevant to the interpretation of recent research.

B. Inclusion and Exclusion Criteria

The inclusion and exclusion criteria for this systematic review were carefully defined to ensure the selection of studies that directly addressed the research questions, specifically focusing on the intersection of Graph Neural Networks (GNNs), Social Network Analysis (SNA), and Public Sentiment Uncovering. By establishing clear criteria, the review aimed to maintain a narrow focus on studies that were most relevant to the core objectives, ensuring the final selection was aligned with the review's aims and scope [18].

Inclusion criteria were defined at two levels. First, the core review corpus included peer-reviewed research articles published in English between 2023 and 2026 that directly addressed the application of GNNs and/or SNA to public sentiment analysis or closely related social media tasks. Second, a small number of foundational pre-2023 studies were retained only when they were necessary to explain the methodological evolution of GNN-based sentiment analysis, SNA-driven interaction modeling, or hybrid graph-learning architectures. These foundational studies were used for contextual interpretation and were not included in the PRISMA-based quantitative count of the final corpus.

Exclusion criteria were equally important in refining the selection process. Surveys or Systematic Literature Reviews (SLRs) were excluded from the review, as these types of studies would overlap with the goals of the review, which were to focus on primary research articles. Additionally, studies published in languages other than English were excluded, as this review was limited to English-language sources. Finally, any studies that did not directly address the application of GNNs or SNA in public sentiment or social media analysis, particularly those that focused on other fields such as healthcare, finance, or physical sciences, were excluded. This ensured that the review remained focused on the specific domain of public sentiment analysis within the context of social media and GNNs/SNA methodologies.

C. Study Selection Process

The study selection process was conducted in two stages. In the first stage, titles and abstracts were screened to remove clearly irrelevant articles. In the second stage, full texts were assessed against the predefined inclusion and exclusion criteria. After duplicate removal, relevance screening, and full-text eligibility checking, 75 studies were retained as the core review corpus. These studies formed the basis of the PRISMA-based synthesis. In addition, a limited number of earlier foundational studies were cited selectively in the discussion sections to clarify the methodological roots of recent developments, but these were not included in the final PRISMA count [19].

D. Data Extraction

Data extraction involved a detailed process to systematically collect relevant information from each of the selected articles. The goal was to capture key data points that would provide insight into the applications and effectiveness of GNNs and SNA for sentiment analysis on social media platforms. The following information was extracted from each article: 1) Author(s) and Year of Publication: To trace the development of ideas and methodologies over time. 2) Research Objectives: To understand the primary focus of each study (e.g., sentiment analysis, fake news detection, anomaly detection). 3) Methodology: A summary of the techniques and algorithms used, such as the specific GNN architecture, SNA methods, or hybrid models. 4) Applications: Detailed information about the real-world applications of GNNs and SNA, such as social media sentiment analysis, detection of misinformation, or the identification of malicious user behaviors. 5) Key Findings: The main outcomes and conclusions drawn from each study, particularly regarding the effectiveness and challenges of using GNNs and SNA in public sentiment analysis. 6) Challenges and Limitations: Any issues faced by the studies in applying GNNs and SNA, including computational challenges, data limitations, or model robustness. This structured extraction process ensured that relevant insights were gathered systematically across all 75 included studies, providing a consistent basis for qualitative synthesis and cross-study comparison [6], [13].

E. Data Synthesis

Following the data extraction, a qualitative synthesis was performed to address the research questions. The synthesis aimed to highlight the trends and patterns in the literature regarding the application of GNNs and SNA for sentiment analysis. The analysis focused on identifying the strengths and limitations of current methodologies, the types of sentiment analysis tasks tackled by GNNs and SNA, and the specific domains of social media (e.g., Twitter, Facebook, etc.) where these techniques have been most effective. The synthesis also provided a detailed examination of the hybrid approaches combining GNNs with other machine learning techniques, such as deep learning or reinforcement learning [1]. Additionally, the review assessed the challenges faced by researchers in applying GNNs and SNA to real-world sentiment analysis problems, as well as the solutions proposed to overcome these challenges. The following research questions were used to guide the synthesis:

- RQ1: How do Graph Neural Networks (GNNs) enhance the analysis of public sentiment on social media platforms?
- RQ2: What are the benefits and limitations of integrating Social Network Analysis (SNA) with GNNs for detecting anomalies and malicious behaviors in social media?
- RQ3: What challenges arise when applying GNNs and SNA for sentiment analysis, and how can these challenges be mitigated?
- RQ4: How effective are hybrid models that combine GNNs with other machine learning techniques for improving sentiment analysis accuracy on social media?
- RQ5: What is the role of GNNs in predicting user behavior and personalizing recommendations based on social media interactions?

F. Prisma Flow Diagram

The systematic review process is summarized visually in Fig. 1, which presents the PRISMA flow diagram used to trace study identification, screening, eligibility assessment, and final inclusion. The diagram highlights the rigor and transparency of the review procedure.

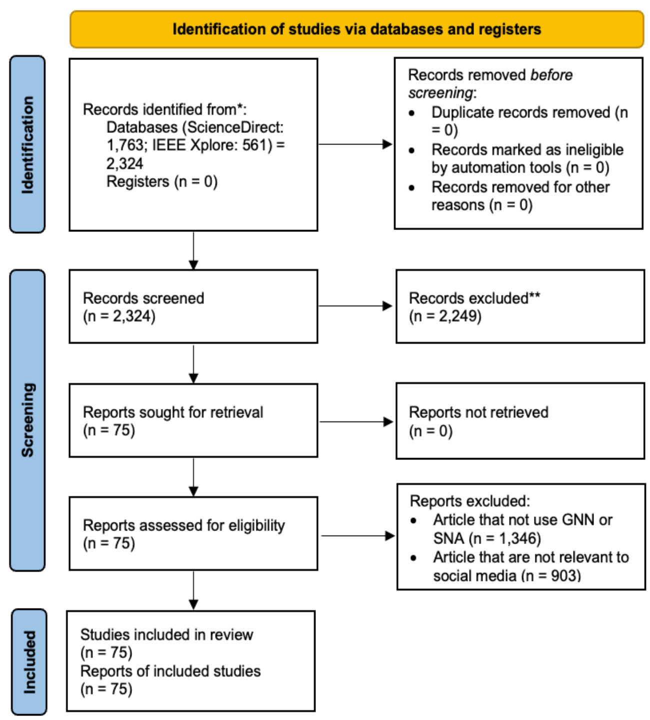

Fig. 1. PRISMA Diagram as Guideline.

III. Results and Discussion

The rapid evolution of social media as a primary channel for public discourse has generated vast amounts of user-generated content characterized by high velocity, diversity, and complex interaction patterns.

Effectively extracting meaningful insights from such data requires advanced analytical frameworks capable of capturing not only textual semantics but also the structural relationships and dynamic behaviors inherent in online communities. Graph Neural Networks (GNNs) have emerged as a powerful approach in this regard, enabling the integration of network topology, multimodal information, and temporal dynamics into a unified learning framework. When combined with techniques from Social Network Analysis (SNA) and other machine learning paradigms, GNNs offer unprecedented capabilities for tasks such as sentiment analysis, anomaly detection, misinformation tracking, and personalized recommendations. The following subsections address the five research questions (RQ1–RQ5) that guide this study, drawing on insights from the reviewed literature to explore the role of GNNs in enhancing sentiment analysis, detecting malicious behaviors, overcoming implementation challenges, leveraging hybrid model architectures, and predicting user behaviors in social media contexts.

A. *RQ1: How do Graph Neural Networks (GNNs) Enhance the Analysis of Public Sentiment on Social Media Platforms?*

The analysis of public sentiment on social media requires models that can handle highly interconnected, multimodal, and dynamic data. Graph Neural Networks (GNNs) address these needs by jointly modeling the content of user-generated posts and the structural relationships between users, posts, and communities. This dual capability allows GNNs to capture the complex ways in which sentiment emerges, spreads, and evolves within social platforms.

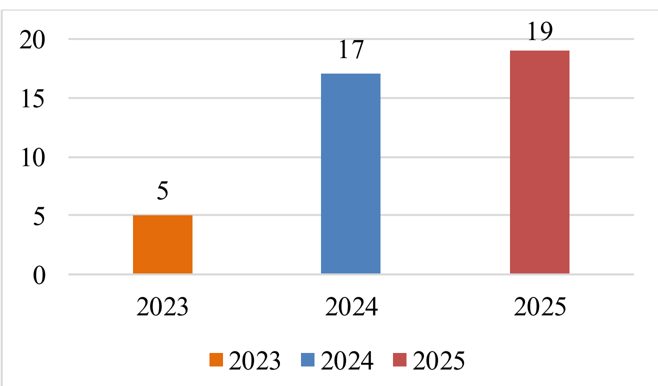

Fig. 2. Publication trend of reviewed studies (2023–2025).

From a thematic perspective, 41 sentiment-oriented studies were analyzed within RQ1. This subset was drawn primarily from the 2023–2026 core review corpus, while a small number of earlier foundational studies were cited only to contextualize the evolution of the field. As illustrated in Fig. 2, publication activity accelerated sharply in 2024–2025, indicating growing research interest in the integration of GNNs, social structure modeling, and sentiment-related tasks. Earlier studies, such as Li and Li [27] and Nguyen et al. [31] are discussed selectively because they introduced methodological ideas that were later extended by more recent work.

with only one study [20]. In 2023, publications expanded to works on dynamic link prediction [21], coupled graph models [22], and sociological hypergraph learning [23]. As illustrated in Fig. 2, the most significant growth occurred in 2024–2025, with over 88% of the total publications produced during this period, reflecting a surge in both direct sentiment modeling [24], [25], [26], [27], and related tasks like misinformation detection [28], [29], [30], [31], malicious user detection [32], [33], [34], [35], [36], and anomaly filtering [37], [38], [39].

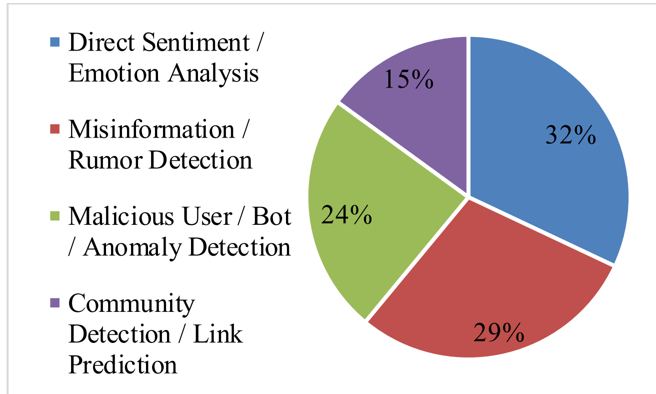

Fig. 3. Distribution of research themes in reviewed studies for RQ1.

As shown in Fig. 3, approximately 32% of the reviewed studies focus on direct sentiment or emotion analysis, 29% address misinformation or rumor detection, 24% deal with malicious user, bot, or anomaly detection, and 15% focus on community detection or link prediction. This thematic spread demonstrates that while direct sentiment analysis remains a major research area, supportive tasks play a critical role in improving sentiment analysis reliability and robustness. One of the most direct contributions of GNNs to sentiment analysis is their ability to exploit network topology to enrich the interpretation of textual content. Li and Li [20] showed that integrating a GNN with Long Short-Term Memory (LSTM) and semantic graph construction produced highly accurate sentiment predictions for short Weibo comments. Similarly, multilayered network approaches [24] have been used to graphically represent tweets, enabling more precise emotion classification even in the presence of sarcasm or mixed emotional cues. Graph embedding methods [25] enhance this further by producing explainable sentiment predictions, allowing researchers to trace how network relationships influence classification outcomes. The robustness of sentiment analysis can also be strengthened through improved network modeling techniques. The coupled graphs and tensor factorization framework [22] and the heterogeneous graph attention with motif cliques [40] both improve community detection, which is essential for identifying clusters of users with shared sentiment orientations. Concept stability entropy [41] provides a quantitative measure of group cohesion, offering insights into how strongly communities hold particular opinions.

Social media sentiment is not confined to text; it emerges from the interplay of language, images, videos, and user behaviors. Several GNN-based models integrate these signals to provide a multimodal view of sentiment. Zhang and Lee [27] combined emotion analysis with user behavior modeling to improve misinformation detection, indirectly strengthening sentiment analysis by filtering emotionally manipulative content. Similar work by Zhang et al. [26] integrates heterogeneous neural networks with fine-tuned language models, capturing context-dependent emotions more effectively. Multimodal rumor detection [18] and multi-granularity misinformation detection [28] show that GNNs can align heterogeneous data sources into coherent sentiment profiles. Recommendation systems can also play a role in shaping sentiment exposure. Self-supervised graph transformer networks [42] and micro-video hashtag recommendation frameworks [43] indirectly influence public sentiment landscapes by controlling content dissemination pathways. Even stance similarity models for fake news detection [44] contribute to sentiment understanding by identifying opinion alignment or divergence in relation to controversial topics.

High-quality sentiment analysis depends on clean and trustworthy network data. Malicious accounts [32], [33], [34], [36], fake reviewers [34], [35], and spam bots [29] can distort sentiment signals. GNN-based malicious user detection frameworks [36] and hybrid CNN approaches [29] effectively identify and remove such actors. Similarly, fake review detection using contextual GNNs [35] ensures that sentiment datasets represent genuine opinions. Graph imputation models [45], regression-based graph signal learning [46], and anomaly detection in attributed networks [38], [39] address data completeness and integrity issues, which are critical when building sentiment graphs from noisy social media streams. Mixed substructure learning [47] improves the representational power of GNNs, enabling the capture of subtle sentiment variations that might otherwise be lost.

Public sentiment is inherently dynamic, shifting over time in response to events and influencer activity. Temporal graph convolutional networks [48] can model such time-sensitive relationships, enabling the detection of evolving sentiment trends. Deep reinforcement learning for influence maximization [49] identifies key opinion leaders who drive sentiment shifts across communities. Link prediction models [21], [50], [44] reveal potential future connections that may become sentiment transmission channels. Rumor and misinformation detection frameworks also reveal how sentiment reacts to credibility cues. Social psychology-based rumor detection [51] and knowledge graph, GNN hybrids for psychological emergency detection [52] show that understanding the interplay between emotion, cognition, and network structure is crucial for accurate sentiment modeling in crisis contexts. Although not explicitly developed for sentiment analysis, many GNN advancements in other domains are highly transferable. NACNet's context-aware architecture [53] from medical prediction can be adapted for health-related sentiment tracking. Event relation extraction using dynamic latent graphs [54] can help identify sentiment triggers. Visualization techniques [55] and self-supervised hypergraph learning [23] enhance the interpretability of large sentiment networks.

The techniques like hybrid GCN-BERT co-attention for fake news detection [30], high-order heterogeneous GNN learning [56], and hybrid Hopfield CNNs for bot detection [34] all contribute to a more trustworthy sentiment analysis pipeline by removing distortions and modeling deeper semantic relationships. Taken together, the synthesis demonstrates that GNNs enhance public sentiment analysis not merely by classifying the emotional tone of individual posts but by enabling a network-aware, multimodal, and temporally adaptive understanding of sentiment. They improve context capture [20], [24], [25], community and influence modeling [22], [40], [41], multimodal signal integration [17, 18, 23, 35], and data quality assurance [32], [45], [34], [35], [36], [39]. The rapid growth in publications and the diversity of methods suggest a sustained research trajectory toward integrated, explainable, and resilient sentiment analysis systems for social media platforms.

B. RQ2: What are the Benefits and Limitations of Integrating Social Network Analysis (SNA) with GNNs for Detecting Anomalies and Malicious Behaviors in Social Media?

Detecting anomalies and malicious behaviors in social media platforms requires analytical frameworks capable of capturing both the structural patterns of online interactions and the behavioral signals embedded within user activities. Social Network Analysis (SNA) offers a principled framework for representing user–user, user–content, and community relationships, while Graph Neural Networks (GNNs) excel at learning high-dimensional, context-aware representations from such relational structures. By integrating SNA with GNNs, researchers can jointly model the network topology and behavioral dynamics of users, enabling more accurate and robust detection of malicious activities across varied social contexts.

From a bibliometric perspective, the reviewed literature shows a clear upward trend in research on SNA–GNN integration for security tasks in social media. The earliest example, Sansonetti et al. [57], incorporated social context into deep learning for detecting unreliable users on Twitter. However, the majority of publications emerged between 2024 and 2025, reflecting rapid methodological diversification. These include community-based detection methods [58], hybrid architectures for bot and spam detection [33], [34], anomaly detection in attributed networks [38], [39], multi-modal malicious account identification [59], [32], and link prediction approaches for pre-emptive threat detection [50], [44].

TABLE I. DISTRIBUTION OF RESEARCH THEMES IN REVIEWED STUDIES FOR RQ2

Research Theme	Ref.	Percentage
Bot and Spam Detection	[57], [33], [34]	28%
Fake Account / Fake Reviewer Detection	[59], [10], [32]	24%
Anomaly Detection in Attributed / Heterogeneous Networks	[38], [39], [36]	22%
Malicious Login & Coordinated Attack Detection	[5], [57]	18%
Link Prediction for Pre-emptive Threat Detection	[44], [50]	8%

As shown in Table I, bot and spam detection represents the largest share of the reviewed studies (28%) [33], [34], [44], indicating a sustained focus on mitigating automated threats that distort social media discourse. Fake account and fake reviewer detection follows at 24% [59], [35], [32], reflecting the need to ensure authenticity in user-generated content and online interactions. Anomaly detection in attributed or heterogeneous networks accounts for 22% [38], [36], [39], highlighting efforts to identify structural and behavioral deviations associated with malicious activity. Malicious login and coordinated attack detection comprise 18% [60], [58], underscoring the importance of early warning systems against infiltration and organized campaigns. The remaining 8% of studies rely on link prediction techniques [50], [44] to identify suspicious future connections before harmful behavior spreads.

Methodologically, enriching GNN inputs with SNA-derived features such as ego-network connectivity, interaction frequency, and cross-community linkages enhances detection accuracy. Sansonetti et al. [57] and Cheng et al. [35] show that this combination uncovers coordinated malicious patterns that would be invisible to content-only models. Community detection approaches, like the GCN–Fuzzy C-Means method of Al-Andoli et al. [58], identify overlapping clusters that often function as operational bases for coordinated attacks or misinformation campaigns. Multi-modal pipelines also benefit from SNA integration: Tang et al. [32], [59] combine graph-based non-textual features with textual attention to achieve high detection performance, while Lin and Jian [32], [59] demonstrate improvements in fake account detection by combining SVM, GNN, and clustering.

Scalability is supported by subgraph-centric frameworks such as SEAL+ [44], [50] and link prediction models [50], which reduce computational costs while preserving relational context. Architectures like CGNN [33] illustrate that embedding SNA concepts directly into GNN designs can achieve state-of-the-art results with significantly fewer parameters and shorter training times. Techniques like sparsification and graph attention [38], [39] further enhance robustness by filtering noisy edges, while adaptive anomaly scoring [39] integrates structural, embedding, and density indicators.

Despite these benefits, limitations remain. Data quality and completeness are critical bottlenecks, as public datasets often lack comprehensive interaction histories or contain noisy, incomplete connections [57], [35]. The scarcity of labeled training data [36] and cross-platform variability [59] complicate generalization. Computational complexity can be prohibitive for methods such as overlapping community detection [58] and exhaustive subgraph extraction [44], especially on large or dynamic networks. Behavioral camouflage, where malicious actors mimic legitimate user patterns, presents another challenge, particularly in weak-tie contexts like dating platforms [32], necessitating complex multi-modal models that risk overfitting [34]. GNN oversmoothing remains a concern in heterogeneous networks [33], and sparsification or attention mechanisms introduce new hyperparameter sensitivities [38], [39]. Severe class imbalance continues to hinder performance, although focal loss and staged training have shown partial success [35].

The empirical evidence suggests that SNA–GNN integration delivers significant improvements in detecting malicious behaviors, from bot and spam suppression [33], [34] to identifying coordinated fake reviewing [35] and early-stage malicious logins [60]. By embedding behavioral analysis within a network-aware framework, this integration improves detection accuracy, enhances interpretability, and offers proactive defense capabilities. Addressing challenges in data quality, scalability, heterogeneity, and interpretability will be key to advancing the practical deployment of these systems in dynamic, real-world social media environments [58], [36], [59], [38], [44], [35], [39].

C. RQ3: What Challenges Arise When Applying GNNs and SNA for Sentiment Analysis, and How Can These Challenges Be Mitigated?

Integrating Graph Neural Networks (GNNs) with Social Network Analysis (SNA) for sentiment analysis offers significant potential by allowing the modeling of both structural aspects of social networks and content in user posts. This combined approach enables more accurate and nuanced sentiment analysis, capturing how sentiment evolves, spreads, and interacts within social networks. However, several challenges emerge when applying these methodologies to real-world, dynamic social media environments.

Recent studies show a notable increase in the application of GNNs and SNA for public sentiment analysis, particularly in the years 2024–2025. Early works, such as Sentiment Analysis of Weibo Comments Based on Graph Neural Network [20] and Detecting Fake Reviewers from the Social Context with a Graph Neural Network Method [35], highlight the potential of combining content analysis with network features. Since then, there has been a rapid expansion of research into fake account detection, misinformation identification, and emotion-based sentiment analysis [34], [27], which are crucial for improving sentiment classification accuracy in social media. Key Challenges and Mitigation Strategies when applying GNNs and SNA for sentiment analysis as follows.

1) Complexity and scalability: One of the primary challenges in using GNNs and SNA for sentiment analysis is the computational complexity of these models. gnns require significant computational resources, especially when applied to large-scale social networks with millions of nodes and edges. For instance, studies like enhanced group influence maximization in social networks using deep reinforcement learning [49] and co-embedding of nodes and edges with graph neural networks [61] demonstrate how scaling GNNs for large datasets can lead to prohibitive computational costs. To address this issue, graph sampling techniques can reduce the size of the graph while preserving its structural information. Additionally, distributed learning and parallel processing can be leveraged to alleviate the computational burden, allowing for the efficient training of GNN models on large datasets [49][61].

2) Handling noisy and unstructured data: Social media data is inherently noisy and unstructured, making sentiment analysis challenging. as highlighted in sentiment analysis of weibo comments based on graph neural network [20] and fake reviewer detection [35], irrelevant, misleading, or manipulated content can distort sentiment signals, complicating sentiment detection. to address this issue, effective preprocessing techniques, such as text normalization, stop-word removal, and outlier detection, are essential for cleaning data before it is input into the model. Furthermore, adopting multi-modal models, as demonstrated in emotion analysis using multilayered networks [24], can help by combining textual data with additional sources like user metadata and images, enhancing the model's ability to classify sentiment accurately [20][35][24].

3) Model interpretability and transparency: GNNs, while powerful, often act as "black-box" models, making it difficult to understand how certain predictions are made. This lack of interpretability is particularly problematic when GNNs are used for sensitive applications, such as social media monitoring and misinformation detection, as emphasized in explaining deep graph networks via input perturbation [62]. To improve the transparency of GNN models, explainability frameworks such as Shap (Shapley additive explanations) and lime (local interpretable model-agnostic explanations) can be used to identify the key features influencing the model's predictions. These frameworks allow users to gain insight into the reasoning behind specific sentiment classifications, enhancing trust and understanding of the model [62].

4) Imbalanced data and class discrepancy: Another challenge in sentiment analysis with GNNs and SNA is the imbalance in sentiment data. Positive sentiments often dominate social media platforms, while negative or neutral sentiments are underrepresented. This imbalance is highlighted in misinformation detection in social networks using emotion analysis and user behavior analysis [27] and fake account detection [34], where the overwhelming amount of authentic content can reduce the effectiveness of sentiment models. To address this issue, data augmentation techniques, such as SMOTE (synthetic minority over-sampling technique), can help address class imbalance by generating synthetic samples for underrepresented sentiment classes. Furthermore, focal loss can be employed to prioritize the minority classes during training, improving the model's ability to classify rare sentiment types more accurately [27][34].

5) Capturing implicit relationships and emotions: While GNNs excel at capturing explicit relationships, such as user-to-user or post-to-post interactions, they struggle to capture implicit emotional cues that are essential for accurate sentiment analysis. This challenge is particularly evident in applications like emotion-based sentiment analysis and psychological feature analysis for rumor detection [51], [24], where emotional states and underlying psychological factors are critical for understanding sentiment. To overcome this, emotion-aware embeddings should be incorporated into GNN models to explicitly represent emotional states and psychological attributes. Multi-layered attention mechanisms, as shown in emotion analysis using multilayered networks [24], can be employed to emphasize emotionally significant interactions, helping the model capture subtle emotional nuances more effectively [51][24][24].

The integration of GNNs and SNA for sentiment analysis presents significant benefits, such as more accurate modeling of sentiment dynamics and improved detection of malicious behaviors. However, challenges like computational complexity, data noise, interpretability, class imbalance, and the difficulty of capturing implicit emotional cues persist. By employing strategies such as graph sampling, data preprocessing, explainability techniques, and emotion-aware embeddings, these challenges can be mitigated, paving the way for more efficient, robust, and interpretable sentiment analysis systems for social media platforms.

D. RQ4: How Effective are Hybrid Models that Combine GNNs with Other Machine Learning Techniques for Improving Sentiment Analysis Accuracy on Social Media?

Enhancing sentiment analysis accuracy on social media requires analytical models that can capture both the linguistic complexity of user-generated text and the relational patterns embedded in online interaction networks. Hybrid architectures that combine Graph Neural Networks (GNNs) with other machine learning techniques, such as recurrent neural networks, attention-based transformers, large language models (LLMs), or specialized feature selection methods provide a promising framework for this task. GNNs are highly effective in learning graph-structured dependencies between users, posts, and communities, while complementary models excel at extracting semantic, temporal, and contextual information from textual content. The combination allows for richer representations that address the informal, dynamic, and context-dependent nature of online discourse.

Empirical evidence from the reviewed studies supports the effectiveness of these hybrid approaches in sentiment analysis and related affective computing tasks. Li et al. [20] employ a GNN combined with Long Short-Term Memory (LSTM) networks to capture both graph topology and temporal linguistic patterns, achieving a sentiment classification accuracy of 95.25% on Weibo comments. Maazallahi et al. [26] integrate Heterogeneous Neural Networks (HNNs) with fine-tuned LLMs for emotion recognition closely aligned with sentiment analysis, yielding over a 5% improvement compared to baseline models. These works demonstrate that coupling graph reasoning with deep semantic representation significantly boosts classification accuracy.

While some studies are not exclusively focused on sentiment analysis, their methodologies are highly transferable because they also require joint modeling of content and relational structures. For example, Soga et al. [31] combine stance similarity analysis with GNNs for fake news detection; Zhang et al. [30] integrate Graph Convolutional Networks (GCN) with BERT through a co-attention mechanism; and Li et al. [51] use Graph Attention Networks (GAT) enhanced with psychological and emotional features from LLMs for rumor detection. Chang et al. [63] demonstrate the potential of integrating memory-augmented transformers with GCNs for temporal–structural analysis, while Kumar et al. [34] achieve 98.4% accuracy in spam bot detection using a hybrid deep learning pipeline—methods that could be adapted to sentiment-related tasks.

Other works contribute to hybrid GNN research by improving graph representation and processing efficiency, indirectly benefiting sentiment tasks. For example, Bacciu & Numeroso [62] enhance explainability for GNN-based models through perturbation techniques; Kumar et al. [64] combine GCN with Fuzzy C-Means for community detection; Xiao et al. [65] integrate GCN and GRU to model diffusion patterns; Zhu et al. [66] use adaptive jumping GNNs with self-attention for recommendation accuracy; Chen et al. [67] leverage graph attention autoencoders in self-supervised clustering; Yuan et al. [37] detect anomalies using motif-augmented GCN with temporal self-attention; Skarding et al. [68] explore heterogeneous GNN ensembles; Li et al. [42] introduce a self-supervised graph transformer for social recommendation; Huang et al. [33] design a compatibility-aware GNN for bot detection; Jiang et al. [61] co-embed node and edge features; Mirzaei & Kobti [48] propose a temporal GCN model for evolving relationships; and Lee et al. [50] employ synergetic fusion in GCNs for link prediction. Although these studies address tasks such as recommendation, anomaly detection, and link prediction, their architectural innovations in combining GNNs with complementary models can be directly applied to improve sentiment analysis in complex social media networks.

TABLE II. EFFECTIVENESS OF HYBRID GNN-BASED MODELS

Ref	Hybrid Model	Performance	Strengths
[20]	GNN + LSTM	95.25% accuracy	Combines graph structure analysis & temporal text context
[26]	HNN + Fine-tuned LLM	+5% accuracy over baseline	Captures deep semantic and relational features
[31]	GNN + Stance Analysis	Outperforms traditional methods	Models stance influence in news spread
[51]	GAT + Emotion & Social Features (LLM)	+5.87% accuracy	Integrates social psychology into graph models
[30]	GCN + BERT + Co-attention	Improved detection accuracy	Combines structural and semantic features
[34]	BGSO (feature selection) + HHD2SCNN	98.4% accuracy, F1 98.4%	Highly efficient and accurate bot detection

Table II summarizes these studies, detailing the type of hybrid model, application domain, performance gains, key strengths, and limitations. It shows a consistent trend: across diverse social media applications, hybrid GNN-based methods outperform single-model baselines by leveraging both graph-based relational reasoning and deep semantic understanding. Nevertheless, challenges remain. Integrating computationally intensive modules like LLMs or transformers with GNN layers can reduce scalability [66], [26], [30]. Handling the informal and multilingual nature of social media text [20], [26] and adapting to evolving network structures [31], [63], [51] complicates model generalization. Balancing the contributions of graph and text modules is non-trivial, with risks of overfitting to platform-specific patterns [34]. Interpretability remains a critical issue, especially for complex hybrid pipelines [62], [30]. These demonstrate that hybrid models combining GNNs with complementary machine learning techniques significantly enhance sentiment analysis accuracy on social media [50], [62]. By jointly modeling network structure and textual semantics, these systems achieve superior performance, context awareness, and resilience to noisy, informal content. Addressing challenges in scalability, cross-domain adaptation, and interpretability will be key to their wider adoption in real-world sentiment analysis applications.

E. RQ5: What is the Role of GNNs in Predicting User Behavior and Personalizing Recommendations Based on Social Media Interactions

Graph Neural Networks (GNNs) have proven to be instrumental in both predicting user behavior and personalizing recommendations in social media environments, primarily because of their ability to capture complex relational, temporal, and attribute-based structures within user interaction networks. By modeling connections between users, posts, and communities, GNNs enable systems to anticipate future behaviors and deliver tailored content, products, or connections with higher accuracy. For behavior prediction, GNN-based models can identify and forecast diverse patterns ranging from link formation to user churn. Sahay et al. [69] leverage spatial-temporal architectures to predict learning interactions in Social Learning Networks (SLNs), achieving an AUC of 0.99. Muro et al. [21] extend predictive capability to both link and unlink prediction in dynamic networks, integrating temporal and structural cues. Han et al. [70] demonstrate that combining GCN with Correct and Smooth (C&S) significantly improves churn prediction in MMORPGs, while Chen et al. [71] incorporate the Theory of Planned Behavior (TPB) features into GATs to anticipate cyberviolent behavior. These approaches illustrate that GNNs are well-suited for capturing evolving interaction dynamics and behavior-driving factors.

For personalized recommendations, GNNs excel when combined with complementary methods that enhance content understanding and contextual awareness. Kumar et al. [64] and Shah et al. [72] improve community detection accuracy, enabling better group-based recommendations. Zhu et al. [66] address node degree imbalance in recommendation graphs with adaptive jumping GNNs and matrix completion, boosting recommendation accuracy while mitigating over-smoothing. Li et al. [20] and Li et al. [43] integrate GNNs with LSTM or hybrid filtering to enhance sentiment-aware and content-based recommendations. Jiang et al. [61] propose a co-embedding framework that learns from both node and edge features, improving link-based recommendations. Mao et al. [73] introduce meta-learning-based dynamic graph embedding, improving adaptability to changing user preferences.

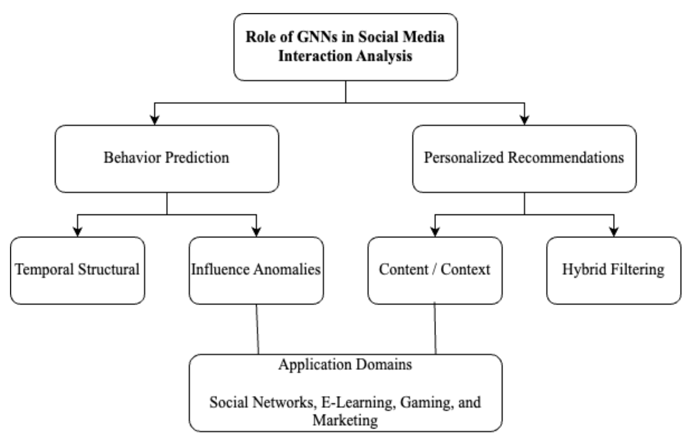

Fig. 4. Role of Graph Neural Networks (GNNs) in predicting user behavior and personalizing recommendations on social media.

Some studies also link behavior prediction with personalization by integrating influence modeling and anomaly filtering. Ghosh et al. [49] combine GNN embeddings with deep reinforcement learning to optimize seed selection for influence maximization—critical in viral marketing. Liang et al. [74] ensure minority-class behavior patterns are preserved in predictions via minority-weighted GNNs, while Zhang et al. [75] use contrastive learning with generative adjacency matrices to enhance graph embeddings, benefiting both behavioral analytics and recommendations. Filtering manipulative or malicious accounts also improves personalization quality; Lin and Jian [59] and Huang et al. [33], [76] [20] address this through GNN-based detection of fake accounts and bots. The diversity of applications and methods in the reviewed literature is summarized in Fig. 4, which categorizes studies by focus area, GNN contribution, methodological integration, and application domain.

F. Discussion

This review synthesizes findings from five research questions (RQ1–RQ5) to provide a comprehensive understanding of the role of Graph Neural Networks (GNNs) in social media analysis. Across all areas of investigation, a consistent pattern emerges: GNNs serve as a crucial bridge between content-level understanding, encompassing semantic, contextual, multimodal information, and structure-aware reasoning that models network topology, community dynamics, and temporal evolution.

In the context of sentiment analysis (RQ1), GNNs show clear advantages through the joint modeling of textual semantics and user–content–community relationships [20], [24]-[27]. This dual modeling capability enables the detection of nuanced emotional signals, even in the presence of sarcasm or mixed sentiment expressions. Reliability in sentiment measurement is further enhanced when GNN pipelines incorporate malicious account detection mechanisms [32]-[36], ensuring that distortive network actors are filtered out before sentiment modeling occurs. When integrated with Social Network Analysis (SNA) (RQ2), GNNs are able to identify bots, fake accounts, and coordinated attacks more effectively by enriching structural representations, such as ego-network density and motif cliques with behavioral indicators [33], [34], [38], [39], [59]. This integration exposes malicious patterns that content-only models often fail to detect. Nevertheless, issues related to scalability, severe class imbalance, and behavioral mimicry remain significant obstacles to widespread deployment.

The analysis of RQ3 reveals several recurring challenges, including computational complexity [49], [61], noisy and incomplete datasets [20], [35], limited interpretability ([69]), class imbalance [27], [34], and difficulties in capturing implicit emotional cues [24], [77],[51]. Mitigation strategies identified in the literature include graph sampling to improve scalability, multimodal preprocessing to handle noise, the use of explainability tools such as SHAP and LIME to enhance transparency, and the incorporation of emotion-aware embeddings to better capture subtle affective signals. In the domain of hybrid modeling (RQ4), approaches that combine GNNs with complementary architectures—such as GNN + LSTM [20], GCN + BERT [30], and GAT augmented with emotion features [51], consistently outperform single-model baselines. These hybrid systems achieve notable gains in sentiment classification, stance detection, and misinformation identification by uniting semantic depth with relational inference. However, they often incur high computational costs, exhibit platform-specific dependencies, and face generalization challenges [26], [31], [34].

Lastly, in RQ5, GNNs emerge as a dual enabler of user behavior prediction and personalized recommendations. Applications include predicting link formation ([21], churn [70], and cyberviolent behaviors [33], [71], as well as powering recommendation systems that adapt to evolving user preferences while preserving content integrity. The latter is particularly effective when manipulative or malicious accounts are identified and removed from the network [33], [59]. From a theoretical standpoint, these findings position GNNs as a unifying framework for modeling network-aware, multimodal social media data, offering richer representations of sentiment dynamics, trust relationships, and user behaviors than text-only approaches. In practice, the reviewed methods provide actionable solutions for real-time opinion monitoring, early detection of coordinated manipulation campaigns, and personalized content delivery that is both accurate and ethically responsible. For platform operators, adopting hybrid GNN–SNA architectures could significantly enhance both content moderation and user engagement strategies.

The current state of the art in GNN-based social media analytics is characterized by four converging trends: the integration of multimodal sentiment signals through heterogeneous architectures [26], [28]-[28] the rise of hybrid models combining GNNs with LSTMs, Transformers, or large language models [20], [26], [28], [30], [31], [51]; advances in temporal and dynamic graph learning to capture evolving sentiment, rumor propagation, and influence dynamics [21], [48]-[50]; and the incorporation of explainability mechanisms, such as motif analysis [40], visualization [55], and perturbation-based methods [62], to increase transparency and stakeholder trust.

Despite these advances, several research gaps remain. Scalability continues to limit applicability in large-scale, real-time environments, and cross-platform adaptation is underexplored, with few studies validating their models on heterogeneous or multilingual datasets [33], [59]. Modeling implicit emotions—especially those tied to cultural or contextual factors—remains a complex challenge [24], and ethical considerations, including fairness and bias mitigation, are often secondary in current research. Addressing these gaps presents clear directions for future work. Developing real-time GNN frameworks capable of processing streaming and incremental updates without full graph recomputation is critical. Cross-domain and multilingual graph learning could enhance model robustness across diverse platforms, while emotion-aware embeddings that incorporate psychological and socio-linguistic cues may improve the detection of subtle sentiment shifts. Embedding bias and fairness auditing directly into training and inference could help prevent discriminatory outcomes, and human-in-the-loop explainability, combining automated interpretability tools with expert review, could increase decision reliability. Finally, integrating GNNs with generative simulation models offers potential for forecasting sentiment evolution and misinformation spread, enabling proactive interventions before harmful narratives gain traction.

G. Future Research Directions

Future research should move beyond broad thematic recommendations toward testable research programs. One promising direction is the development of real-time and streaming GNN frameworks for sentiment analysis. A concrete research question is: How much performance can incremental graph updating preserve compared with full graph recomputation under high-velocity social media streams? A related hypothesis is that incremental temporal GNNs can maintain at least comparable F1-score while substantially reducing latency and computational cost. This can be tested using time-sliced social media datasets with controlled update intervals and evaluation metrics such as macro-F1, latency, memory usage, and update efficiency.

A second direction concerns cross-platform and multilingual generalization. A useful research question is: Can GNN–SNA models trained on one platform or language transfer reliably to another without substantial performance degradation? The hypothesis here is that heterogeneous graph alignment combined with multilingual text encoders will improve robustness across platforms and languages. Experimental protocols should involve training on one platform or language setting and testing on another, with evaluation based on transfer F1-score, calibration error, and fairness across language groups.

A third direction involves emotion-aware and psychologically informed graph representations. The key question is whether adding latent emotional, cognitive, or behavioral signals can improve the detection of implicit sentiment, sarcasm, or emotionally manipulated discourse. This can be tested by comparing standard text-graph models against models enriched with emotion embeddings, social-psychological features, and community-level influence signals. Metrics should include not only classification accuracy but also explainability and robustness to adversarial or misleading content.

A fourth priority is fairness and explainability. Future studies should formulate explicit hypotheses on whether fairness-aware training objectives, bias auditing, and human-in-the-loop explanation workflows can reduce discriminatory model behavior without sacrificing predictive performance. Experimental designs should report subgroup performance, calibration, explanation consistency, and user trust assessments. Such protocols would provide more actionable guidance for real-world deployment than high-level recommendations alone.

IV. Conclusion

This systematic literature review has explored the integration of Graph Neural Networks (GNNs) and Social Network Analysis (SNA) techniques for public sentiment analysis within social media platforms. The findings underscore GNNs' capacity to bridge the gap between content-level understanding and structure-aware reasoning, making them indispensable for modeling complex social interactions. By jointly capturing textual semantics, network dynamics, and temporal shifts, GNNs provide a powerful tool for sentiment analysis, anomaly detection, misinformation tracking, and personalized recommendations. Despite substantial advancements, the integration of GNNs and SNA presents several challenges. These include scalability issues, class imbalance, interpretability concerns, and the complexity of modeling implicit emotional cues in social media discourse. However, strategies such as hybrid model architectures, graph sampling, multimodal preprocessing, and the incorporation of emotion-aware embeddings show promise in addressing these challenges. Additionally, the role of hybrid models, combining GNNs with other machine learning paradigms like LSTMs and large language models (LLMs), is proving effective in boosting performance and reliability.

Theoretical advancements highlight the significance of GNNs as a unified framework for network-aware sentiment analysis, providing deeper insights into how public sentiment evolves, spreads, and interacts within digital communities. Practically, GNNs, especially when paired with SNA, offer valuable solutions for real-time opinion monitoring, early threat detection, and tailored content delivery, enabling more informed and ethical social media strategies. Looking ahead, future research should focus on overcoming scalability and generalization limitations, developing real-time frameworks, and ensuring the ethical deployment of these models. As GNNs continue to evolve, integrating techniques like generative simulation models for sentiment forecasting and bias auditing will be crucial to ensuring the sustainability and fairness of sentiment analysis systems in dynamic, large-scale social media environments.

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