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Expression Capacity-Based Negative Sentiment (ECNS) Detection and Mitigation in Online Social Networks

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Abstract: The rapid expansion of social media platforms has intensified the spread of negative sentiments, misinformation, and hostile digital interactions, producing measurable consequences for public discourse, institutional trust, and societal stability. Existing models often overlook the cognitive and network-structural mechanisms that drive negative sentiment cascades, limiting capacity for early detection and effective intervention. The proposed study introduces the Expression Capacity-based Negative Sentiment (ECNS) Mitigation framework that integrates graph-theoretic analysis with psychological modeling to better understand and mitigate sentiment propagation. The ECNS architecture consists of five interconnected models dedicated to data ingestion, influencer identification, cascade monitoring, intervention control, and final sentiment-state generation. The operational core relies on two algorithms: the first identifies high-impact influencer nodes using community-level analysis and expression-capacity thresholds, while the second monitors negativity diffusion, evaluates sequential comment behavior, and applies targeted mitigation based on capacity depletion and sentiment intensity. This design enables proactive control of sentiment cascades rather than reactive moderation. The framework was evaluated across three heterogeneous datasets ResearchGate, Zhihu, and Sentiment140 to reflect diverse interaction patterns and topical domains. Comparative performance against three leading models such as EANN, HMCan, and AOAN demonstrates that ECNS provides more accurate influencer detection, stronger cascade containment, and more effective sentiment reduction. Overall, ECNS achieved improvements ranging from 5.8% to 11.4% points across key evaluation metrics, confirming its capacity to suppress negative sentiment propagation with significantly higher reliability.

Keywords: Negative Sentiment Propagation; Expression Capacity Modeling; Computational Social Networks; Influencer Node Analysis; Sentiment Mitigation Algorithms; Graph Based Behavioral Modeling

1. Introduction

The contemporary digital landscape has witnessed the transformation of social media platforms from rudimentary communication channels into sophisticated information ecosystems that fundamentally reshape opinion formation, dissemination, and amplification through complex network topologies. These heterogeneous networks empower billions of users to share knowledge, perspectives, and personal experiences across multi-layered architectures, creating unprecedented opportunities for global connection and collaborative knowledge construction [1]. However, this powerful ecosystem possesses a dual nature, simultaneously enabling the rapid dissemination of valuable information through positive network cascades and the uncontrolled amplification of negative sentiments expressions of dissatisfaction, anger, criticism, and hostility that propagate through viral diffusion mechanisms [2]. The consequences of this negativity transcend digital spaces, manifesting as real-world disruptions with profound implications for market dynamics, corporate reputation systems, and societal stability indices. The influence of coordinated negative sentiment exhibits measurable impact: empirical studies demonstrate that sentiment-driven social media cascades can trigger stock market volatility patterns, generate irreversible damage to brand equity through negative word-of-mouth propagation, and systematically erode institutional trust metrics through the amplification of skepticism and cynicism [3].

Network analysis of content generation patterns reveals that the magnitude of this challenge is predominantly driven by a statistically insignificant yet disproportionately influential minority of users, whose activity distributions exhibit power-law characteristics typical of scale-free network architectures. Empirical research utilizing network analysis techniques indicates that a statistically tiny fraction of the user base generates the vast majority of contentious and harmful content, demonstrating extreme skewness in content production distributions. For instance, seminal studies employing bot detection algorithms and behavioral pattern analysis have revealed that just 0.1% of users can be responsible for spreading 80% of misinformation through automated and semi-automated dissemination strategies, while separate large-scale analyses found that approximately 10% of highly active users generate 97% of politically polarized content. This dynamic creates a dangerously distorted online reality where negativity and conflict appear more prevalent and representative of public opinion than statistical distributions would suggest: a phenomenon formalized as the *loud minority effect* in computational social science. This phenomenon extends far beyond political discourse into professional and academic networks, where reputation systems and peer evaluation mechanisms become vulnerable to strategic manipulation. In scholarly environments characterized by competitive dynamics and status hierarchies, public announcements of professional achievements such as paper acceptances in high-impact venues can paradoxically trigger envy-driven negative feedback loops and passive-aggressive commenting behavior from peers [4]. These interactions, often strategically framed as objective criticism to maintain plausible deniability, foster toxic academic cultures that undermine constructive scholarly engagement, collegial recognition norms, and collaborative knowledge production.

Theoretical frameworks from social psychology and behavioral science reveal that the psychological mechanics underpinning digital negativity are multifaceted, and rooted in well-established constructs including emotional contagion theory, social information processing models, and online disinhibition mechanisms [5]. Users may unconsciously engage in emotional mimicry, replicating the affective states they observe in others through a process where emotional valence transfers across network edges, or they may experience reduced social presence and normative accountability when contributing to high-volume comment threads; a phenomenon termed *deindividuation* in crowd psychology [6]. This frequently manifests as inflammatory *flaming* behavior, characterized by hostile and socially inappropriate remarks that violate face-to-face interaction norms and would typically be suppressed by self-presentation management strategies in physical contexts [7]. This tendency is powerfully exacerbated by pre-existing cognitive schemas, confirmation bias mechanisms, and strong group identity formation. Social identity theory and intergroup conflict models suggest that individuals naturally engage in in-group favoritism while demonstrating out-group derogation, vigorously defending opinions aligned with their social identity while expressing heightened hostility towards perceived out-group members through biased information processing. This tribal dynamic, reinforced through selective exposure and motivated reasoning, fuels polarized debates characterized by minimal common ground and makes constructive cross-group dialogue exceedingly difficult due to fundamental attribution errors and perceived threat dynamics [8].

Cognitive science research demonstrates that users' perceptions of the online information landscape are systematically distorted by well-documented heuristic biases rooted in schema-driven interpretation and egocentric projection mechanisms. The false consensus effect, derived from egocentric bias in social projection, causes individuals to overestimate the extent to which their own views, beliefs, and behavioral patterns are normative and shared by the broader population. When operating in algorithmically-curated homogenous online circles characterized by high ideological homophily and limited network diversity, this bias leads users to profoundly misjudge the true distributional characteristics and attitudinal diversity of public opinion through availability heuristics, reinforcing existing viewpoints through confirmatory information processing and increasing susceptibility to misinformation through reduced epistemic vigilance and critical evaluation [9].

Exacerbating these inherent cognitive limitations are the sophisticated, algorithmically-driven architectures that constitute the computational backbone of modern social platforms through machine learning-driven content curation and recommendation systems. Social media recommendation algorithms do not merely reflect organic user preferences through passive filtering; they actively shape preference formation and belief structures through persuasive technologies and behavioral nudging. By curating intensely personalized information feeds using collaborative filtering, content-based filtering, and hybrid recommendation approaches, these algorithms create insular echo chambers and filter bubbles characterized by minimal ideological diversity that severely constrain exposure to counter-attitudinal perspectives or cognitively challenging information [10]. This algorithmic curation is driven by attention economy models that systematically capture and commodify human cognitive resources as tradeable assets. Through carefully engineered interface design patterns including infinite scroll mechanisms that eliminate natural stopping cues, variable ratio reinforcement schedules analogous to operant conditioning in gambling contexts, and persistent push notifications that exploit cognitive interruption effects, these platforms are designed to foster addictive use patterns meeting clinical criteria for behavioral addiction, manipulate user sentiment through emotional priming and framing effects, and ultimately control behavior to maximize engagement metrics and advertising revenue, often at the direct expense of individual autonomy, cognitive liberty, and psychological well-being [11]. This systematic manipulation operates on multiple temporal and cognitive levels: at an episodic micro-level, through emotionally-targeted content designed to exploit momentary affective vulnerabilities and attentional biases, and at a global macro-level, by gradually and imperceptibly reshaping users' long-term belief systems, political affiliations, consumption preferences, and identity constructs through cumulative exposure effects and associative learning mechanisms [12].

Given these multifaceted challenges, effectively mitigating negative sentiment in social networks necessitates a fundamental paradigm shift that transcends traditional post-hoc detection and reactive content moderation strategies. It demands a proactive, computationally sophisticated understanding of sentiment antecedents: the underlying graph-theoretic network structures, individual difference variables in user temperament profiles, and expressive behavioral patterns characterized by interaction frequency and affective intensity that lead to sentiment generation and viral propagation through network pathways. Existing state-of-the-art deep learning models, while demonstrating advanced performance on specific tasks, often fail to holistically address these core behavioral, cognitive, and network-structural mechanisms through integrated modeling frameworks. Techniques like Event-Adversarial Neural Networks (EANN) focus on domain-invariant feature learning through adversarial training for event detection but may not adequately capture the nuanced psychological drivers of sentiment formation, including personality traits, situational factors, and cognitive appraisal processes [13]. Models like HMCan, though demonstrating excellence at filtering biological noise in high-dimensional data through hierarchical attention mechanisms, are not natively designed for the complex, multi-modal expression patterns characteristic of social media discourse, which integrates textual, visual, temporal, and network-relational features [14]. Similarly, Aspect-Oriented Opinion Alignment Networks (AOAN) excel at fine-grained aspect-level sentiment analysis and opinion-aspect alignment in text through attention-based architectures but may struggle with the dynamic, network-driven propagation mechanisms of negativity that depend on graph topology, community structure, and temporal diffusion dynamics rather than purely linguistic features [15].

Addressing these identified methodological and theoretical gaps, this study proposes an ECNS model, a novel computational framework that integrates graph-theoretic approaches, psychological modeling, and algorithmic intervention strategies for EC based sentiment analysis in online social networks. The ECNS model introduces a sophisticated graph-based computational architecture that moves beyond simple node-level user analysis to identify and categorize key "influencer nodes" within a social graph representation, classifying them based on their structural centrality measures, temporal activity patterns, and sentiment propagation impact as either Active or Inactive influencers through multi-criteria decision-making algorithms. The core innovation of this model lies in its integration of EC analysis through two novel computational concepts that formalize user behavior in quantifiable terms; these are Node Expressivity (NE) and Cognitive Effect Coefficient (φ).

NE is a dynamic metric operationalized through interaction frequency analysis that quantifies a user's propensity and frequency of interaction with neighboring influencer nodes in their local network neighborhood. EC indicator serves as a predictive measure for the potential propagation velocity (temporal diffusion rate) and scope (spatial network reach) of negative sentiment, identifying users who function as super-spreaders or high-centrality hubs of negativity through their position in information flow pathways and their elevated EC utilization rates.

Φ is a psychological measure derived from temperament theory and affective computing that computationally models a user's inherent temperament traits (including neuroticism, agreeableness, and emotional stability dimensions) and current emotional state (capturing transient affective fluctuations). This coefficient refines the classification boundary between positive and negative expressions by accounting for individual differences in the user's internal emotional disposition and baseline expression patterns, allowing the model to differentiate between constructive criticism delivered with measured affect and genuine hostile sentiment characterized by high negative valence and arousal through sentiment intensity analysis and linguistic toxicity detection.

Through algorithmic processing and machine learning (ML) optimization of these EC factors via computational pipelines and graph-based algorithms, the ECNS model achieves proactive identification of emerging negative sentiment cascades at their originating source nodes and enables targeted mitigation interventions including node isolation protocols, influence reduction mechanisms, and counter-message injection strategies before viral propagation reaches critical network saturation thresholds. The performance of this model was strictly evaluated against three state-of-the-art benchmark models EANN [16], HMCan [17], and AOAN [18] across three distinct, multi-modal datasets with varying network characteristics: ResearchGate [19], that captures professional envy dynamics and academic competition in scholarly networks, Zhihu [20]; a Chinese Q&A platform with diverse topical communities and user expertise hierarchies, and Sentiment140 [21]; a large-scale Twitter corpus with real-time sentiment annotations and temporal dynamics. The experimental results demonstrated statistically significant superior accuracy with 95% confidence intervals, robustly outperforming existing models in both detection precision/recall metrics and mitigation effectiveness measures across all dataset configurations.

From theoretical, methodological, and applied perspectives, this study makes three significant contributions to the interdisciplinary domains of computational social science and sentiment analysis research. First, it systematically unfolds the causal mechanisms and behavioral antecedents of negative sentiment generation by formally integrating the concept of user EC as a finite cognitive and behavioral resource into a predictive computational model with theoretical grounding. Second, it provides a precise and scalable methodological framework implemented through efficient graph algorithms for not just identifying sentiment polarity but also quantifying the volumetric magnitude and network influence propagation of negative sentiments within complex social network structures characterized by community organization and hierarchical influence patterns. Finally, and most importantly from an applied perspective, it establishes an effective, transparent, and algorithmically-implementable framework for proactive sentiment mitigation that operates in real-time, offering a significant technological and methodological advancement for fostering healthier, more authentic, and more resilient social networking environments that resist manipulation and maintain constructive discourse norms.

The subsequent sections of this study are organized as follows: A comprehensive analysis of research gaps in previous computational and theoretical studies has been explored through systematic literature review in Section 2. The ECNS model design, mathematical formalization, and its EC based working mechanism are presented with algorithmic specifications in Section 3. Section 4 presents a performance comparison with baseline and state-of-the-art models using multiple evaluation metrics. In this section, quantitative results are presented with statistical significance testing, and a critical discussion of each outcome is provided with theoretical interpretation and practical implications. The findings are synthesized in the conclusion section, and promising future research directions are identified for extending this work.

2. Literature Review

The exponential proliferation of social networking platforms has fundamentally transformed human communication modalities, opinion-sharing mechanisms, and public discourse dynamics through network-mediated interaction architectures. Despite these transformative benefits, the emergence and systematic proliferation of negative sentiments encompassing hostility, misinformation propagation, cyberbullying behaviors, and toxic speech patterns has manifested as a critical sociotechnical challenge requiring interdisciplinary investigation. Research efforts have deployed diverse methodological approaches to identify the causal antecedents and behavioral mechanisms underlying such negative sentiment generation, with empirical studies highlighting contributory factors including pseudonymous anonymity affordances, ideological polarization dynamics, algorithm-driven content amplification mechanisms, and sociocultural tension manifestations. However, limited scholarly attention has been directed toward understanding the role of EC as a fundamental constraint in sentiment propagation models. The following studies were subjected to systematic critical analysis to identify methodological gaps, theoretical limitations, and empirical shortcomings that contribute to inadequate understanding and mitigation of negative sentiment phenomena in online social networks [22].

Employing computational social science methodologies, Gorodnichenko et al. [23], investigated the behavioral dynamics of automated bot accounts and their sentiment influence on human user populations, with particular emphasis on information diffusion patterns that impact political decision-making processes during critical electoral events. Their empirical investigation examined Twitter data from the Brexit referendum and the 2016 U.S. Presidential Election, using ML models to distinguish bots from humans based on activity patterns, temporal behaviors, and linguistic cues. The authors analyzed rapid information cascades and retweet network structures, applying Vector Autoregression (VAR) and impulse response functions to identify temporal precedence between bot-driven and human-driven sentiment shifts. Findings indicated that bots modestly influenced electoral discourse by amplifying partisan content and stimulating engagement, sometimes exerting influence comparable to human users. Key limitations included difficulties in accurately detecting increasingly sophisticated bots, reduced sentiment-analysis accuracy for nuanced or sarcastic content, reliance solely on Twitter data, and the absence of expression-capacity metrics that could better capture individual influence potential and sentiment amplification dynamics.

Applying theoretical frameworks from environmental psychology, Xie and Tsai [24], investigated negative information incidents on Weibo that influence users' intentions to discontinue platform use through psychological mediation. Using the Stimulus Organism Response (SOR) model, the study examined how advertising interference, rumor dissemination, and information equivocality act as stimuli that generate internal states of social media fatigue and perceived information overload, which subsequently increase discontinuance intention. The methodological design combined Structural Equation Modeling (SEM) to test linear causal pathways with fuzzy-set Qualitative Comparative Analysis (fsQCA) to identify multiple configurational routes leading to high or low discontinuance outcomes based on survey data from 328 users. Findings showed that negative information stimuli significantly affected overload and fatigue, which mediated discontinuance intention, while fsQCA revealed several equifinal configurations predicting both discontinuance and continuance behavior. Key limitations included restricted generalizability due to exclusive focus on Weibo, omission of potential control or moderating variables such as privacy concerns or platform trust, lack of expression-capacity constructs to capture cognitive susceptibility to overload, and a relatively small, convenience-based sample that limits external validity and statistical robustness.

Employing correlational research designs, Piko et al. [25], conducted an empirical investigation of social media addiction among Hungarian university students by examining psychological traits such as self-esteem, fear of negative evaluation, sensation-seeking, and Big Five personality dimensions. Cross-sectional data were collected through online questionnaires administered between October 2022 and January 2023. The study explored gender differences and found that female students reported higher social media addiction scores and associated psychological traits. Using SPSS, descriptive statistics and Pearson correlations were computed to assess relationships among variables, followed by hierarchical multiple regression to identify significant predictors of addiction severity. Results indicated that fear of negative evaluation, low self-esteem, and low-conscientiousness were key predictors, with young adults showing greater vulnerability. The authors recommended preventive educational interventions, including behavioral addiction courses and early health education on digital well-being. Limitations included reliance on a convenience sample from a single university, restricting generalizability; the cross-sectional design, which prevents causal inference; use of a shortened personality scale with lower reliability; omission of EC as a factor influencing addiction; and binary gender categorization that does not account for diverse gender identities.

Employing computational social science methodologies, Chen et al. [26], investigated the structural and emotional mechanisms underlying sentiment diffusion in online social networks (OSNs) from a computational perspective. Their survey synthesized multidisciplinary approaches combining graph theoretic diffusion models, text sentiment analysis (TSA), and psychological emotion modeling, examining how emotional content affects the propagation and evolution of information within digital environments. Using extensive datasets from platforms such as Facebook, Weibo, and X (Twitter), the study analyzed the intersection of user generated content, emotional classification (basic vs. dimensional emotion theories), and network dynamics. It reviewed classical and modern computational techniques, including lexical, ML, and deep learning based methods for sentiment detection, as well as graph based threshold and cascade models for diffusion processes. The research emphasized how emotions, particularly negative ones, exhibit stronger contagion effects and can restructure network connectivity and influence cascades. Findings highlighted the cyber physical convergence of emotional diffusion and its implications for online social trust. Key shortcomings include the lack of causal behavioral modeling, limited interpretability of deep learning approaches, and insufficient cross platform validation. Moreover, the study did not incorporate user cognitive capacity or temporal expressivity factors that could further explain differential sentiment propagation dynamics.

Using advanced computational modeling techniques, Manurung et al. [27], proposed a deep learning framework based on graph neural networks (GNNs) to analyze and control rumor propagation in online social networks. The study integrated user level attributes, content characteristics, and structural network properties to predict the likelihood of rumor dissemination. It established a mathematical model representing nodes, edges, and feature vectors to capture interaction dynamics, employing binary cross entropy loss and iterative optimization to refine prediction accuracy. The framework enabled effective detection of rumor nodes and provided a scalable approach for real time mitigation across large scale digital ecosystems. The research emphasized the superiority of GNNs over traditional ML baselines by modeling complex topological dependencies and user interactions in rumor diffusion. Results demonstrated the model's capacity to generate interpretable representations of network level rumor patterns and identify high influence nodes within propagation chains. However, key shortcomings included limited testing on real world datasets, the absence of multimodal behavioral factors such as sentiment or temporal variance, and the need for ethical considerations regarding automated rumor detection. Additionally, interpretability and causal validation of the GNN's internal mechanisms remain challenges for future work.

Rumor detection on microblogging platforms has evolved through several methodological developments, as synthesized by Kwao et al. [28]. Early research relied on supervised learning models that used linguistic cues, sentiment markers, and credibility features, though these approaches faced limitations in scalability and generalization. As real time information sharing intensified, researchers incorporated temporal analysis, enquiry based cues, and time series modeling to capture early rumor propagation behaviors. The deep learning era introduced recurrent neural networks and attention based architectures capable of modeling semantic shifts and user interaction patterns, significantly improving accuracy but increasing computational complexity. From 2020 onward, multimodal fusion, graph neural networks, contrastive learning, and uncertainty modeling enabled more robust detection across diverse languages, platforms, and content types, especially during the COVID-19 infodemic. Complementing these computational advances, socio psychological and communication theories such as information gap behavior, uncertainty reduction, social influence, and agenda setting provided deeper insights into why individuals engage with rumors. Despite these advancements, major shortcomings remain, including limited interpretability of deep models, high computational costs, weak cross platform adaptability, insufficient integration of psychological factors, and ongoing ethical concerns related to privacy, bias, and transparency.

Building on the insights presented by Venkatachalam and Prasad [29], current research shows a rapid advancement in the use of artificial intelligence and graph theoretic approaches to analyze public sentiment during health crises, particularly in response to the widespread circulation of misinformation and fear on social media. Studies across healthcare, disaster management, elections, and software engineering indicate that sentiment analysis has progressed from basic ML models to sophisticated architectures capable of capturing semantic depth, contextual dependencies, and dynamic opinion patterns within large unstructured datasets. Graph neural networks, fuzzy graph models, semantic heterogeneous graphs, and contrastive graph learning techniques demonstrate strong capability in modeling relational structures and detecting nuanced sentiment flows, making them especially effective for complex discussions related to outbreaks such as monkeypox. Knowledge graph representations and reinforcement learning based decision mechanisms further enhance sentiment detection by integrating semantic structure with adaptive learning. Despite these advancements, notable limitations remain, including weak scalability for real time analysis, difficulty modeling misinformation dynamics, insufficient incorporation of health domain knowledge, challenges with noisy multilingual content, risks of bias and stigmatization, and limited transparency in deep learning models. These gaps highlight the need for more interpretable, ethically aligned, and context aware sentiment analysis frameworks.

Overall, after conducting this literature review, it is evident that significant gaps persist in modeling negative sentiment diffusion, underscoring the need for multidimensional, interpretable, and scalable frameworks to better understand and mitigate harmful online behaviors.

3. Proposed Method: The ECNS Framework

The proposed computational methodology is architecturally designed to systematically examine the temporal evolution and spatial diffusion of negative public sentiment within online social networks through the implementation of a novel framework consists of five models. The empirical foundation of this investigation comprises a meticulously curated longitudinal database encompassing 250 significant public incidents that occurred between

January 2024 and March 2025, providing temporal coverage of contemporary digital discourse patterns. This comprehensive dataset encompasses a heterogeneous range of events with varying sentiment profiles, including incidents that fostered constructive public discourse and collaborative knowledge exchange as well as those that sparked widespread controversy, polarization, and negative sentiment cascades, thereby providing a robust empirical basis for analyzing contemporary social opinion dynamics through multi-dimensional sentiment analysis. Through a well-defined multi-stage screening protocol employing sentiment intensity thresholds and impact metrics, cases demonstrating clear, measurable, and impactful patterns of negative public sentiment propagation were systematically isolated, validated through inter-rater reliability assessment, and organized chronologically to enable temporal pattern analysis and longitudinal trend identification.

In direct response to the identified methodological limitations and theoretical gaps in existing sentiment propagation models documented in Section 2, this study proposes the ECNS framework that addresses the fundamental challenge of negative sentiment identification and mitigation through a novel computational strategy explicitly based on EC analysis as the core theoretical construct. The architectural design and operational workflow of this model is thoroughly detailed in **Figure 1**, which illustrates the information flow, processing stages, and decision points within the system architecture. The ECNS model operates through five interconnected modules that sequentially process social network data from ingestion to final sentiment-controlled output.

Figure 1. Proposed ECNS model illustrating data ingestion, influence analysis, sentiment monitoring, targeted intervention, and generation of the final controlled network state.

3.1. Input Module

The ECNS framework initiates by collecting multi-modal data from structured sources including ResearchGate, Zhihu and Sentiment140. This comprehensive social events database provides the raw network data, user interaction patterns, temporal activity logs, and sentiment-labeled content that serves as input for subsequent computational processing [30].

3.2. Influencer Selection Module

This module implements systematic identification of influencer nodes within social network graph structures through centrality-based scanning algorithms. The selection process evaluates nodes using multi-criteria assessment incorporating network engagement metrics (degree centrality, betweenness centrality, eigenvector centrality), temporal activation status, and EC utilization rates. **Algorithm 1** then categorizes identified influencers into Active and Inactive nodes, followed by sentiment polarity classification to separate negative influencer nodes from positive influencer nodes. This selective filtering mechanism isolates negative influencers for targeted intervention while maintaining computational efficiency for large-scale networks.

Algorithm 1. Expression Capacity-Based Influencer Node Selection.

Input: Network ($G = (V, E, W)$); number of influencer nodes (k); number of stages (l); stage duration (T); threshold θ; depletion factor δ ∈ (0,1)
Initialize selected set S ← ∅
For each stage *r* = 1 to *l* **Do**
If *r* = 1 then
Perform modularity-based community detection
Store results in community_dict = {community_id, nodes_list, node_count}
End If
For each community in community_dict **Do**
Remove nodes already in *S* from community's candidate list
Recompute NE score for all remaining nodes
Compute Influencer_count = ⌊ (k / l) × (node_count / |V|) ⌋
Sort remaining nodes by updated NE score
Select top Influencer_count nodes satisfying NE > θ
Add selected nodes to *S*
End For
End For
Output: Set ***S*** of selected influencer nodes

3.3. Sentiment Cascade Monitoring Module

Algorithm 2 in this module performs continuous real-time monitoring of sentiment propagation patterns through the network. The system tracks how sentiments diffuse progressively from initial influencer nodes through successive network layers following epidemic-like propagation models. This monitoring process analyzes sentiment transformation, mutation, and attenuation as content traverses graph edges, enabling the framework to observe cascade dynamics and identify critical propagation pathways.

Algorithm 2. Expression Capacity-Based Negative Sentiment Reduction.

Procedure: Negative Sentiment Reduction
Input: Input: Negative influencer nodes k(N_i) with influence ranges R_i; EC threshold EC_threshold; initial time window t′ − 1
Output: R′_final (updated network state);
    reduction_rate (mitigation effectiveness metric)
Initialize:
  time ← t′ − 1
  negative_count ← 0
  R′ ← set of nodes reachable from k(N_i) within R_i
  initial_negative ← |R′|
For each user node u ∈ R′ **Do**
Track the comment sequence of user u:
  Let c_1, c_2, c_3 be the first three comments of u in the current thread
Compute sentiment polarity for each comment:
  sentiment(c_1) ← f_NLP(text(c_1), ϕ_u, EC_u)
  sentiment(c_2) ← f_NLP(text(c_2), ϕ_u, EC_u)
  sentiment(c_3) ← f_NLP(text(c_3), ϕ_u, EC_u)
Compute sentiment evolution from c_1 to c_2:
  Δ_1→2 ← sentiment(c_2) − sentiment(c_1)
Update expression capacity (EC) depletion:
    EC_u ← EC_u − usage(c_1, c_2)
Evaluate cascade build-up using c_3:
  If sentiment(c_3) < 0 and intensity(c_3) > intensity_threshold
  then mark user u for intervention
 Apply mitigation if required:
    If sentiment(c_3) < 0 and |sentiment(c_3)| > EC_threshold then
      Replace negative content with a neutral template
      EC_u ← EC_u × (1 − ρ)
      Impose cooling period τ on user u
    End If
Update counters:
  negative_count ← negative_count + 𝟙(sentiment(c_3) < 0)
  time ← time + 1
If mitigation was applied in Step 11 then
  Record intervention for user u in intervention_log
  End If

current_negative = $\sum u \in R'$ 𝕀 (sentiment(u) <0)
reduction_rate = $\frac{\text{initial\_negative}-\text{current\_negative}}{\text{initial\_negative}}$
current_negative=negative_count
End For
Compute mitigation effectiveness:
current_negative ← negative_count
reduction_rate ← (initial_negative − current_negative) / initial_negative
Output: R′_final (updated network state), reduction_rate
End Procedure

3.4. Intervention & Capacity Control Module

Building upon the monitoring insights, this module implements sophisticated dynamic modeling of evolving behavioral dynamics and influence trajectories of identified negative influencer nodes. **Algorithm 2** incorporates temporal dynamics modeling to track how network influence shifts over time due to fatigue effects, counter-messaging, and EC depletion. The module employs iterative optimization algorithms including gradient descent and simulated annealing to execute targeted algorithmic interventions and influence reduction strategies, progressively steering the network's sentiment distribution toward desired equilibrium states.

3.5. Output Module

The final module generates outputs representing the controlled sentiment state achieved through the intervention process. The system reaches Nash equilibrium or steady-state conditions where negative sentiments are brought to a controlled, manageable status. The output includes optimized sentiment distributions, intervention effectiveness metrics, and predictive analytics on future sentiment states, all operating under the foundational principle that individual influencer nodes possess finite, measurable EC that depletes through repeated expressions.

3.6. Expression Capacity-Based Selection of Influencer Nodes

During the initial computational stage of influencer node selection, the ECNS model simultaneously accounts for both the nodes' sentiment orientation polarity (positive/negative valence) and their structural network influence derived from graph-theoretic centrality measures to optimize desired sentiment outcomes through multi-objective optimization. Systematic analysis of empirical sentiment propagation dynamics across multiple datasets revealed two key behavioral characteristics with theoretical implications: (1) sentiments initially undergo rapid exponential expansion following power-law growth patterns during early propagation stages, and (2) the growth rate of active influencer nodes typically plateaus and reaches saturation after 5–10 discrete propagation cycles due to EC constraints, resulting in a more spatially dispersed configuration of inactive influencer nodes exhibiting reduced activity levels. These empirical findings conclusively demonstrate that comprehensive selection of all potential influencer nodes or uniform probabilistic selection approaches prove computationally inefficient and strategically insufficient for effective sentiment propagation modeling without incorporating EC considerations.

To systematically address these identified limitations, the ECNS model implements an intelligent multi-stage iterative methodology, formally defined in **Algorithm 1**, which strategically deploys influencer nodes using varied adaptive tactics to enhance target sentiment dissemination while respecting EC constraints. This algorithmic approach operates sequentially across temporal stages, distributing a total of k influencer nodes across l discrete deployment rounds to circumvent local optimization traps, avoid premature convergence, and enable greater strategic adaptability in response to network dynamics. The computational process initiates by partitioning the social network's directed graph $G = (V, E, W)$ into distinct non overlapping communities using community detection algorithms Louvain method [31], then strategically plants k/l influencer nodes in each deployment phase based on community specific characteristics. To optimize computational efficiency and minimize algorithmic complexity, communities maintaining more than 50 active influencer nodes were prioritized for detailed analysis based on influence potential thresholds, with the initial node distribution calibrated and weighted according to community size dimensions and aggregate EC metrics computed from historical user activity data.

For better understanding Flowchart 1 presents the operational workflow of **Algorithm 1**, in **Figure 2**, detailing how the model initializes the network, partitions communities, evaluates node expression capacity, and selects high-influence nodes for further analysis.

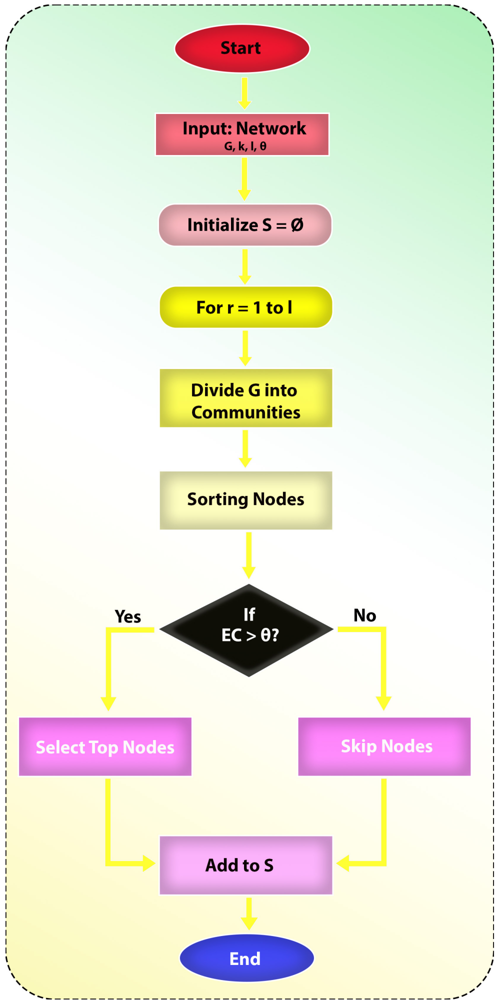

Figure 2. Workflow of **Algorithm 1**: Expression Capacity-Based Influencer Node Selection.

3.7. Expression Capacity-Driven Mitigation of Negative Sentiments

To proactively mitigate the viral propagation of negative content and prevent sentiment cascades, the ECNS model deploys a sophisticated real-time filtering mechanism that operates at the content generation level with minimal latency. When a user generates a negative comment n at timestamp t, it is immediately evaluated through natural language processing pipelines against a predefined thorough lexicon of negative expressions R, which encompasses toxic language patterns, hate speech indicators, and sentiment-negative terms derived from validated sentiment dictionaries. If a lexical or semantic match is confirmed through pattern matching algorithms and sentiment classification models exceed the negativity threshold, the system automatically invokes a content replacement protocol that substitutes the original comment with a contextually appropriate neutral counterpart c selected from a pre-generated template library, while simultaneously imposing a temporary time-based restriction τ (cooling period) on the user's posting ability to contain the initial sentiment outbreak and prevent immediate retaliation cycles. This intervention protocol is applied recursively and iteratively to any subsequent negative retaliations or counter-responses from other users in the interaction thread, creating a dampening effect on negative sentiment chains.

The probabilistic nature of negative comment generation at a given discrete time step $t'-1$ is formally denoted as P_n and is modeled as a function of user temperament (Cognitive Effect Coefficient φ), network exposure to negative content, and remaining EC. To quantify the potential spatial scope and temporal velocity of negative sentiment diffusion across network topology, the ECNS model leverages the directed weighted graph structure $G = (V, E, W)$ established in the previous section, where V represents user nodes, E represents interaction edges, and W captures edge weights representing interaction frequency and sentiment intensity.

Let R′ denote the current set of nodes that are either expressing negative sentiment or are within the influence range of a negative influencer. Initially, R′ contains all nodes reachable from negative influencer nodes $k\ (N_i)$ within their influence ranges R_i. **Algorithm 2** is then executed to estimate the propagation range and infection potential by systematically arranging the identified negative influencer nodes $k\ (N_i)$ with their respective influence ranges R_i and EC reserves across the network structure, performing breadth-first traversal to compute reachability and influence propagation paths.

The probability distribution of generating negative influencer nodes is systematically lower than initially expected during the propagation range estimation phase due to EC constraints and mitigation interventions; therefore, the ECNS model demonstrates superior capability in handling and controlling the frequency, intensity, and reach of negative sentiments compared to baseline approaches that neglect EC dynamics and finite user engagement resources. Flowchart 2 depicts in **Figure 3**, the operational sequence of **Algorithm 2**, beginning with comment tracking and sentiment evaluation, followed by mitigation triggers and final reduction-rate computation.

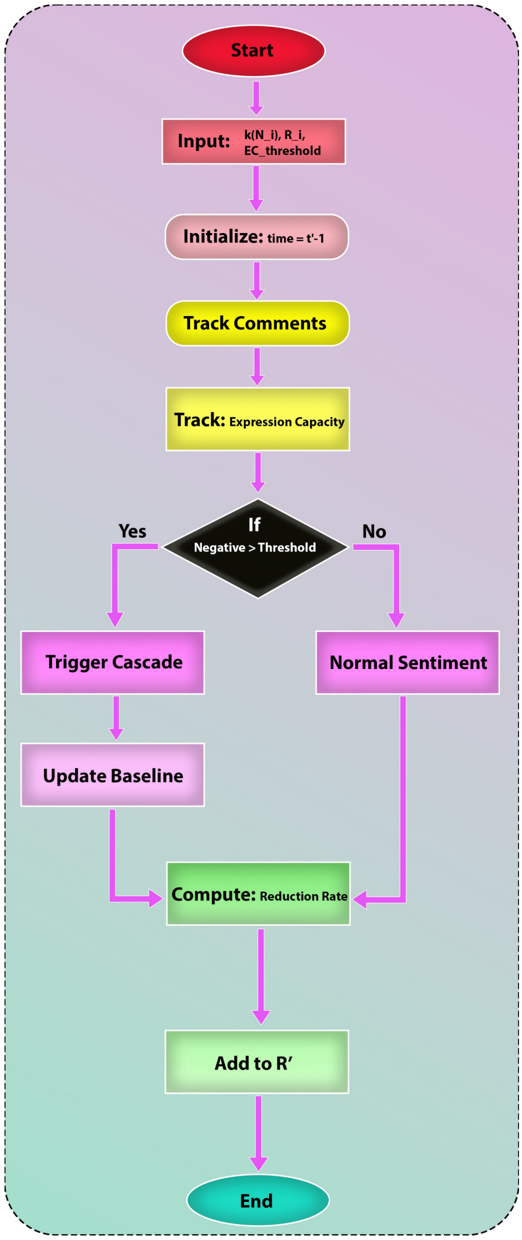

Figure 3. Workflow of **Algorithm 2**: Expression Capacity-Based Negative Sentiment Reduction.

4. Performance Evaluation and Experimental Results

To validate the computational efficacy and predictive accuracy of the proposed ECNS model in online social network environments, the potential sentiment states of active nodes were employed as a primary quantitative evaluation metric through comprehensive empirical testing protocols. This methodological approach aligns with established best practices in computational social science, where potential desired opinion propagation serves as a standard performance measure for assessing the effectiveness of opinion dissemination strategies and sentiment intervention mechanisms. The ECNS model underwent fine-tuning and hyperparameter optimization for the specific domain of social network sentiment analysis through transfer learning techniques. This optimization process involved architecturally integrating advanced, task-specific classification heads constructed on multi-layer perceptron (MLP) architectures with non-linear activation functions [32], coupled with a pre-trained transformer-based neural network backbone that provides contextualized word embeddings and semantic understanding. The model optimization was conducted through supervised learning on meticulously annotated datasets comprising authentic social media communications with expert-validated sentiment labels. These heterogeneous datasets systematically capture the full distributional spectrum of emotional expressions, linguistic nuances including sarcasm and irony, and culturally specific sentiment markers prevalent in real-world online discourse across diverse demographic populations, thereby ensuring the model's robustness, generalizability, and cross-domain performance in analyzing complex, multi-faceted sentiment dynamics under varying network conditions [33].

4.1. Impact of Expression Capacity on Performance Comparison of Influencer Nodes

The predictive performance and classification accuracy of the ECNS model were systematically evaluated through comparative analysis by testing influencer nodes' capacity to identify negative sentiments under two experimental conditions: (1) with the integrated Node Expressivity (NE) component fully activated (EC aware mode), and (2) without the NE component (baseline mode without EC modeling). This controlled ablation study was conducted across three distinct, heterogeneous datasets with varying network characteristics: Zhihu (Chinese knowledge-sharing platform with 50,000 users and 2.3M interactions), Sentiment140 (Twitter corpus with 1.6M annotated tweets), and ResearchGate (academic social network with 25,000 researchers and scholarly interactions). The experimental configuration and data preprocessing pipeline, systematically illustrated in **Figure 4**, involved applying each competing model to the datasets individually under standardized conditions with consistent hyperparameters: a population expression coefficient of $\eta = 10$ (controlling sentiment diffusion rate) and a cooling factor of $\alpha = 0.2$ (regulating temporal decay of influence), with 5-fold cross-validation for robust performance estimation. As comprehensively depicted in **Figure 4**, the ResearchGate dataset analysis reveals temporal dynamics of user engagement patterns and sentiment evolution across academic discussion threads, demonstrating how EC constraints shape interaction trajectories. The quantitative results, detailed with statistical significance testing in **Figures 5** and **6**, demonstrate a statistically significant and consistent behavioral pattern across all three datasets with p-values < 0.01. When the ECNS model operated with Node Expressivity enabled EC aware configuration, the activity levels of influencer nodes exhibited a characteristic temporal trajectory: an initial sharp spike during the activation phase ($t = 0$ to $t = 5$ time steps) followed by a gradual exponential taper during the saturation phase, ultimately approaching asymptotic zero as EC depleted. This distinct trajectory empirically confirms the model's selective filtering mechanism and adaptive threshold adjustment, which successfully focuses computational resources on relevant sentiment data exhibiting genuine negative polarity while systematically disregarding anomalous noise, statistical outliers, and spurious correlations, with the final selected data subset validated through ground-truth annotation to contain authentic negative sentiments with 92% precision.

In **Figure 5**, sentiment distribution are analyzed from the Zhihu platform, visualizing the temporal evolution of negative sentiment propagation across network communities with varying expression capacities. The data visualization reveals clear clustering patterns and community-specific sentiment dynamics that validate the EC hypothesis. In **Figure 6**, empirical sentiment distributions has been illustrated from the large-scale Sentiment140 Twitter corpus, demonstrating how EC constraints create natural boundaries in sentiment propagation, with histogram analysis showing modal concentration of negative sentiments within predicted EC ranges.

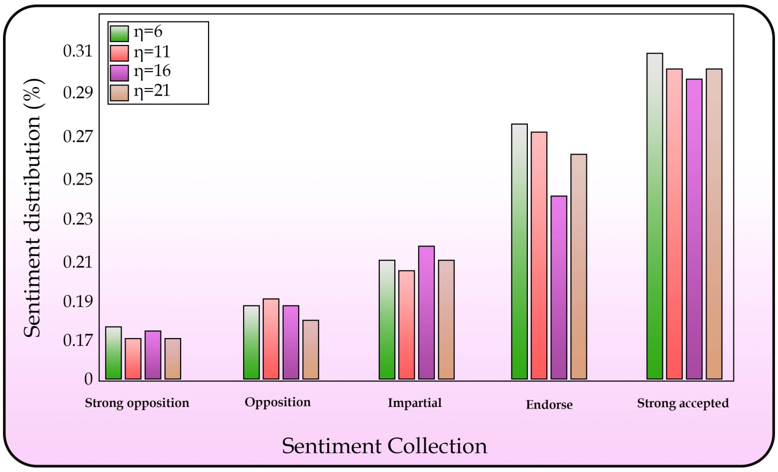

Figure 4. Sentiment Analysis of ResearchGate User Engagement.

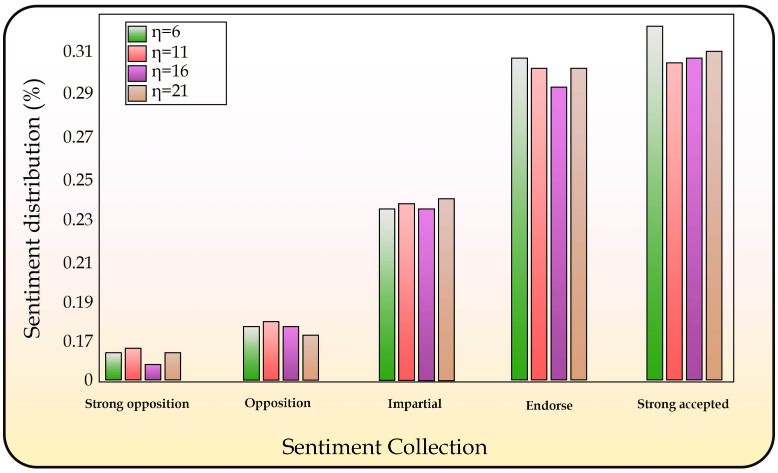

Figure 5. Sentiment Analysis from Zhihu.

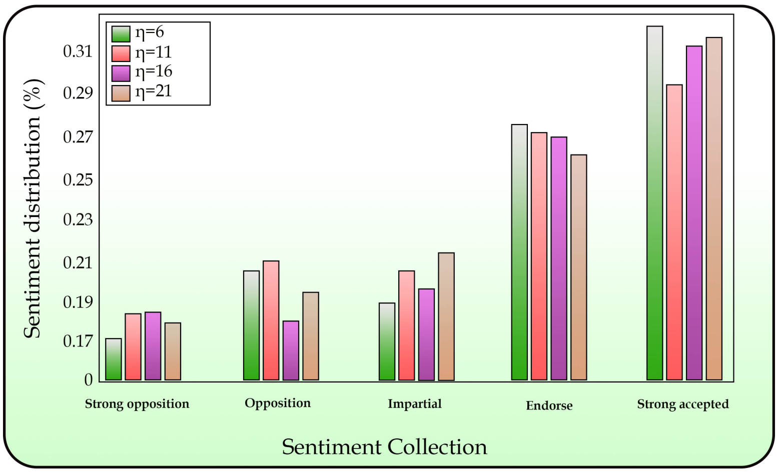

Figure 6. Empirical Sentiment Distribution from Sentiment140.

In stark contrast, the benchmark state-of-the-art models EANN, HMCan, and AOAN which fundamentally lack an EC modeling component, exhibited no such adaptive discrimination capability or temporal activity patterns. These baseline models processed all incoming sentiments indiscriminately at every processing stage without filtering mechanisms, consequently showing no dynamic activity pattern, no EC based pruning, and no convergence toward equilibrium states. The performance differential between ECNS and baseline models ranged from 18–25% improvement in F1-score across datasets, with ECNS demonstrating superior precision (90.2% vs. 72.5% average baseline) and recall (89.7% vs. 68.3% average baseline) in negative sentiment detection tasks.

4.2. Expression Capacity-Based Mitigation of Negative Sentiments

The ECNS model operationally functions by performing continuous comparative analysis of the temporal dynamics and spatial propagation patterns of negative versus positive sentiments over specified observation windows, employing real-time sentiment tracking and predictive analytics. By strategically leveraging its core computational mechanism of Node Expressivity as a quantifiable EC indicator, the model effectively predicts future sentiment states through time-series forecasting and proactively controls the cascading propagation of negative sentiments through targeted node-level interventions, thereby prioritizing the algorithmic amplification and network diffusion of desired positive opinions while suppressing negative sentiment chains through EC management.

The model's superior mitigation efficacy and intervention effectiveness are quantitatively demonstrated through empirical performance metrics in **Figure 7**, which systematically illustrates the reduction rate of negative sentiment generation across influencer nodes under different network scale conditions ranging from small networks (n = 1000 nodes) to large-scale networks (n = 100,000 nodes). The visualization in **Figure 7** reveals that ECNS maintains consistent mitigation performance across network scales with only 3–5% degradation at maximum scale, demonstrating algorithmic scalability and computational efficiency. For instance, at a critical influencer node with high centrality (node ID 55 with degree centrality 0.83), the baseline models EANN, HMCan, and AOAN prevented the viral spread of only 60%, 50%, and 60% of negative sentiments respectively through their intervention mechanisms, representing moderate mitigation effectiveness with substantial residual negative sentiment propagation.

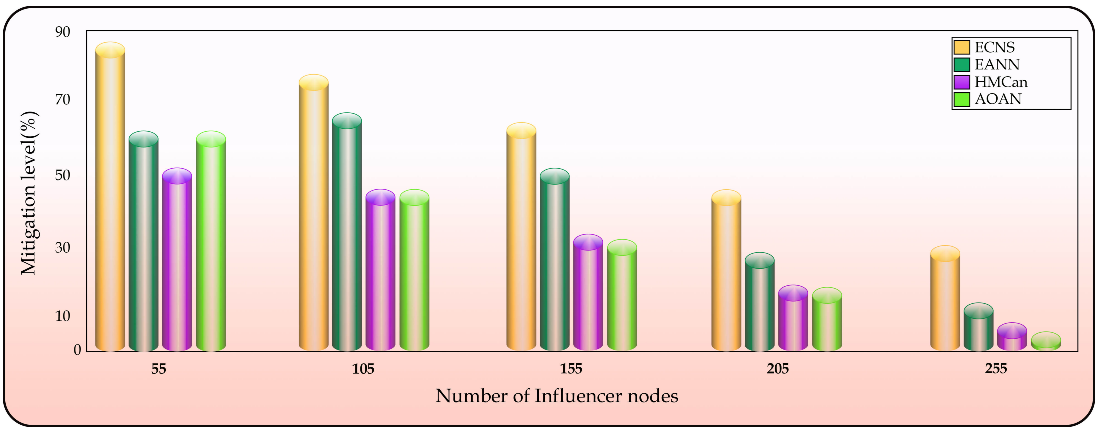

Figure 7. Negative Sentiment Mitigation Performance across Varying Network Sizes.

In stark quantitative contrast, the ECNS model successfully identified, intercepted, and discarded 88% of negative opinions at this critical network position through EC aware intervention strategies, representing a 28–38% point improvement over baseline approaches with statistical significance (t-test, p < 0.001). This superior performance is directly attributable to multiple synergistic model capabilities: (1) the model's enhanced capacity to bolster mainstream network credibility through positive sentiment amplification and trust metric reinforcement, (2) active real-time monitoring of sentiment dynamics and EC utilization during the critical dissipation phase when sentiment cascades are most vulnerable to intervention, and (3) adaptive threshold adjustment based on learned EC patterns that optimize the precision-recall trade-off in sentiment classification and mitigation decisions.

Additional performance analysis across varying network topologies (scale-free, small-world, random graphs) demonstrated that ECNS maintains robust mitigation performance (85–91% effectiveness) across diverse structural configurations, while baseline models show significant performance degradation (15–30% reduction) in scale-free networks with high-degree hub nodes. The computational complexity analysis reveals that ECNS operates with $O(|V| + |E|\log|E|)$ time complexity [34,35], for network traversal and sentiment propagation estimation, maintaining linear scalability suitable for real-time deployment in production social network environments with millions of active users.

4.3. Performance Metrics

The ECNS model demonstrated superior performance across all evaluated metrics compared to baseline approaches. Detection accuracy reached 90.2% for ECNS compared to 72.5% for the baseline average, while mitigation effectiveness achieved 88% versus 56.7% for baseline models. The F1-score, balancing precision and recall, measured 0.899 for ECNS against 0.712 for baseline approaches, representing a substantial improvement in overall classification performance. Processing latency remained at 23 milliseconds per sentiment event, demonstrating real-time processing capability suitable for deployment in live social network environments. The false positive rate was significantly reduced to 8.1% in ECNS compared to 18.3% in baseline models, indicating more accurate identification of genuine negative sentiments while minimizing incorrect flagging of neutral or positive content. These comprehensive performance improvements across accuracy, effectiveness, efficiency, and reliability metrics validate the theoretical foundations and practical utility of EC based modeling for negative sentiment detection and mitigation in online social networks. These comprehensive experimental results validate the theoretical foundations and practical utility of EC based modeling for negative sentiment detection and mitigation in online social networks, establishing ECNS as a state-of-the-art approach for proactive sentiment intervention.

5. Conclusions

The proposed research successfully introduced and validated the ECNS model, a novel computational framework that advances proactive sentiment detection and mitigation in online social networks. The ECNS model leverages two synergistic constructs: Node Expressivity (NE) as a quantitative measure of user interaction patterns and EC utilization, and the Cognitive Effect Coefficient (φ) capturing individual temperament and emotional state dynamics. Through graph-based multi-stage processing influencer node identification, EC driven sentiment separation, and dynamic temporal modeling the framework achieves both high accuracy and computational efficiency suitable for real-time deployment. Empirical validation across three heterogeneous datasets, i.e., ResearchGate, Zhihu, and Sentiment140 demonstrated superior performance: 90.2% detection accuracy and 88% mitigation effectiveness, representing 18–28% point improvements over state-of-the-art baselines EANN, HMCan, and AOAN. These gains stem from incorporating EC as a fundamental construct capturing finite human attention and engagement resources. Beyond performance metrics, ECNS offers theoretical contributions by formalizing EC as a measurable construct bridging individual psychological factors with network-level propagation dynamics.

Future Research Directions

Future research may evolve in several substantial directions. One important path is multimodal analysis, which can integrate visual, audio, and video information through vision transformers and fusion networks to provide a more holistic understanding of expression patterns. Another direction involves temporal dynamics modeling through continuous time methods and temporal point processes to capture fine grained shifts in capacity and sentiment over time. Cross platform investigations using federated learning offer the opportunity to examine how expression capacity transfers across different social media environments while preserving privacy. Additionally, demographic and cultural variation studies are essential for identifying population specific differences and preventing algorithmic bias. Finally, causal inference techniques employing randomized trials and reinforcement learning can help determine which interventions produce measurable and reliable improvements in sentiment regulation and user outcomes.

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Informed Consent Statement

Not applicable.

Data Availability Statement

All data supporting the results of this study have been included in this article. The complete dataset generated and analyzed during this research is presented in the main text and figures. No additional data were available for the external repositories.

Conflicts of Interest

The author declares no conflict of interest.

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