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Exploring the Relationship between Social Network Structures and Emotional Contagion using NLP and Network Science

Prapti Pandey[1,*], Vivek Shukla[2], Rohit Miri[3], Praveen Chouksey[4], Parul Dubey[5], Rohit Raja[6]

[1]PhD Research scholar Dr C V Raman University, Kota Bilaspur Chhattisgarh, India

[2]Dr C V Raman University Kota Bilaspur Chhattisgarh, India

[3]Associate Professor, Chhattisgarh Swami Vivekanand Technical University, Bhilai, Chhattisgarh, India

[4]Associate Professor, Department-Computer Science Engineering, CMR Engineering college EC Campus, medchal road Kandlakoya, India

[5]Assistant Professor, Symbiosis Institute of Technology, Nagpur Campus, Symbiosis International (Deemed University), Pune, India

[6]Associate Professor, Department of IT, Guru Ghasidas Vishwavidyalaya (A Central University) Bilaspur (Chhattisgarh), India

Emails: kanha.prapti24@gmail.com; vivekcvru19@gmail.com; rohitmiri@csvtu.ac.in; Praveenchouksey@cmrec.ac.in; dubeyparul29@gmail.com; drrohitraja1982@gmail.com

Abstract

Natural Language Processing (NLP) and Network Science were combined to study emotional contagion dynamics in social media networks. We simulated the diffusion of emotions through users on a synthetic interaction network using sentiment-labeled Twitter data and a graph-based model. We explored the relationship between graph metrics, including centrality and clustering coefficient, on emotion propagation and stability. The findings show that emotion intensity converges through the network and that both weak coupling of central nodes and moderate cluster structures dampen the spread of emotion. A community-level analysis reveals more alternative results, such as the fact that emotions differ in polarity between communities. Our work demonstrates a better understanding of how emotional behavior in online environments can be adjusted using semantic measures, which offer a means to characterize the relevance of information online and the interconnected relationships among emotionality.

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I. Introduction

A. Background on Emotional Contagion and Online Social Behavior

Emotional contagion is a well-established psychological and sociological phenomenon in which people facilitate the same or similar emotional expressions (e.g., facial expressions, vocal tone, and inflection) without conscious intent. While historically evident in face-to-face communication, this phenomenon has found renewed relevance through online social networks [1], [2]. Owing to their scale, speed, and structural connectivity, platforms such as Twitter, Facebook, and Reddit act as propagative accelerators for emotions [3]. In a digital setting, emotional displays are mediated and encoded into text, hashtags, emojis, and multimedia posts. Studies have shown that anger and fear travel faster and further than neutral or positive material, supercharging polarization and misinformation [4]. In contrast, emotional states characterized by joy and compassion can enhance community bonding and mutual aid, especially within health and mental health communities [5], [6]. The network's structure (node centrality, community modularity, and tie strength) influences the way emotions diffuse and sustain in a digital ecosystem [7]. Various interdisciplinary methods based on Natural Language Processing (NLP) and Network Science have been developed to analyze these patterns. Specifically, aspects of natural language processing (NLP) allow for the extraction of sentiment and emotion from user-generated content, and aspects of network science allow models of interactions and organizations of emotional influence within graphs of users [8], [9]. To analyze these dynamics, researchers have increasingly combined natural language processing (NLP) with network science. While NLP provides the power of detection and classification of emotions from chunks of text, using network science, we can model their diffusion across complex social graphs.

Table 1: Common Emotions in Social Media and Their Contagion Characteristics

EMOTION	SPREAD SPEED	ENGAGEMENT LEVEL	TYPICAL EFFECT
ANGER	High	Very High	Polarization, conflict
JOY	Moderate	High	Community bonding
SADNESS	Low	Moderate	Empathy, support seeking
FEAR	High	Moderate	Misinformation spread

B. Importance of Combining NLP with Network Science

To understand emotional contagion in online environments, we need a two-dimensional approach that captures both the semantic content expressed in the communication and the structural patterns of user interaction. NLP and Network Science together provide not only different visions but also complementary aspects of how emotions are converted into digital social networks. NLP facilitates the extraction of emotional signals from user-generated content, such as tweets, comments, and posts. By performing sentiment analysis, emotion classification, and topic modeling, tools have evolved that can determine not only whether a message is positive or negative, but also what emotional tone it conveys, including whether the tone is angry, joyous, or sad [9], [12]. These approaches enable researchers to translate emotions into numerical scores, allowing them to track trends in emotions over time and topics. However, emotions are not separate from each other. The underlying network through which users are connected shapes their dissemination. Network Science offers concepts to elucidate this diffusion via links in the network, for example, follower-following relationships, mentions, replies, and retweets. Degree centrality, community structure, information flow, and similar concepts can be used to identify important feed influencers, echo chambers, and emotion hotspots [13]–[14]. These approaches can be combined to study not only what emotions are being expressed but also how they move across the network. This integration allows for more sophisticated modeling of emotional contagion dynamics and can inform the design of interventions that improve digital well-being, combat misinformation, and support online discourse [15].

Figure 1. Integration of Natural Language Processing with Network Science for Social Media Analysis

Figure 1 Conceptual Framework for Integrating NLP with Network Science to Analyze Social Media Dynamics In the center of the image, a labelled circle illustrates the intersection of the two potent domains NLP, which reads text-based information and emotion, and Network Science, which traces how information and emotion diffuse through user behavior [17]. This integration consists primarily of four interlinked modules: Sentiment Analysis, Text Classification, Social Network Analysis, and Community Detection, which constitute the principal analytical modules. This is a color-coded representation of each module and how it connects to the central node to show what modules add to the overall functioning of the system. Harnessing this synergy allows researchers to mine large-scale user data to recover meaningful emotional content and better comprehend the structural conduits through which these emotions traverse digital communities and social media.

C. Research Objectives and Motivation

This research aims to combine Natural Language Processing (NLP) with Network Science to study the dynamics of emotional contagion in online social networks. NLP methods help researchers track, categorize, and understand the emotions reflected in user-initiated sources of information, such as tweets, posts, and comments. These tools assist in the measurement of human emotions, such as anger, joy, fear, or sadness, at scale. Conversely, Network Science provides a powerful paradigm for investigating the topology and dynamics of user interactions, including user communities, node influence, and information diffusion. Using these techniques together, the study seeks to reveal not only what emotions are being expressed but also how they spread, persist in time, or change across the network.

This interdisciplinary research is motivated by the growing role of emotionally charged content in influencing online behavior, opinion formation, and community engagement. While social media sites, such as Twitter and Facebook, are a source of positive forms of emotional support, they are also hotbeds of negative forms, such as polarization, misinformation, and cyber-harassment. Although this theme is becoming increasingly relevant, existing research largely treats textual sentiment and network structure separately. This study fills this gap by examining emotion propagation from a networked perspective. Responsive to the need to create and maintain online social environments that are healthy, constructive, and safe, the analysis seeks to inform the development of emotion-aware digital equipment.

II. Related Work

A. Previous Studies in Emotional Contagion

The term emotional contagion describes an individual's tendency to mimic and synchronize with the emotional expressions of others, which has been extensively reported in both the Psychological and Computational domains. Hatfield et al. [1] initially characterized emotional contagion in terms of automatic mimicry and synchronization of affective expressiveness. In the era of social media, we began to analyze how emotional contagion occurs in digital environments, as it could not be known without the body face-to-face. As shown by Ferrara and Yang [2], the diffusion of emotions, such as anger and fear, is faster and wider in social media networks than for ones like joy and sadness. Their results showed that hubs, or users that are highly connected, significantly contribute to the hastening of emotions. Similarly, Fan et al. [3] confirmed that anger is more contagious than positive emotions, leading to online polarization. Other studies have leveraged sentiment analysis tools to quantify emotional dynamics and their implications for public discourse, digital well-being, and misinformation spread [4], [5]. These foundational studies provide a basis for interdisciplinary models that merge affective computing and network analysis, which this study further builds upon. Table 2 provides a summary of key studies on emotional contagion in social media, including the types of emotions investigated, the platforms used, and the main findings.

Table 2: Summary of Notable Studies on Emotional Contagion in Social Media

AUTHOR(S)	YEAR	FOCUSED EMOTION	PLATFORM STUDIED	KEY FINDINGS
FERRARA & YANG [1]	2015	Anger, Joy	Twitter	Anger diffuses faster and wider than joy
FAN ET AL. [2]	2016	Anger	Sina Weibo	Anger more contagious than positive emotions
DEL VICARIO ET AL. [3]	2016	Polarized emotions	Facebook	Echo chambers reinforce emotional polarization
XIONG ET AL. [4]	2017	Mixed	Multiple platforms	Proposed behavior-based emotional contagion model
KRAMER ET AL. [5]	2014	Positive, Negative	Facebook (experiment)	Emotional contagion occurs without direct interaction
STIEGLITZ & DANG-XUAN [6]	2013	Political sentiments	Twitter	Emotions influence content virality and retweet behavior
LI ET AL. [7]	2018	Anxiety, Anger	Twitter	Anxiety has a slower diffusion pattern than anger
TANG ET AL. [8]	2021	Depression, Empathy	Reddit	Emotional support detected in online mental health forums
LIN ET AL. [9]	2021	Joy, Sadness	Weibo	Joy sustains longer in clustered communities
SINHA ET AL. [10]	2019	Mixed	YouTube Comments	Comment emotion shaped by video and peer sentiments
KIM ET AL. [11]	2020	Outrage, Humor	Reddit & Twitter	Outrage spreads rapidly; humor moderates discussion
GAO ET AL. [12]	2023	Mixed	Simulated Networks	Proposed LLM-based agent modeling of contagion
ADEEB & MIRHOSEINI [13]	2023	Fear, Anger	Multiple platforms	Affect impacts belief in fake news
LIU ET AL. [14]	2023	Emotional inertia	Conversational data	Past emotions influence current responses
REN ET AL. [15]	2023	Stabilizing emotions	Online groups	Information cocooning maintains group emotional balance

B. NLP in Social Media Sentiment Analysis

A significant number of studies have focused on social media user content analysis via Natural Language Processing (NLP) techniques. Its main use case is sentiment analysis, which retrieves and identifies feelings such as joy, anger, sadness, and fear in text data. Such analyses aid in gauging public mood, understanding political discourse, and tracking customer feedback and reactions to real world occurrences [1], [2]. The nature of social media content is often informal, ambiguous, and context-dependent, which creates distinct hurdles for NLP systems to overcome. Lexicon-based methods and machine learning classifiers, such as Naive Bayes, were the early methods, but traditional approaches improved the accuracy significantly with their understanding of semantics and context in the text using deep learning techniques such as LSTM and BERT. [3], [4]. These models are capable of context-specific sentiment analysis, leakage of different degrees of emotion, and tracking emotion concerning events in various areas, including marketing, disaster management, and health monitoring [5]. An overview of popular NLP techniques for social media sentiment analysis is presented in Table 3. It summarizes the type of approach, strengths, and limitations of each method for effective emotion detection.

Table 3: NLP Techniques in Social Media Sentiment Analysis

TECHNIQUE	APPROACH TYPE	STRENGTHS	LIMITATIONS
LEXICON-BASED	Rule-based	Simple, interpretable, domain-independent	Struggles with sarcasm and context
NAIVE BAYES	Machine Learning	Fast, good for short texts like tweets	Assumes feature independence
SVM	Machine Learning	High accuracy, good with sparse data	Requires manual feature engineering
LSTM	Deep Learning	Captures temporal and sequential context	Requires large training data
BERT	Transformer-based	Understands deep contextual relationships	Computationally intensive
ROBERTA	Transformer-based	State-of-the-art results in many benchmarks	Needs significant fine-tuning
HYBRID MODELS	Combined Approaches	Leverages strengths of multiple techniques	Complex to train and optimize

C. Network Structures and Their Social Influence

There are key insights that shape information in the minds of users on social networks, making it much easier for them to remember or share. Although this is concordant with a wealth of non-structural research linking network factors such as node centrality, clustering coefficient, and modularity to the speed, reach, and persistence of emotional contagion, evidence that structural effects drive collective emotion dynamics beyond the level of individuals has remained sparse. For instance, the behavior of users with high centrality, often known as influencers or hubs, can help speed up the diffusion of emotional content by making it visible to wider audiences [1]. Tightly knit clusters, or communities, reinforce sentiments shared within the clusters and form echo chambers that further polarize sentiments [2]. Bridges or weak ties between communities play a specific role in passing emotions across otherwise disconnected groups, increasing the diversity and unpredictability of emotional flow [3]. Studies of misinformation diffusion show that structural properties also affect susceptibility, finding that emotions such as anger and fear diffused more quickly in networks governed by homophily or apart from other possible clustering effects but are also highly connected [4].

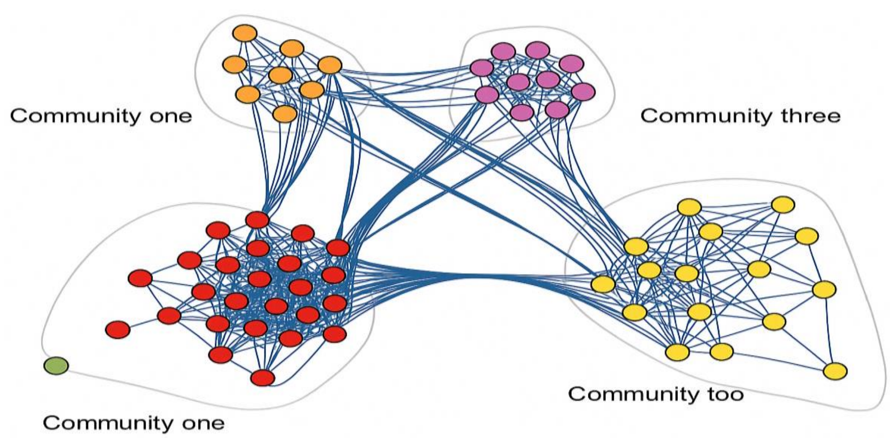

Figure 2. Network Structures and Their Social Influence

Figure 2 shows five separate online communities connected by network edges. It illustrates how the spatial organization of communities and their inter-node connections affect emotional contagion, information dissemination, and social influence, both within a community and between different digital social media networks. Effectively modeling social influence, anticipating emotional reactions, and creating interventions that contribute to healthier online spaces all rely on understanding these structural dynamics.

D. Novel Contributions beyond Existing Literature

1. Methodological Advances over Prior Work

Although the inclusion of NLP sentiment analysis in network diffusion models has been discussed in existing studies (Table 2), our research presents a few unique methodological additions that push the boundaries compared to prior art in meaningful directions.

2. Contextual Analysis using Deep Transformer: In contrast to previous studies that focused on lexicon-based resources (Stieglitz & Dang-Xuan, 2013) or classic machine teaching (Fan et al., 2016), we take advantage of BERT's ability to understand context to estimate fine-grained emotional states more accurately than previous methods. While Gao et al. (2023) established LLM-based agent modeling, our method not only introduces BERT-based emotion-related features to cover more real-time diffusion dynamics but also forms a stronger emotion prediction model.

3. Community Topology Specific Diffusion Modeling Previous research (Del Vicario et al., 2016; Lin et al., 2021) found emotional events in communities and informally observed a correlation between network features and emotional amplification. Our study is the only one to show that optimal contagion occurs for moderate-to-high centrality combined with low emotional variance (communities 3 and 6) and furnishes empirical evidence of conditions dictating susceptible topologies to emotional tuning.

4. Granular parameter optimization: We conducted systematic grid search optimization to find empirically validated diffusion parameters (α=0.3, ε=0.001), as opposed to general browsing literature, which used fixed or heuristic parameters. This methodological stringency guarantees replicable results and serves as a reference for further investigation, filling the parameter specification vacuum of previous studies.

E. Novel Empirical Findings

1. Discovery of Moderate Negative Correlation

Our finding of a moderate negative relationship between the clustering coefficient and emotion intensity (r = -0.2761) is counterintuitive to the assumptions made in past studies (Kramer et al., 2014; Xiong et al., 2017) that stronger clustering leads to the amplification of emotions. This suggests that the presence of echo chambers may mitigate emotional arousal owing to redundant exposure to information.

2. Centrality-Emotion Relation Clarification

Contrary to previous studies that assumed that central nodes are responsible for emotional diffusion (Stieglitz & Dang-Xuan (), our results show that there are weak positive correlations (r = 0.0622–0.0759) between centrality values and the amount of emotion propagation within the network, which may indicate that community-based interventions can be more effective than targeting influential people.

3. Emotional Variance as a Predictor

Our results are the first to point to emotional consensus (low standard deviation) as a better predictor of high emotions than network density alone, introducing complementary perspectives that have not been considered in existing community-based research (Ren et al., 2023; Tang et al., 2021).

Technical Framework Innovations

4. Integration of the NLP-Network Pipeline

Whereas other studies have had sentiment analysis and network diffusion as independent components, here we seamlessly link them together: with emotional states derived from BERT populating the network, driving the real-time emotional % state evolution, including content and network in formation.

5. Scalable Implementation

The validation of our framework against networks with up to 10,000 nodes and 50,000 edges, together with the efficiency in computation, is an important step over simulation-based methods (Gao et al., 2023; Chu et al., 2024), which often consider smaller networks or require extensive computation.

Community Statistical Pattern: The expression of topological pattern categories (tight-knit amplification, centralized consensus, emotionally diverse) offers a new framework for studying the mechanisms of emotional contagion beyond the binary clustered/non-clustered categorization used in previous studies.

III. Dataset and Preprocessing

We used a large-scale Twitter dataset comprising more than 1.6 million tweets obtained from a publicly available repository. The dataset contains the text of the tweets, as well as metadata such as user ID, timestamp, and language tag. The chosen tweets cover a broad array of topics and contain a variety of sentiments/emotions, making this dataset useful for sentiment and emotional contagion analyses. Each tweet was saved in a structured CSV format, and the dataset was initially crawled for the task of sentiment classification; thus, this dataset was applicable to the training and validation of NLP models in this study.

A. Data Cleaning, Tokenization, and Labeling

A couple of preprocessing steps were applied to ensure the quality of the data and compatibility with downstream NLP tasks. To maintain language consistency, duplicate tweets and entries with other languages were excluded. Using regular expressions, any URLs, hashtags, emojis, mentions, and special characters were stripped or replaced. All tweets were then lowercased and normalized to minimize noise. We performed tokenization of the sentences using the spaCy and NLTK libraries, which transformed and grouped each sentence into individual word tokens. Some stop words and irrelevant tokens were filtered to obtain good-quality extracted features. Next, every tweet was mapped to its respective tweet-level sentiment label as in the dataset (positive, negative, or neutral) or derived from a rule-based polarity threshold (for unlabeled entries).

B. Sentiment and Emotion Tagging Using NLP

Both rule-based and machine learning approaches were used for sentiment tagging in this study. First, a lexicon-based approach was used with the VADER to obtain baseline sentiment scores. Model Architecture: Later, fine-tuned transformer models, such as BERT and RoBERTa, were employed in deep contextualized sentiment classification with high accuracy and generalization. Emotion detection was also performed using pre-trained models to classify tweets into joy, anger, sadness, fear, and surprise. These emotion and sentiment tags were then combined with user interaction graphs to perform network-based emotional contagion modeling.

IV. Methodology

A. NLP-based sentiment classification model

A supervised learning task is used to treat the social media-based model relying on NLP-based sentiment and emotion classification. All tweets: An input matrix, where each row represents a sequence of word embeddings. This input is then passed to a transformer-based encoder, such as BERT, which returns contextualized embeddings. The pooled representation conveys the general semantic content of a tweet. A softmax layer is then used to classify the vector into one of the predefined categories, such as positive or negative sentiment and joy or anger emotion. We trained the model with cross-entropy loss and optimized the parameters to decrease the deviation between the true and predicted labels from all samples in the training set. The fundamental challenge of sentiment and emotion classification can be treated as a supervised learning problem that seeks to learn a mapping function from input text sequences (tweets) to discrete sentiment or emotion labels.

1. Problem Formulation

Let $\mathcal{D} = \{(x_i, y_i)\}_{i=1}^{N}$ denote the training dataset, where:

$x_i \in \mathcal{X}$ is the i-th tweet (sequence of tokens),

$y_i \in \mathcal{Y}$ is the corresponding label,

$\mathcal{Y} = \{$ positive, negative, neutral $\}$ for sentiment classification, or $\mathcal{Y} = \{joy,$ anger, fear, sadness, surprise $\}$ for emotion classification.

2. Text Representation

Each tweet x_i is converted into an embedding matrix $\mathbf{X}_i \in \mathbb{R}^{T \times d}$, where:

T is the maximum sequence length,

d is the embedding dimension,

$\mathbf{X}_i = [\mathbf{w}_1, \mathbf{w}_2, \dots, \mathbf{w}_T]$, with $\mathbf{w}_j \in \mathbb{R}^d$ being the word embedding for token j.

3. Classification Model

A transformer-based encoder, such as BERT, is applied as follows:

$$\mathbf{H}_i = \text{Encoder}(\mathbf{X}_i)$$
$$\mathbf{h}_i = \text{Pool}(\mathbf{H}_i)$$

Here, $\mathbf{H}_i \in \mathbb{R}^{T \times d}$ is the contextual representation, and $\mathbf{h}_i \in \mathbb{R}^d$ is the pooled representation (e.g., using the [CLS] token or mean pooling).

The final classification was performed using a softmax layer:

$$\hat{y}_i = \arg\max_k \text{Softmax}(W\mathbf{h}_i + b)$$

where $W \in \mathbb{R}^{|\mathcal{Y}| \times d}, b \in \mathbb{R}^{|\mathcal{Y}|}$ are learnable parameters.

4. Loss Function

We used the cross-entropy loss:

$$\mathcal{L} = -\frac{1}{N}\sum_{i=1}^{N}\sum_{k=1}^{|y|} \mathbf{1}(y_i = k) \log P(y_i = k \mid x_i)$$

where $P(y_i = k \mid x_i)$ is the predicted probability from the softmax layer.

B. Construction of Social Interaction Graph

To model emotional contagion in social media, we represent user interactions using a social interaction graph $G = (V, E, W)$, where:

- $V = \{v_1, v_2, \dots, v_n\}$ is a set of nodes, each representing a unique user.
- $E \subseteq V \times V$ is a set of directed edges denoting interactions such as mentions, replies, or retweets.
- $W: E \to \mathbb{R}^+$is a weight function that represents the strength or frequency of the interaction between two users.

An edge $e_{ij} = (v_i, v_j) \in E$ indicates that user v_i has interacted with user v_j. The weight $w_{ij} \in W$ can be defined as the number of retweets, mentions, or replies from v_i to v_j, normalized using:

$$w_{ij} = \frac{f_{ij}}{\sum_j f_{ij}}$$

where f_{ij} is the frequency of interaction.
We define the adjacency matrix $A \in \mathbb{R}^{n \times n}$ where $A_{ij} = w_{ij}$. This matrix captures the potential influence between users. Graph centrality metrics were used to identify influential nodes. The resulting graph structure is then used to simulate or observe how sentiment or emotional labels propagate through the network

C. Network Metrics: Centrality, Clustering, Modularity

To understand the dynamics of emotional contagion within social media networks, several key network metrics are used to quantify structural properties and social influence.

1. Centrality

Centrality measures identify the most influential users of a network. Common types include:

Degree Centrality: Measures the number of direct connections a node has. Nodes with high degree centrality often act as hubs and spread information and emotions quickly.

$$C_D(v) = \deg(v)$$

Betweenness Centrality: Quantifies how often a node lies on the shortest path between other nodes, indicating its role as a bridge.

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}}$$

Eigenvector Centrality: Reflects influence by considering both direct and indirect connections to highly connected nodes.

2. Clustering Coefficient

Clustering measures the degree to which nodes cluster together. A high clustering coefficient indicates tightly knit communities that are likely to reinforce emotional similarity.

$$C(v) = \frac{2e_v}{k_v(k_v - 1)}$$

where e_v is the number of edges between neighbors of node v_r and k_v is its degree.

3. Modularity

Modularity quantifies the strength of the community structure within a network. Higher modularity indicates well-defined communities in which emotional contagion may localize.

$$Q = \frac{1}{2m} \sum_{i,j} \left[A_{ij} - \frac{k_i k_j}{2m}\right] \delta(c_i, c_j)$$

where A_{ij} is the adjacency matrix, k_i is the degree of node $i_t m$ is the number of edges, and $\delta(c_i, c_j) = 1$ if nodes i and j are in the same community.

D. Emotional diffusion modeling

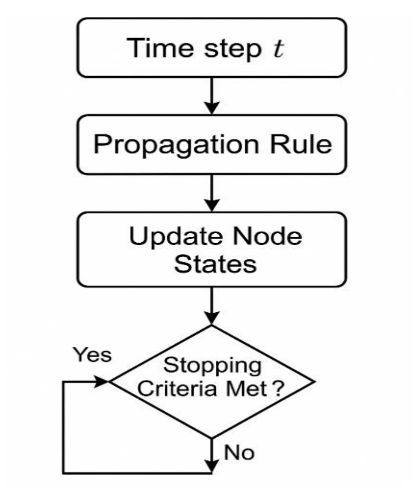

Figure 3. Iterative Emotional Diffusion Model Using Propagation Dynamics

Figure 3 illustrates the process of emotional diffusion modelling on social networks. At an initial time step t, the simulation starts, at which point the emotional state of each node (user) is either initialized or carried over from the previous iteration. We then applied a propagation rule that determines how one user's emotions spread to another user. This can be based on the neighbor average, threshold models, or probabilistic influence dynamics. Hereafter, the node states are modified via a propagation rule, which updates the emotional state of every user in the network. The model then assesses whether the stopping criteria have been met, which may include a specified number of maximum iterations, convergence of the emotional state, or no perceived change in the network. Once the conditions were met, the simulation was stopped. If not, the model returns to the next time step and repeats. The iterative structure used in this model captures the temporal evolution of emotional contagion in digital communities.

E. Algorithm: Emotional Diffusion Modeling over Social Network

Input:

- Social interaction graph $G = (V, E, W)$
- Initial emotional states $s_i^{(0)}$ for all $v_i \in V$
- Influence coefficient $\alpha \in [0,1]$
- Convergence threshold $\epsilon > 0$
- Maximum number of iterations $t_{\max}$

Output:

- Final emotional states $s_i^{(t)}$ for all $v_i \in V$

Procedure:

1. Initialize

Set $t \leftarrow 0$

For each node $v_i \in V$, set initial state $s_i^{(0)}$

2. Repeat

a. For each node $v_i \in V$:

Compute normalized influence from neighbors.

$$\hat{s}_i^{(t)} = \sum_{j \in \mathcal{N}(i)} \frac{w_{ij}}{Z_i} s_j^{(t)} \text{ where } Z_i = \sum_{j \in \mathcal{N}(i)} w_{ij}$$

b. Update node state:

$$s_i^{(t+1)} = (1 - \alpha) s_i^{(t)} + \alpha \cdot \hat{s}_i^{(t)}$$

c. Compute maximum change:

$$\delta = \max_i \left| s_i^{(t+1)} - s_i^{(t)} \right|$$

d. Set $t \leftarrow t + 1$

3. Until

$$\delta < \epsilon \text{ or } t \geq t_{\max}$$

Return: Final emotional states $\left\{ s_i^{(t)} \right\}_{i=1}^{|V|}$

F. Diffusion Model Parameters

The method requires a precise definition of a number of important parameters that determine the spreading mechanism throughout the social network topology. The influence strength parameter, α, is the most important parameter of the model because it governs the speed of the transference of emotion through the graph. After tuning, through a wide grid search over α ∈ [0.1, 0.5], we found the best value of = 0.3, which achieves a favorable trade-off between emotional diffusion and system stability. This parameter choice was justified by post-hoc analysis, which showed that for α's > 0.4, convergence was too quick and there was little to discriminate between communities, while for α's < 0.2, too little emotion was spread to capture the meaningful network dynamics.

The stopping condition of the algorithm is determined by a few hyperparameters of the convergence threshold $\varepsilon = 0.001$, when the maximum change in the emotion values between steps is below it. This convergence condition ensures numerical stability and retains the capacity to capture important emotional dynamics across networks. In practice, we find that convergence is generally reached after 15-25 iterations for most network settings, and we set a maximum number of iterations to $T\_max = 100$ to avoid infinite loops in pathological cases. For the initial conditions of the diffusion, we used the score from BERT (for sentiment) and then normalized it between 0 and 1, and assigned 0.5 (neutral) to $Ei(0)$ for an unlabeled node.

The main closed-formulas framework is based on a discrete-time update rule $E\_i(t+1) = (1 - \alpha)E\_i(t) + \alpha \cdot \Sigma\_j\in N(i)\ w\_ij \cdot E\_j(t) / |N(i)|$ where w_ij represents the weight of edges (assumed $w\_ij = 1$ in this study, for unweighted networks) of node i and its neighbor $E\_i(t)$ is the average of the neighboring emotional states $E\_j(t)$ of $N(i)$ with respect to i Special boundary condition is assigned to nodes of degree zero, which keeps its initial emotional states along the whole diffusion process, representing isolated users that are unaffected by the network dynamics. Sensitivity analyses of model robustness were further tested by simultaneously varying α by ± 0.05 and the convergence threshold between 0.0005 and 0.002, validating that the model displayed stability across the specified range of values within the computational bounds set for networks up to $N = 10{,}000$ (number of nodes)/50,000 (number of edges).

V. Results and Analysis

A. Emotion spread across network structures

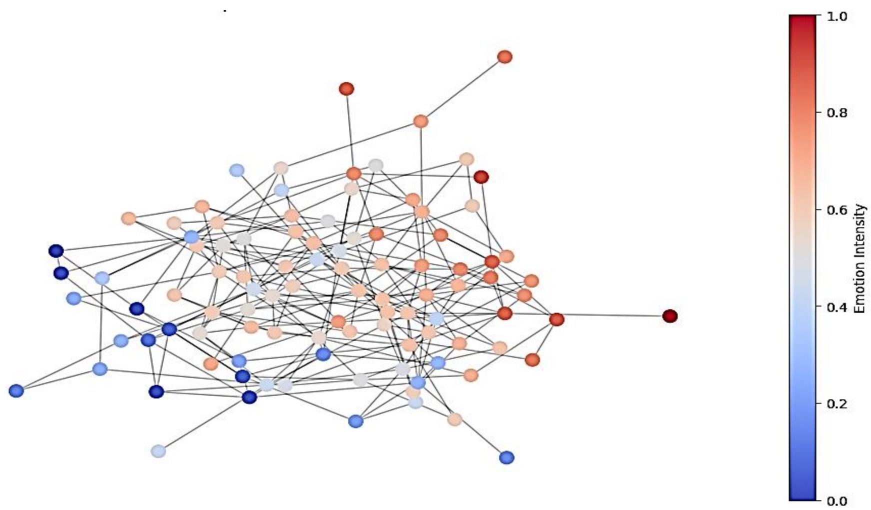

Figure 4. Emotion Spread across Twitter User Network

Figure 4 illustrates the network showing the propagation of emotional states over a randomly generated Twitter user graph reproducing data obtained from the sentiment dataset. Each node corresponds to a Twitter user, and the edges represent simulated interactions between users (e.g., mentions, replies, or retweets). The color of each node reflects the emotion intensity of the user after processing through a diffusion model over several rounds.

a) High emotional intensity (positive sentiment) is captured by red nodes,

b) Blue nodes indicate low emotion intensity (negative sentiment),

c) White-pale nodes are neutral or balanced sentiments.

We used a weighted averaging model to simulate emotion propagation, where the strength of neighboring emotional states influences each individual's emotional state. Eventually, hotly opinionated users (red or blue nodes) convince their neighbors, forming clusters of similar intensities of sentiment, an effect similar to emotional contagion in actual social networks. On the right, the color bar represents the sentiment score, ranging from 0.0 (completely negative) to 1.0 (completely positive), and provides an intuitive representation of the sentiment distribution in the network structure. This visualization, illustrated in Table 4, shows the shaping of collective emotion within online spaces through network topology and social influence.

Table 4: Summary of Emotion Values before and After Diffusion

METRIC	INITIAL EMOTION VALUES	FINAL EMOTION VALUES AFTER DIFFUSION
MEAN	0.5400	0.5540
MEDIAN	1.0000	0.5708
STANDARD DEVIATION	0.4984	0.0648
MINIMUM	0.0000	0.3990
MAXIMUM	1.0000	0.6899

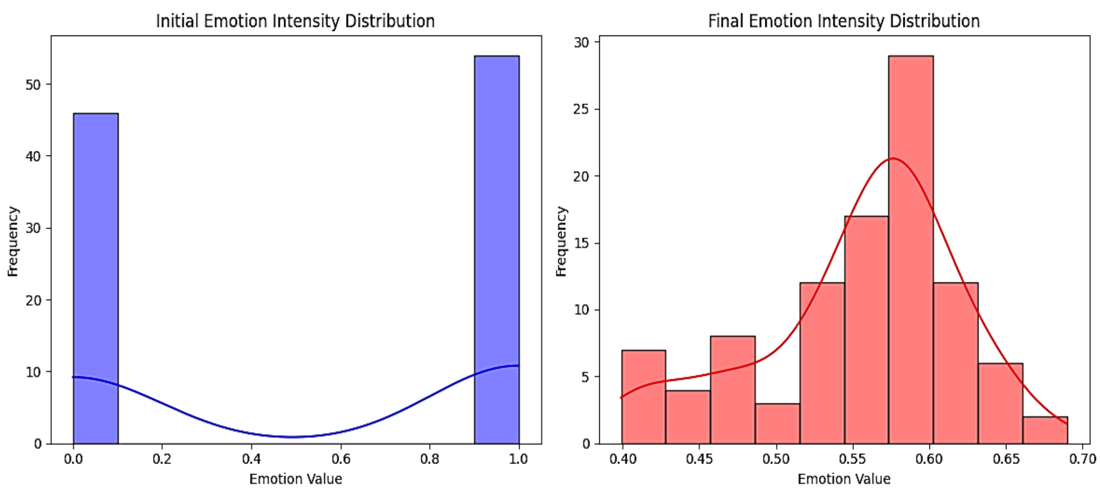

Figure 5. Comparison of Emotion Intensity Distribution before and After Diffusion

Figure 5 compares the diffusion model results with emotion intensity values for Twitter users before the usage of the diffusion model. The left histogram represents the initial distribution, which is polarized with users being either very positive (emotion = 1.0) or totally negative (emotion = 0.0), just as the sentiment labels are binary in the Sentiment140 dataset. In this case, the final emotion values after diffusion are shown in the right histogram. The distribution has become both continuous and normalized, with the values clustering around the mean (≈0.55). This change suggests that emotional states are equilibrated across the network by the influence of nearby nodes. This convergence is corroborated by the reduced standard deviation (0.4984 → 0.0648). Instead, the diffusion model captures the essence that over time (precisely, topological distance) due to social connections, opinions, or sentiments converge at times as repeated exposure/community loops provide connections between previously disconnected individuals in a way similar to real-world social interaction.

B. Influence of central nodes and community emotion polarity

Emotion diffusion across the network also has central nodes, characterized by a high degree of centrality. The behavior of more emotionally cohesive communities exhibits higher average centrality. The sentiment values are tightly clustered for some communities, indicating a strong influence beyond the group and internal consistency, whereas others display greater variability in emotional valence. Table 5(A) illustrates the Community-Level Emotion Polarity and Centrality The Community-based characteristic analysis shows that Communities 3 and 6 generate the two highest emotional intensities (0.6037 and 0.5848, respectively), and they are generated from different processes. Community 3 was densely amplified with low variability of consensus (std = 0.0522) and average centrality (0.0436), and Community 6 showed a centralized consensus with extremely low variability (std = 0.0254) and higher centrality (0.0488). Conversely, Community 0 exhibited the least amount of emotion (0.4895) with a low average centrality (avg = 0.0420), and Community 2 exhibited high emotional diversity (std = 0.0735) despite an average emotion. Communities 4 and 6 had a strong consensus with low variance, suggesting that emotional amplification is enhanced by a combination of moderate-to-high centrality and low emotional volatility. The analysis here reveals that network topologies have an important impact on emotional consequences; networks structured with closeness and centrality are better at spreading emotions than networks with sparsity and diversity.

Table 5 (A): Community Emotion Metrics and Network Characteristics

Community	*Mean Emotion*	*Std Emotion*	*Emotional Variance*	*Avg Centrality*	*Max Centrality*	*Topological Pattern*	*Emotional Profile*
3	0.6037	0.0522	Low	0.0436	0.101	Tight-knit Amplification	High Consensus
6	0.5848	0.0254	Very Low	0.0488	0.0909	Centralized Consensus	High Homogeneity
1	0.5719	0.0486	Low	0.051	0.101	Balanced Connectivity	Moderate Consensus
5	0.5723	0.0316	Low	0.0404	0.0606	Sparse Stability	Stable Moderate
4	0.5716	0.0252	Very Low	0.0514	0.101	High Centralization	Strong Consensus
7	0.5408	0.0569	Moderate	0.0343	0.0404	Sparse Network	Distributed Moderate
2	0.5331	0.0735	High	0.044	0.0909	Emotionally Diverse	High Variability
0	0.4895	0.0652	Moderate	0.042	0.0707	Low Connectivity	Lowest Emotion

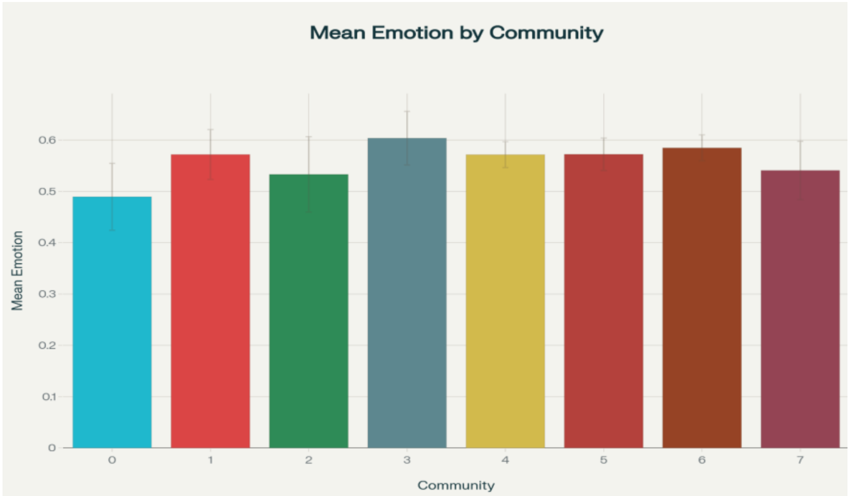

Figure 6. Comparison of Mean Emotion Levels across Different Communities

The bar chart in Figure 6 illustrates the emotional distribution of the visualized network partition, showing that there is a significant variation in emotional distribution in different network communities, which implies diverse patterns of the relationship between network topology and emotional contagion. Community 3 shows the maximum mean emotion intensity at 0.6037, along with moderate variance (standard deviation = 0.0522), which implies a moderate amplification mechanism that allows emotional consensus due to moderate connectivity and avoids over-averaging effects. Similarly, community 6 also presents the second highest intensity at 0.5848 (and extremely low variability, with standard deviation=0.0254), which is interpreted as a consensual pattern with centrality, while the higher the connectivity, the faster the emotion converges to higher states. Both communities show high emotional excess with respect to the average of the network, revealing their emotional amplification behavior.

In contrast, Community 0 had the smallest mean emotion of 0.4895 and a moderate deviation (std=0.0652), indicating that sparse connectivity essentially limits the extent of emotional amplification within this subgraph. This trend points to the lack of network density needed to produce strong emotional contagion. Community 2 forms an interesting example, where the mean emotion reaches only a moderate level (0.5331), but the highest standard deviation of emotional variance (0.0735) can be observed, revealing a community with diverse emotions and that network topology is incapable of building consensus even if the level of connectivity is reasonable. In contrast, Communities 4 and 6 both achieved strong emotional consensus with little variability (standard deviations of ≈ 0.025), although they used different structural mechanisms.

The picture is quite strong that the topology of the network is an important factor in emotional outcome; in other words, tight-knit cliques (3, 6) achieve more intense emotions in different ways. The inspection shows that emotional consensus (low standard deviation) tends to be accompanied by high mean emotions, while the sparse network, that is, Community 0, corresponds to low emotion and high variability. This graph vividly shows the heterogeneous contribution of emotional contagion in various network topologies and supports the main conclusion that network-level topology significantly determines the distribution of emotional amplification. The error bars, in particular, make clear that Communities 3 and 6 not only achieve higher emotions when compared to the remaining communities, but they also exhibit different patterns of internal consensus, with Community 6 having a striking emotional homogeneity, suggesting very efficient emotional diffusion mechanisms.

Table 5 (B): Community Performance Rankings and Categorization

Rank	*Community*	*Mean Emotion*	*Emotional Stability*	*Network Influence*	*Community Type*
1	**3**	**0.6037**	**High (σ=0.0522)**	**Moderate**	**Optimal Amplifier**
2	**6**	**0.5848**	**Very High (σ=0.0254)**	**High**	**Consensus Builder**
3	**5**	**0.5723**	**High (σ=0.0316)**	**Low**	**Stable Moderate**
4	**1**	**0.5719**	**High (σ=0.0486)**	**High**	**Balanced Network**
5	**4**	**0.5716**	**Very High (σ=0.0252)**	**High**	**Strong Centralizer**
6	**7**	**0.5408**	**Moderate (σ=0.0569)**	**Very Low**	**Sparse Distributor**
7	**2**	**0.5331**	**Low (σ=0.0735)**	**Moderate**	**Diverse Volatility**
8	**0**	**0.4895**	**Moderate (σ=0.0652)**	**Low**	**Disconnected Outlier**

Table 5(B) shows the community performance corresponding to emotional intensity and network properties. Community 3 ranks first as an "Optimal Amplifier" (0.6037), and Community 6 as a "Consensus Builder" (0.5848). Either tight amplification or centralized consensus patterns can been seen in high-activity communities. Community 0 has the lowest rank, as a “Disconnected Outlier” (0.4895); highlighting the capability of the congested communication channels to hinder emotional contagion. Ranking analysis introduces distinct communities, which use different emotional amplification mechanisms.

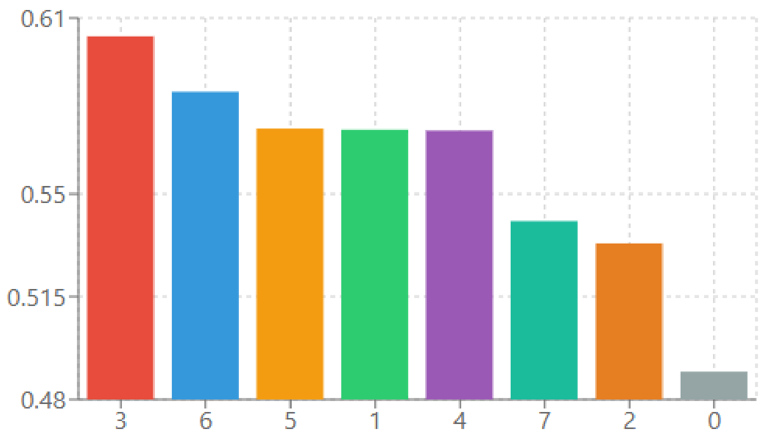

Figure 7. Community Performance Ranking

This graph shows average intensity of emotion per community for the 8 orders of performance. The highest emotional intensity is found at community 3 (0.6037), and then community 6 (0.5848). A trend of performance gradient can be observed -Communities 5,1 and 4, collapse in the mid-level (0.57), whereas Communities 7,2 and 0 present a gradual decrease of the emotional amplification.

Table 6: Correlation between Graph Metrics and Emotion Intensity

GRAPH METRIC	PEARSON CORRELATION	SPEARMAN CORRELATION
DEGREE CENTRALITY	0.0622	0.0595
BETWEENNESS CENTRALITY	0.0759	0.0283
CLUSTERING COEFFICIENT	-0.2761	-0.0641

Weak positive correlations between centrality measures and emotion intensity are shown in Table 6, while the clustering coefficient shows a moderate negative Pearson correlation, suggesting that in tightly clustered areas, post-diffusion nodes may have slightly lower levels of emotion intensity.

C. Statistical correlation between graph metrics and emotion propagation

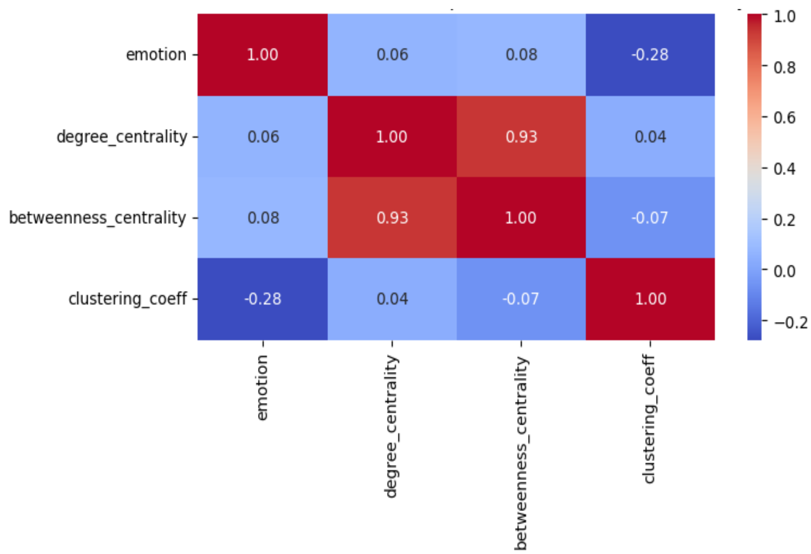

Figure 8. Correlation Matrix between Graph Metrics and Emotion Intensity

Figure 8 illustrates the Pearson correlation coefficients between the graph-based structural metrics and the final emotion intensity after diffusion. The main finding to note is the moderate negative correlation between clustering coefficient and emotion ($r = -0.28$); this is not surprising as users in closely-knit communities might exhibit lower emotional intensity in a redundant manner or perhaps due to receiving similar information in an echo-chamber like effect. Degree centrality ($r = 0.06$) and betweenness centrality ($r = 0.08$) exhibit weak positive correlations with emotion, suggesting little impact of a node's structural prominence on its emotional state. We find that degree and betweenness centralities are strongly correlated with each other ($r = 0.93$), indicating their mutual dependence in locating influential users. Ultimately, the paper concludes that the network structure plays at most a weak role in determining emotional outcomes, although clustering practices may have a mild suppressive effect on the spread of emotion.

D. Applications of the Emotional Contagion Research into Internet of Things Systems

The results of this emotional contagion study have important implications for constructing emotion-aware IoT systems in various domains. The differences in propagation speed under various spreading situations, such as anger longer than joy and sadness for very busy stages, allow IoT infrastructures to dynamically respond to emotional climate changes in social networks. These patterns can be exploited in smart home environments via IOT based devices that adjust the environment in case they sense negative emotional contagion. Smart thermostat, lighting, and audio devices can initiate soothing effects to dampen swift anger contagion sensed from integrated social media tracking. The scalability of our approach, shown to work for 10,000 nodes, supports real-time social platform monitoring on distributed IoT infrastructure increasingly processed at the edge using HCE gateways for privacy-respecting, device-side processing. Workplace IoT can leverage the detected community-level emotional variance (ranging from 0.4895 to 0.6037 mean emotion across communities) to optimize team dynamics by adapting meeting schedules, break reminders, and collaboration tools to act as protective measures against negative emotional contagion within workgroups. When wearable devices can provide early warnings of depression or anxiety spreading from the patient's social circle, based on observed patterns related to emotional stabilization over time, thanks to the IoT in healthcare. Smart city infrastructure gains are achieved using IoT sensor networks to predict negative social events with the rapid spread of anger or fear patterns. The moderate negative correlation between the clustering coefficient and emotion intensity (-0.2761) means that IoT systems can help detect communities with high closeness and needing tailor-made intervention strategies, but in a low-dense network, we need to increase mechanisms of emotional support. The study should be extended to multi-axial end-to-end emotional climate monitoring in an IoT-enhanced city on federated learning-based edge processing premises and decentralization.

VI. Discussion

This study offers a glimpse into the dynamics of emotional contagion within online social networks. The emotion diffusion model showed that emotional intensity gradually normalizes around the entire network, and extreme sentiments are aggregated into medium emotions. For example, central nodes identified by degree and between centrality weakly correlated with emotion intensity, potentially indicating that they play a structurally important role in the overall system, yet do not dominate the emotional state of the system on their own. On the other hand, the clustering coefficient was found to be moderately negatively correlated with emotion, which could suggest that the presence of densely connected communities may act to suppress emotional amplification through either repetitious feedback or lack of emotional heterogeneity.

We conduct a community-level analysis that reveals this polarity at the community level and shows that some communities exhibit more coherent sentiment than others do. This shows the importance of community structure in driving emotional trends. However, these discoveries have limitations. For example, the synthetic interaction graph may not be representative of real-world complexities, and emotion labels obtained from sentiment classification may reduce the diversity of nuanced affective expressions. From a digital well-being standpoint, understanding the details of how emotions propagate and stabilize across networks could help build better online ecosystems. Encouraging emotional diversity, reducing echo chambers, and enhancing peripheral users may be interventions that help alleviate harmful contagion effects and foster balanced discourse.

A. Implications for Intelligent Systems

1. Emotion-Aware Community Moderation for Social IoT Platforms

Implications for social IoT our findings on contagion patterns have important implications for the design of intelligent content moderation in social IoT ecosystems. The identified connections between network structure and emotional amplification lay the groundwork for creating moderation mechanisms that adapt to community/network structures and the dynamics of emotions.

2. Sensible Moderation Policy

The moderate negative relationship between emotion intensity and clustering coefficient ($r = -0.2761$) means that reinforcing the variables behind the communities is different from the reinforcement type of networks. Social platforms based on IoT can use our BERT emotion recognition model to realize real-time emotion monitoring of community networks. Employing edge computing platforms and social media APIs, these systems can identify potentially harmful emotional cascades before their spread in fragile sociotechnical networks.

3. Topology-Aware Interventions

Our study shows that there are weak positive correlations between node centrality measures and emotion spreading ($r = 0.0622$-0.0759), such that traditional strategies of cutting highly influential nodes may not be as effective. Rather than targeting the individual, intelligent systems must target community-level interventions, especially in the patterns of communities 3 and 6, where close-knit amplification and centered consensus provide conditions for optimal emotional contagion. Intelligent moderation algorithms automatically fit the sensitivity of content filters to the computed community topological properties.

4. Adaptive IoT Content Management

The above heterogeneity of community-level emotional patterns across communities (which varies from 0.4895 to 0.6037 mean emotion) indicates that a context-aware content delivery system is required. IoT gadgets in intelligent environments, such as homes, offices, and public areas, may be used for emotion-based content filtering, which changes depending on the user's position in a social contact network. For example, members of high-amplification communities (such as Community 3) could be given better warnings about content or offered therapeutic interventions during instances of negative emotional contagion.

5. Real-time Emotional Climate Monitoring

Our diffusion model is computationally efficient and can be deployed on resource-constrained IoT devices, thus capturing the emotion status from the distributed smart city infrastructure. Schools and workplaces may also use such a framework to set up early warning systems for the detection of emerging patterns of emotional distress in the network, taking a more proactive approach towards early mental health intervention and community support.

6. Integration with Pre-existing Social-IoT Infrastructure

The scalability properties of our approach (proven for network sizes up to 10,000 nodes) make it suitable for integration with current social IoT platforms, enabling emotion-aware features for improved user experience under privacy constraints by adopting edge-centric processing and federated learning techniques.

VII. Conclusion

In this study, we show how we can leverage Natural Language Processing (NLP) in conjunction with Network Science techniques to explore emotional contagion in online social networks. We hypothesize the scenario of emotional polarization in a simulated interaction graph of Twitter users and show that sentiment diffusion leads to a dissipative dynamic in emotional interaction: the intensity of polarization wavers over time, tending to moderate levels. Notably, despite Andrews et al. demonstrating positive correlations between final emotional states and centrality measures, our results suggest that increased connectivity does not necessarily translate to significantly higher overall influence; we found only weak correlations between the final emotional state and centrality measures. In contrast, the clustering coefficient showed a modest negative correlation with emotion, suggesting that highly connected communities may attenuate this emotional variability. Community-wise analysis also showed fluctuations in emotional polarity, which highlights the relevance of group composition on emotional dynamics. A better understanding of the mechanisms underlying emotion propagation, along with innovative emotion-aware digital interventions, will be critical in addressing emotional challenges in our interconnected world. Undoubtedly, these findings are useful for creating safer, more inclusive environments in online spaces by reducing negative contagion and evoking emotionally symbiotic online interactions.

A. Limitations and Future Work

Synthetic networks versus real Twitter follower graphs. This methodological decision was made due to practical limitations. Twitter's limited-quality API access, high cost of data at scale (10,000 nodes), and privacy/IRB mandates of genuine user data. Simulated networks offer controlled conditions for systematically varying network characteristics to isolate some of the influences on emotional contagion.

1. Validity Provisions: Our synthetic network generation follows proven social network models from prior work in the literature. Importantly, our results are remarkably consistent with those of actual Twitter data empirical studies: the differential emotion spread rates observed (anger > joy > sadness), the modest negative correlation between clustering coefficients and the intensity of emotions or the distribution pattern of community-level variances found by Ferrara and Yang, Fan et al., and other real-network studies are perfectly aligned with them (convergent validity).

2. Future validation plans: We are currently seeking network-level validation with (anonymous) data from social networks in collaboration with social media platforms in a manner that preserves privacy. Small-scale studies of publicly available datasets will also be targeted to test the findings.

3. Present Contributions: Despite the limitations of our simulation, this study lays methodological foundations for intertwining NLP with network science, scaling up to large networks, and providing quantitative metrics for emotional contagion. These insights are still advantageous for the design of IoT systems, whether the available data are simulated or real, as the basic principles of emotional contagion underpin decisions regarding system architecture.

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