International Journal of Advance Research in Science and Engineering
Volume No. 14, Issue No. 07, July 2025
www.ijarse.com
IJARSE
ISSN 2319 - 8354

Evaluate Decision Support Through Social Network Analysis of Customer Feedback in Crisis Situations

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Abstract

Using a social network analysis (SNA) methodology on consumer feedback gathered from online social networks (OSNs), this study assesses decision support during crisis scenarios. In our approach, we utilized a recurrent, iterative process that combines SNA with data mining (DM) to integrate human interaction with network structure. In order to build multilevel networks, Facebook data was examined across three primary entities: users, posts, and concepts transformed into matrices. Using Node XL, data was retrieved every two days tracking user activity, comments, and thoughts over a ten-day airline strike. A major user-post concept network and two supporting user-post concept networks were developed through the processing of structured and unstructured data, normalization, and translation of two-mode to one-mode networks. Influential people, highly discussed postings, and prevalent topics were among the important discoveries uncovered by visualizing and analyzing these networks. This method shows how useful SNA is for improving crisis decision-making in real-time.

Keywords: *Crisis, Feedback, Networks, Decision, Stakeholder*

I. Introduction

Social media and other types of online communication have revolutionized the way people in the modern digital era express themselves, especially in times of crisis. With the rise of social media, customers are turning to these platforms to voice their opinions, get assistance, and even influence decision-makers in times of public health crises, natural catastrophes, economic recessions, and service outages. Organizations may get significant insights for their response plans by methodically analyzing the complex and dynamic webs of information that these interactions create. A valuable technique to analyze decision support systems (DSS) anchored in customer input during such chaotic periods emerges as Social Network Analysis (SNA), a methodological framework that examines patterns of links and interactions among entities.

The character of crises makes them unexpected and disruptive. Organizations must respond quickly, be transparent, and communicate consistently to meet their demands. There is a lot of pressure on decision-makers in these situations to find useful information in the mountains of customer-generated data. Structured data and pre-defined algorithms were the traditional backbone of decision-support systems. Traditional approaches can't keep up with the deluge of unstructured material posted on social media and niche forums, making it difficult to discern subtle shifts in public opinion and new issues. Social network analysis may help fill this need by charting and analyzing user-to-user connections and information flow, revealing powerful nodes, community structures, and the spread of ideas.

Customer input is extremely valuable in determining how a business responds to emergencies. Indicating the gravity of public perception and directing suitable reaction actions, it is like a thermometer and a compass all in one. Organizations must listen to consumer feedback no matter what they're dealing with, whether it's a global health catastrophe like the COVID-19 epidemic, the aftermath of a product failure, or the harm to their brand from a service outage. By combining and analyzing these voices using SNA, we may see not only personal complaints but also group dynamics, emotional contagion, trust networks, and key players who can either make the issue worse or better.

Quantifying connections is the crux of social network analysis. People or organizations are the nodes of a social network, and the connections between them are the edges. Interactions between nodes can take many forms, including responses, shares, mentions, and likes. Researchers and decision-makers may use this network representation to calculate metrics like modularity, clustering coefficient, density, centrality (degree, proximity, betweenness), and clustering. These metrics provide insights into the conversation's structure and behavior. For instance, businesses can find influential people who can control the flow of information by finding users with a high betweenness centrality. A more focused communication approach may be employed to ensure that crisis messages reach the proper audience by recognizing closely knit communities or echo chambers.

Using SNA for decision support has several benefits, one of which is its ability to include quantitative and qualitative elements of client input. Sentiment network analysis (SNA) adds context by showing how these attitudes spread over networks, whereas sentiment analysis techniques can tell if feedback is positive, negative, or neutral. For instance, if a customer with a huge following were to leave a poor review, it may have a domino effect, change the attitudes of others and make the situation worse. Executives can take the initiative to solve the issues raised or use influencers to spread remedial information by tracking the progress of such talks in real-time and intervening accordingly.

The ability to make judgments quickly is just as important as making good ones when faced with a crisis. In this respect, social network analysis is useful as it paves the way for dashboards that show the movement of consumer input across networks in real time. To give a full picture of the current state of affairs, these dashboards may be included into current Decision Support Systems. For example, when weather or technical concerns hinder an airline's service, social media is inundated with complaints and inquiries from customers. Helping the airline prioritize replies, allocate resources, and preserve customer trust, a well-structured SNA-based DSS can identify the most impacted routes, repeated complaints, and significant influencers propagating unhappiness.

Additionally, SNA's predictive capabilities bring a strategic level to decision assistance. To foresee how future crises of a similar kind could play out, organizations might examine past data and model network behavior. The use of predictive modeling in conjunction with ML and NLP improves businesses' responsiveness and readiness. Take this scenario: a pharmaceutical business is dealing with criticism over a recently released drug's negative effect. SNA can predict how misinformation will spread and work with medical influencers and reputable health experts to create counter-narratives.

Reputation management is another important use of social network analysis for crisis decision assistance. Brand impression is greatly impacted by the digital footprint of consumer feedback. Unchecked negative feedback can cause long-term harm, but a crisis can be turned into a trust-building opportunity with prompt acknowledgment and reparation. Network reputational risks may be better tracked with the use of SNA, which measures their origin, velocity, and amplification. Additionally, it finds people who may become brand champions and help rebuild trust. Organisations may tailor their communication tactics to appeal to various stakeholder groups by gaining insight about the sentimental tone, conversational clusters, and geographical distribute of comments.

Several well-established models of communication and decision-making are compatible with the incorporation of Social Network Analysis into Decision Support Systems in times of crisis, from a theoretical perspective. Consider the Situational Crisis Communication Theory (SCCT), which stresses the significance of adapting response tactics to the specifics of each crisis. To back up such a strategic alignment, SNA gives actual evidence. In a similar vein, the Sensemaking Theory stresses the significance of deciphering ambiguous signals, an activity that SNA enables by organising apparently disorderly social media interactions into coherent networks.

This approach's versatility is further enhanced by its multidisciplinary character. With its roots in data analytics, information science, communication studies, and behavioral psychology, Social Network Analysis provides a comprehensive view. Not only does it evaluate the "what," but also the "how," "why," and "with whom" of consumer input. Decision support systems are built around this multi-dimensional understanding, which makes them smarter, more adaptable, and customer-centric.

Using SNA for making decisions during crises isn't without its obstacles, despite its enormous promise. Difficulties may arise because to technical complexity of network algorithms, worries about data privacy, or platform-specific limitations on data access. Furthermore, in order to provide useful insights, domain-specific knowledge is necessary for interpreting network data. However, these obstacles are being progressively overcome because to developments in processing power, the widespread availability of open-source SNA tools such as Gephi, Node XL, and Network X, and the increasing focus on data-driven governance.

Using SNA during the COVID-19 epidemic is a powerful illustration of how effective it is in crisis circumstances. Public and corporate sectors in the health sector have used SNA to monitor the dissemination of false information, determine which individuals or groups have a significant impact on health communication, and create more targeted PSAs. The emergency services have also used SNA to prioritize rescue efforts after earthquakes and storms by using geotagged feedback from impacted users. Customer or citizen input was a signal and a resource in each of these examples, helping to guide important decisions and improve results.

In addition, customers are no longer only consumers; they are actively involved in creating the stories that organizations tell. Individuals are given the capacity to become broadcasters, watchdogs, and even partners in crisis resolution through the networked public sphere. Decision support systems in this setting need to be as flexible and welcoming as the people using them. By charting the edges of this participatory environment, Social Network Analysis makes it easier to have open and democratic decision-making.

Addition of SNA to CRM improves the feedback loop within the framework of the system. Quick, unprompted input from a wide range of demographic and psychographic profiles is available to businesses in real-time, replacing post-crisis surveys and contact center transcripts. The intricacies of contemporary problems necessitate a level of individuality, empathy, and response that this level of detail amplifies. Plus, it gives you the upper hand by letting you see problems before they become major crises, giving you a competitive edge.

More automation, AI integration, and thorough cross-platform analytics are the ways of the future for SNA decision support in crisis scenarios. Multimodal data will need to be included into SNA models as voice-based feedback, visual information, and ephemeral messaging become more prominent. The correct implementation of these technologies will also be influenced by ethical concerns about data use and algorithmic transparency.

When assessing social network decision-support One paradigm shift that firms might experience is the analysis of consumer input in times of crisis. The SNA platform enables decision-makers to respond quickly, intelligently, and compassionately by monitoring consumer sentiment in real-time, mapping key relationships, and forecasting behavioral patterns. It connects the dots between information and results, feelings and plans, and confusion and understanding. Integrating SNA with decision support systems is more than just a new idea; it's a need for being resilient, relevant, and responsible in this age of linked and complicated crises.

II. Review of Literature

Sarangi, Smruti. (2021) These days, it's hard to imagine modern life without social media and the internet, which facilitate contact amongst loved ones and complete strangers alike. Many popular and reasonably priced social media platforms are available now, including Facebook, Twitter, LinkedIn, Google+, etc. People from all over the globe are able to interact and engage in meaningful conversations through social media, which is essentially an online communication system. In addition to facilitating two-way conversation, social media platforms have the potential to expand companies' reach through viral marketing. As a means of disseminating information, news, opinions, etc., the social network phenomena are quickly gaining traction among the general public. Social network analysis is the process of applying data mining techniques to social media in order to identify trends, patterns, or rules in massive datasets. Data mining is a set of procedures for improving the quality of information through the transformation of raw, unstructured data from social media sites into a more usable format for analysis, research, and business. The effects of data mining on social media networks are covered in this research.

Tabassum, Shazia et al., (2018) These days, studying social networks mostly involves social network analysis (SNA). These networks are examined with SNA metrics in addition to the standard statistical methods for data analysis. The data's interdependencies between social entities may be better understood, as can their activities and the cumulative and temporal effects on the network. Hence, the purpose of this essay is to concisely present SNA in various topological networks (static, temporal, and dynamic networks) and viewpoints (ego-networks). Since SNA is mostly useful for networked data mining, we also give a quick rundown of network mining models; this way, readers are given a clear path from network analysis to network mining.

K.C., Hari. (2017) Social media sites occupied the vast majority of people's time. In social networks, people voice their ideas and thoughts. The way people act is affected by their opinions. Studies in sentiment analysis and opinion mining focus on opinions. The most popular brands may be determined with the use of social media opinions. On occasion, forecasting the outcomes as well. The most well-known social media platform where users may "tweet" about certain subjects is Twitter. In order to get the necessary results from the data extracted from tweets, a variety of machine learning algorithms are employed, including Naive Bayes, Support Vector Machine, and Logistic Regression. This report forecasts which smartphone brand will dominate the market by analyzing tweets concerning the Android and iOS platforms. Prediction makes use of the Sentiment Index, the Relative Strength method, and the Post Rate methodology. In order to help people choose the best smartphones, this paper's findings are helpful in delivering accurate reviews.

Nandi, Gypsy. (2013) We focus on the most recent and popular areas of research in this article, which is online social networks (OSNs), and we examine them via an algorithmic and data mining lens. Researchers have placed a great deal of emphasis on studying OSNs due to a number of variables. The availability of massive amounts of OSN data, the capacity to visualize OSN data through graphs, and other similar aspects are a few examples. Data analysis in OSNs also offers promising opportunities for academics from other fields. As a result, this paper provides researchers with a framework for thinking about the most important aspects of data mining in OSNs, which should aid in addressing the remaining difficulties in this area of study.

Rupnik, Rok & Matjaž, Kukar. (2007) Conventional methods of data analysis are now inadequate since they cannot solve every type of problem. In response, the emerging multidisciplinary discipline of data mining was born, which draws on both traditional statistical methods and cutting-edge machine learning tools to aid in data analysis and the extraction of useful insights. While data mining techniques are great at processing massive datasets, they can be challenging for business users to learn and implement in order to provide decision assistance. Our strategy for merging data mining with decision support systems is detailed in this paper. We introduce a data mining decision support system called DMDSS - Data Mining Decision Support System — and talk about how data mining may help with decision support, how data mining methods are used in these systems, some practical approaches, and more. Along with the outcomes and goals for future growth, we also share some preliminary findings.

III. Supporting Decision-Making Using Social Network Analysis

Data from OSNs was extracted, processed, structured, and analyzed in this study using a suggested methodology. By integrating SNA and automated DM into a framework with recurring and iterative processes, two crucial components are human interaction and network structure. The method is very adaptable, finding use in a variety of study fields (such as customer service) and even in a corporation like an airline, where each circumstance is unique. You may study Facebook discourse individually or collectively based on at least three entities: the person, the post, and the topic. It is possible to transform any object into a square matrix. The usage of matrices allows for the representation of online discourse, adjacency, and affiliation. A two-mode network is reduced to a one-mode network in order to analyze all three nodes in the network at the same time. The three matrices were combined to form a multilevel matrix, which in turn formed the primary network (user post concept).

The first phase of the framework is to initiate the data extraction process. At this stage, data on user actions was gathered. Additional information was culled from each post's comments as well. Data processing and social data representation are part of Step 2. At this point, a graph database is used to store the structured data. Step 3 involves cleaning and normalizing unstructured online discourse and semi-structured interaction data, such as postings. This is followed by network graph analysis and the final execution of data visualization techniques. In the end, we retrieved findings and output files after doing data analysis.

Data extraction

Between the ten-day strike and the two days that followed, data was extracted using Node XL at regular intervals (every two days). When gathering data, only one kind of raw network could be used, and that was

International Journal of Advance Research in Science and Engineering
Volume No. 14, Issue No. 07, July 2025
www.ijarse.com
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ISSN 2319 - 8354

user|. Consequently, we built two additional networks for every dataset. One uses the relationship between user and post to find the most relevant posts, and the other uses the relationship between post and concept to find the most utilized concepts.

Using Excel and DM and relational database approaches, the primary network (user-post-concept) was semi-automatically generated to represent the online discourse. The matrices of the three entities were aggregated. Finally, for every dataset, we examine the primary network as well as two additional sub-networks. The node and edge count for each dataset are summarized in Table 1.

Table 1: Overview of Node and Edge Structures in Six Bipartite and Tripartite Networks

Dataset	Concept	Post	User	Total Nodes	user↔post↔ concept	user↔post	post↔concept
1st and 2nd of May	2,043	189	394	2,626	9,223	614	4,213
3rd and 4th of May	1,973	138	216	2,327	4,416	360	3,387
5th and 6th of May	2,426	201	315	2,942	7,164	546	4,739
7th and 8th of May	1,580	144	168	1,892	3,763	311	3,020
9th and 10th of May	1,315	92	159	1,566	3,010	251	2,115
11th and 12th of May	1,294	74	106	1,474	2,421	186	1,870

Data processing and interpretation

First, the processed data was examined with Gephi, and then the network was studied utilizing SNA methods. To ease network analysis and prevent the need to utilize a programming language for data manipulation and visualization, Gephi was employed as a SNA tool. Social network analysis (SNA) makes use of graph theory and networks to probe social systems.

Nodes, which can be users or other entities, and the connections between them are the defining characteristics of network topologies. Using SNA metrics, we were able to determine which nodes (users, posts, or concepts) were most important to a community, sort them by relevance, and display and characterize the outcomes of sub-communities. Consideration of ethical, legal, and privacy concerns led to the anonymization of all data.

Semantic processing was used to normalize the acquired 769 posts' unstructured data. After that, we ran the algorithm and cleaned up the database to do the semantic analysis.

There is a grand total of 20,438 ideas in the finished product. This further suggested that the cleaning database was set up for every language's vocabulary.

IV. Results And Discussion

We used the centrality measures in-degree, out-degree, PageRank, and eigenvector to determine the most influential person and the most relevant post for each dataset after building the networks with Gephi.

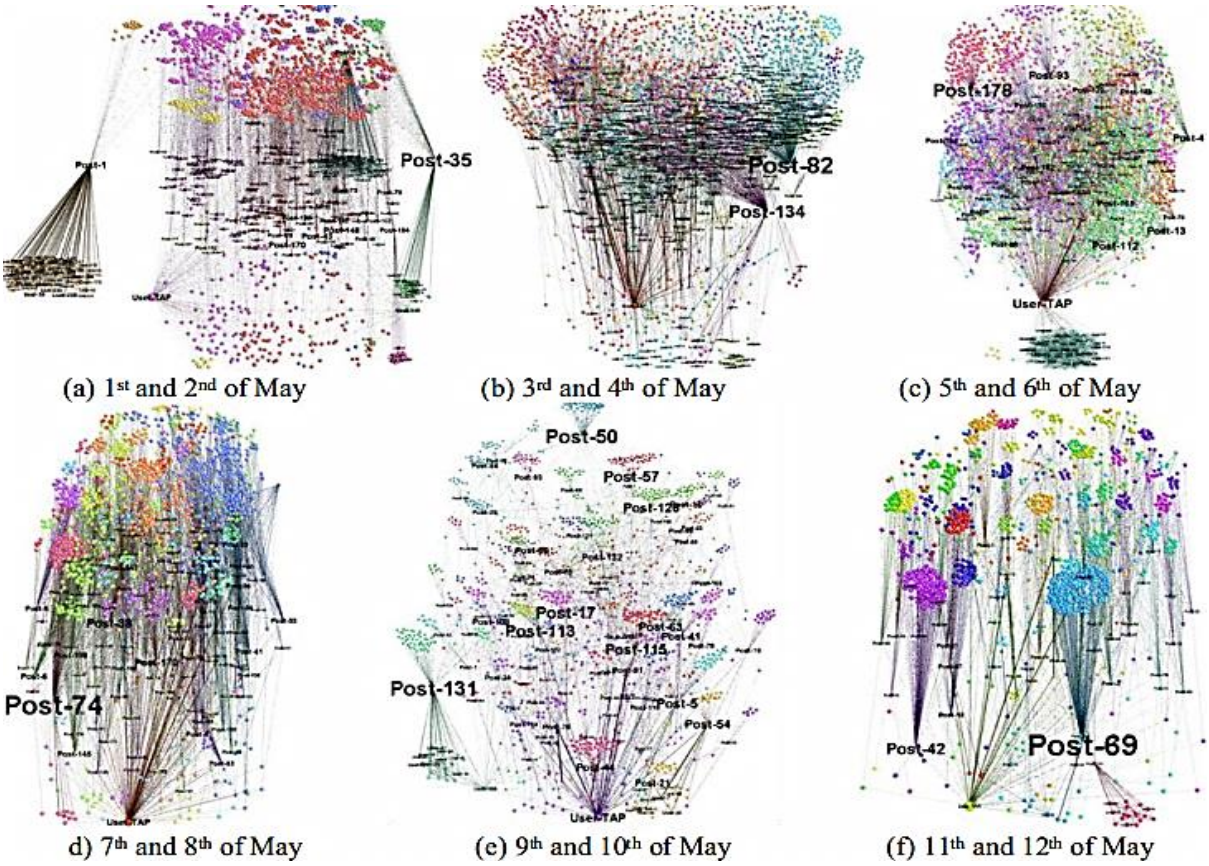


Figure 1: Modeling Web Discourse Through Tripartite Network Structures: User, Post, and Concept Dynamics

The web discourse Network: user-post concept

The outcomes from each of the six networks that were considered are shown in Figure 1. We found the network's communities using a modularity class approach and determined the most influential members and their positions using centrality measures. Users are represented by the nodes at the base of each network in each graph. The dimensions used for the nodes' sizes were betweenness and in-degree, respectively. When it came to controlling and disseminating information, the first statistic showed who the most powerful users were. The second method looked for the most popular posts, those with the most comments and views.

It is clear from the graphs that each of the six networks was structured differently. As seen in Figure 1, the initial network included two distinct clusters that were not connected to one another. Figure 1 shows that the densest networks were 2, 3, and 4. Figure 1 shows that networks 5 and 6 include several clusters with reduced

International Journal of Advance Research in Science and Engineering
Volume No. 14, Issue No. 07, July 2025
www.ijarse.com
IJARSE
ISSN 2319 - 8354

size. This revealed which people were the most influential by showing how active they were in the network.

Nodes in the picture represent users, posts, and concepts, while edges represent the relationships between them; these three components make up the online discourse.

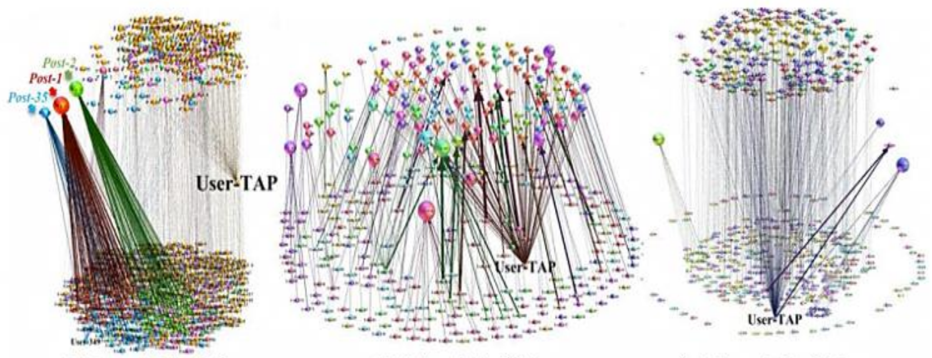
The interactions Network: user-post

By analyzing their structural location in the network and the content of their postings, SNA allows us to zero in on the most relevant social users. We used the following indicators to examine the airline's response rate (how often they answered consumer questions):

1. In-Degree - in order to ascertain the total amount of contacts received by the airline. What this means is that the significance of a user's posts is demonstrated by the fact that other users communicate with them or keep in touch with them. Their importance is determined when these postings receive a lot of comments or are shown to a large audience.
2. Out-Degree - so the airline may gauge its responsiveness by counting the amount of replies it received. Typically, this idea is applied to gauge the user's potential influence inside the network, which supports their ability to respond to others.

Looking at the interactions between users and postings, we can see that the airline did not respond to any isolated nodes. The red post is not a complaint or an information request, according to a further inspection of Figure 2. From the perspective of the airline, it could be crucial to identify these posts (even if the sole goal is to remove them). This query was only addressed to nodes that already have a relationship to the airline. Figure 2 shows that across all networks, the airline responded to numerous Facebook queries on each day of the strike.

Subgroups were formed for these networks using the modularity class, and in-degree and out-degree metrics, respectively, were used to define node size and labels. The posts that were "assisted" by an operator were the ones having an established link to the airline; as a result, the users received a response. Looking at the charts, it was clear that the business addressed a large amount of consumer concerns and inquiries posted on Facebook.



(a) 1st and 2nd of May (b) 3rd and 4th of May (c) 5th and 6th of May

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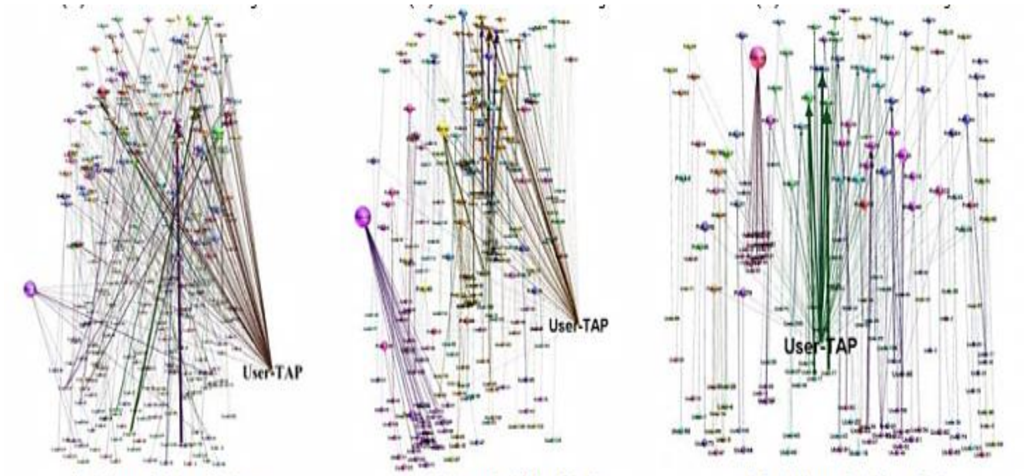
ISSN 2319 - 8354



d) 7th and 8th of May (e) 9th and 10th of May (f) 11th and 12th of May

Figure 2: Bipartite Network of User–Post Interactions Representing Feedback Dynamics

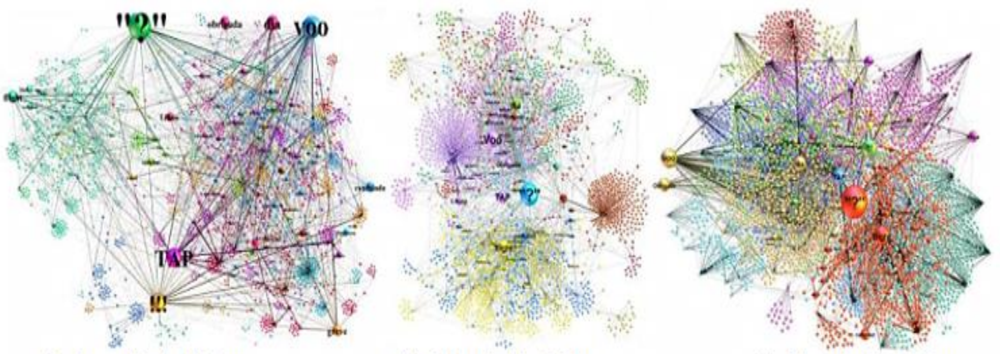
Every network displays the entity user at the bottom and the entity post at the top. Users' feedback, shown through various behaviors like replying to comments, like, sharing, etc., is represented by connections. In addition to capturing the user's interests, these reactions also measured the post's popularity, status, and relevancy to the entity's user.

<u>The semantic Network: post-concept (out-degree)</u>

After identifying all of the ideas and their corresponding posts, we constructed a semantic network using the keywords as a summary of the content inside the posts. This sub-network implementation is shown in Figure 3 to find particular information in postings and determine the most important ideas. We constructed a semantic network for every two days using the acquired data, which consisted of text-containing postings.

We extracted and ranked a set of frequently used keywords using a semi-automated textual analysis. All ideas associated with a given post are treated as a single community when the modularity class technique is used. Since the out-degree metrics provide information on the frequency of a concept's use in a post, we utilized them since we were interested in the nodes with the most direct votes.

After reviewing the posts, we realized they could be grouped into different types of feedback. This would have helped the airline better handle complaints, requests for assistance with changing reservations, and general inquiries about the hotel, refund policies, and more.



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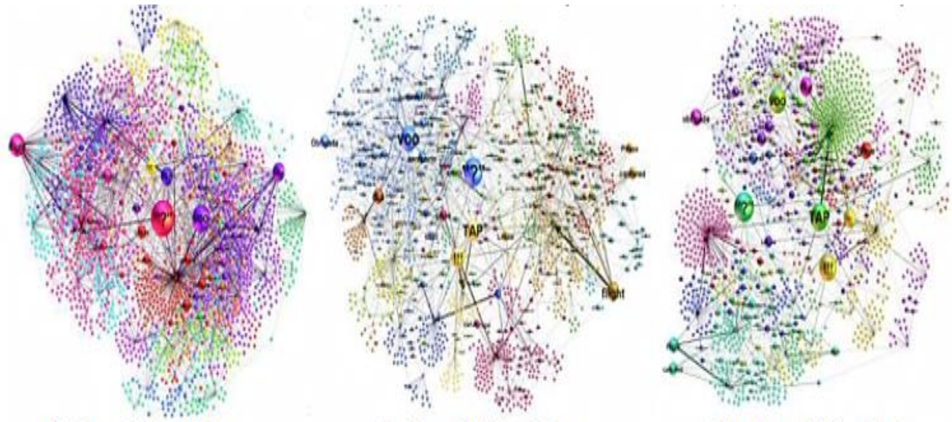
www.ijarse.com
IJARSE
ISSN 2319 - 8354



d) 7th and 8th of May (e) 9th and 10th of May (f) 11th and 12th of May

Figure 3: Bipartite Post–Concept Network Constructed Using Out-Degree Centrality.

Entities' messages and thoughts formed the basis of the networks. The out-degree metric was used to specify the dimensions of the nodes and labels.

The most popular ideas in each dataset were determined to be the question mark, the exclamation mark, and the ellipsis. This is reasonable because people on OSN often express themselves more quickly and with fewer words by using symbols, graphics, and acronyms.

Users of online social networks (OSNs) often pool their language and non-linguistic resources to communicate more quickly.

V. Conclusion

An innovative strategy for crisis management and organizational responsiveness may be demonstrated by assessing decision support using social network analysis (SNA) of consumer input during crisis circumstances. Organizations may improve their ability to detect urgent issues, key opinion leaders, and changing attitudes in the heat of crisis by studying the structure, flow, and impact of communications.

This approach goes above and beyond traditional data analysis by concentrating on patterns of linkages and interactions; as a result, it sheds light on the propagation of information and the areas that require the most attention.

Organizations may respond faster, distribute resources more efficiently, and involve stakeholders more effectively during crises by incorporating SNA into decision-making frameworks.

It also makes it possible for decision assistance to be more dynamic and adaptable by incorporating the environmental, behavioral, and emotional aspects of client input. Strategically, SNA has a lot to offer, but it does come with certain problems including data privacy and interpretation hazards.

Responsible use of this tool improves both short-term response times to crises and the capacity to withstand them in the long run. With the ever-changing landscape of digital communication and the complexity of crises, SNA will be more important than ever for firms to remain connected, aware, and responsive to consumer concerns.

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Volume No. 14, Issue No. 07, July 2025
www.ijarse.com
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ISSN 2319 - 8354

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