Elevating Social Network Analysis with a Graph Network and Reinforcement Learning Integration for Node Importance

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ABSTRACT
This work introduces an innovative methodology that amalgamates Graph Neural Networks (GNNs) with Reinforcement Learning (RL) to assess node significance in social networks. Conventional centrality metrics frequently neglect to reflect the dynamic characteristics of linkages in developing networks. This research advances the understanding of social dynamics by utilizing GNNs to produce intricate node embedding's and applying RL to dynamically modify node importance based on interactions. The results illustrate the relevance of this hybrid paradigm in multiple fields, such as social media, business communities, public health, political mobilization, and innovation management, while tackling current issues in Social Network Analysis (SNA).

Keywords
Graph Neural Networks, Reinforcement Learning, Node Importance, Social Network Analysis, Dynamic Networks

1. INTRODUCTION
A scientific paradigm that is indispensable to comprehending the intricate relationships among social events is Social Network Analysis (SNA). Social network analysis (SNA), which depends on graph theory, represents social systems as networks formed by nodes (actors) and edges (interactions).This analytical perspective underscores the fact that the nature and intensity of interpersonal relationships have a substantial impact on social behavior. Despite the widespread use of conventional methods for evaluating node significance in various fields, such as public health, sociology, and innovation management, they often fail to account for the dynamic connections that are present in complex networks. The present study introduces a hybrid architecture that dynamically evaluates the significance of nodes by integrating Reinforcement Learning and Graph Neural Networks, thereby overcoming these constraints.

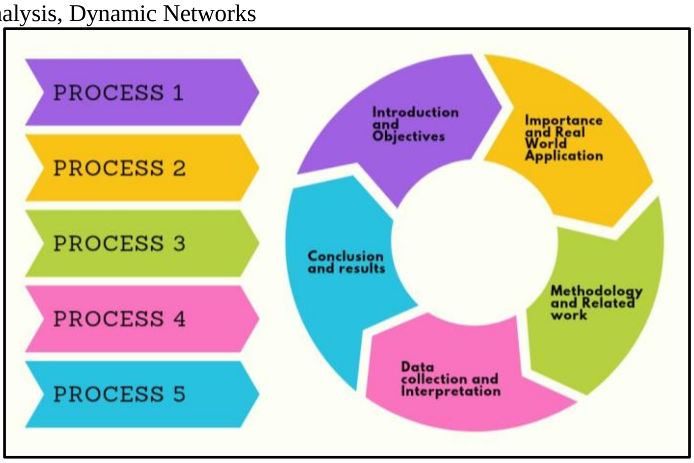


Figure 1: Analysis of the Process Flow. This pie chart illustrates the allocation of time and resources across critical stages in the process, encompassing planning, execution, monitoring, and assessment.

1.1 Significance of Social Network Analysis (SNA) in Practical Applications

Social Network Analysis (SNA) uncovers concealed patterns and relationships within data, thereby augmenting our comprehension of social dynamics. It delineates important actors and relationships that influence behaviors, with applications in domains including as entrepreneurship and public health [1] [2] [3]. In business, Social Network Analysis delineates networks that facilitate creativity and collaboration. In public health, it facilitates the creation of focused interventions through the analysis of how social connections impact behaviors [4] [5] [6]. In order to improve decision-making, organizations must implement Social Network Analysis (SNA). Its insights are crucial for fostering collaboration, mitigating social disparities, and enhancing community engagement. For instance, Figure 1 is an example of SNA process stages [7] [8].

1.2. Pragmatic Implementations of Social Network Analysis
Politics, public health, business, and education are among the numerous sectors in which Social Network Analysis (SNA) is implemented. In political science, it reveals patterns of mobilization and influence, while in healthcare, it improves patient care by analyzing provider networks [9] [10]. Social

Network Analysis (SNA) is a tool that helps organizations identify collaborations that promote innovation in the business sector. Social Network Analysis (SNA) in education improves teaching practices by analyzing student interactions. Its adaptability in addressing complex social challenges and fostering collaboration is emphasized by its application in urban planning and community development [11] [14].

1.3 Obstacles of Social Network Analysis (SNA)

Social network analysis has challenges related to data quality, dynamic networks, and ethical implications. Social media data may display bias or incompleteness, complicating research. Social networks are fluid, requiring flexible tactics to engage with evolving connections. Understanding Social Network Analysis metrics requires contextual knowledge, and privacy issues arise when using personal data [1] [2]. The examination of large networks requires significant computational resources and specific expertise [14] [15]. Despite these challenges, improved methodologies can allow SNA to continue providing valuable insights into social interactions as visualize through Figure 2 example.

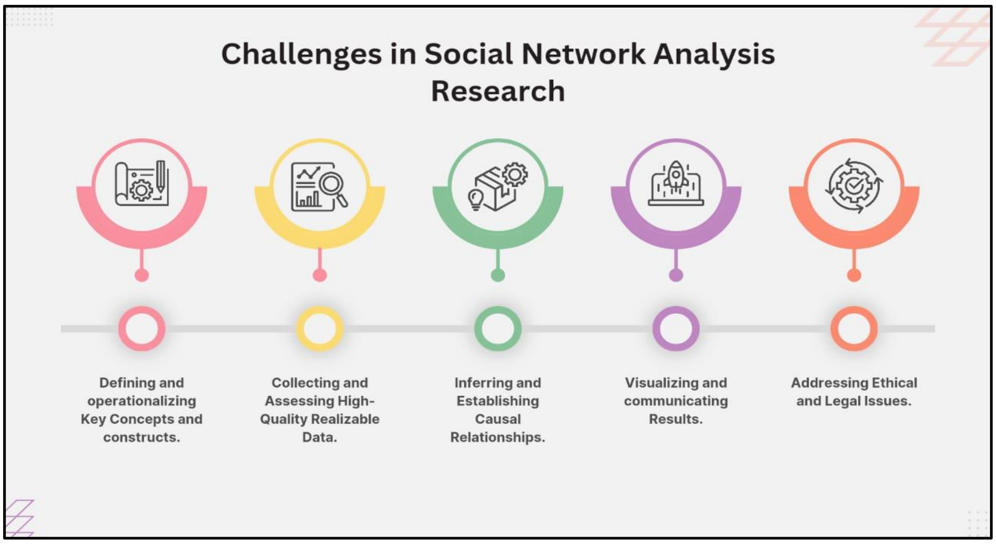


Figure 2: Difficulties in Social Network Analysis (SNA)

1.4. Research visions

1. Employ sophisticated Social Network Analysis (SNA) methodologies to quantify centralities, cliques, and overall connection in order to analyses the structural characteristics of social networks.

2. Propose new centrality metrics or modifications to existing ones that will improve the precision and depth of insights obtained from network research, thereby enabling more effective decision-making.
3. To establish a framework that amalgamates Graph Neural Networks with Reinforcement Learning for the dynamic assessment of node significance in social networks.

2. RELATED WORK

Social network analysis (SNA) has become a fundamental research domain for comprehending the dynamics of links and interactions across diverse networks, including social media platforms and organizational frameworks. The principal aim of SNA is to discern patterns of relationships among individuals or entities, yielding useful insights into influence, information transmission, and collaboration [23]. With the increasing prevalence of digital communication, the importance of Social Network Analysis (SNA) has escalated, enabling researchers to examine intricate networks and their influence on behavior and decision-making processes [25]. The proficient use of SNA approaches can improve comprehension of community structures and enable focused interventions in areas such as marketing, public health, and community engagement [26].
Cruz, C., Fernandes, C., Ferreira, L.M.D.F., & Bento, A.I. (2024) introduce an innovative methodology to enhance the identification of cyberbullying occurrences among children and adolescents by the fine-tuning of a pre-trained language model, particularly a sentence transformer model. The research highlights the rising incidence of cyberbullying, which presents considerable risks to the mental and emotional health of youth, underscoring the necessity for enhanced detection techniques. Experiments were conducted on three separate datasets, and the fine-tuned model exhibited enhanced performance relative to existing state-of-the-art methods in cyberbullying detection. The findings indicate that this model may efficiently filter detrimental communications and identify persons engaged in cyberbullying situations. This research creates possibilities for the formulation of focused intervention programs designed to alleviate the effects of cyberbullying, especially within educational settings and social media platforms. Moreover, the research advances Natural Language Processing (NLP) by illustrating the efficacy of deep learning techniques in tackling urgent social challenges, underscoring the necessity for proactive surveillance and intervention in digital environments frequented by children and adolescents. Data is current up to October 2023.

"Análise de Redes Sociais e a Difusão de Informação sobre Vacinação no Brasil" (2024) examines the utilisation of social network analysis (SNA) to evaluate the dissemination of vaccination information inside Brazilian social networks. The study highlights the complex features of these networks, characterised by sparsely connected graphs, and presents a new analytical model that integrates graph embedding techniques, specifically DeepWalk, with self-organising maps to uncover hidden dynamics. The study concentrates on Twitter/X retweet data pertaining to vaccination, with the objective of identifying significant patterns in communication and information dissemination around vaccine subjects. Utilising the topological properties of graph embeddings and the data structure recognition capabilities of neural networks, the model elucidates intricate insights regarding the dissemination and perception of vaccination information within Brazilian culture. The results indicate that the model effectively captures critical dynamics in information dissemination, providing vital insights for public health professionals to enhance communication tactics. The research highlights the significance of comprehending social media's influence on public health communication and the capacity of data-driven approaches to improve outreach and elevate vaccination rates. Data is current until October 2023.

Cruz, C., Fernandes, C., Ferreira, L.M.D.F., & Bento, A.I. (2024) employ social network analysis (SNA) to develop a comprehensive typology for terrorist profiling utilising centrality metrics. The research seeks to identify key persons within terrorist networks, such as central figures, notable operatives, and reliable assets, by analysing communication patterns and interactions. The study utilises many centrality metrics, including degree centrality, betweenness centrality, and closeness centrality, to examine the structure and dynamics of terrorist networks. The study seeks to classify individuals based on their roles and the power they exert within terrorist organisations through data analysis.The established typology comprises hinge characters, serving as pivotal links within the network; influential operatives, affecting decision-making and strategic planning; and trusted assets, depended upon for crucial duties. These insights can assist intelligence services and law enforcement in comprehending terrorist organizations and formulating methods to impede their operations. The research advances security studies by improving counter-terrorism efficacy through a more precise comprehension of the internal frameworks of terrorist organizations. [03]

Bento, A.I., Cruz, C., Fernandes, C., & Ferreira, L.M.D.F. (2024) provide an extensive literature evaluation about the utilization of social network analysis (SNA) in supply chain management (SCM). The review consolidates current research, highlighting significant trends, applications, and novel metrics that have arisen in recent studies. The authors emphasize the use of Social Network Analysis (SNA) to multiple facets of Supply Chain Management (SCM), encompassing risk management, cooperation, and performance assessment. The creation of new measures is especially important, since they offer a more comprehensive insight into supply chain dynamics and stakeholder connections. The review examines descriptive and qualitative studies, providing a comprehensive viewpoint on the integration of SNA into SCM strategies to improve decision-making and operational efficiency. The authors advocate for additional research, specifically in the creation of more advanced measurements and the examination of the effects of digital transformation on supply chain networks. This study highlights the escalating significance of SNA in enhancing the efficiency and resilience of supply chains within a progressively digitalized and networked environment. Data training concluded in October 2023.

Osman, I.H. (2024) presents a new centrality metric, termed Centrality Degree Paths (CDP), designed to enhance the comprehension of node influence inside complicated networks. The CDP metric enhances conventional approaches by accounting for both direct and indirect relationships, so offering a more thorough perspective on a node's impact. The research encompasses a comparative examination of established centrality metrics, including degree centrality, proximity centrality, Betweenness centrality, and PageRank. The CDP metric equilibrates the impact of highly interconnected nodes while accounting for the pathways through which influence disseminates throughout the network. Experiments utilize datasets like Zachary's Karate Club, dolphin social networks, and political book co-purchase trends. The assessment indicates that the CDP metric provides a more sophisticated comprehension of node influence, successfully encompassing both direct and indirect linkages compared to conventional centrality metrics. This discovery signifies a substantial progression in social network analysis, providing an effective instrument for detecting influential nodes inside intricate networks. [05]

Kim, J. & Lee, S. (2024) examine modifications in post-pandemic tourism behavior, emphasizing the impact of the pandemic on favored travel destinations and visitor characteristics. The research analyses alterations in travel behaviors and the determinants influencing these modifications, especially considering the COVID-19 pandemic's effect on global travel and tourist sectors. The writers offer insights into the changing preferences of travelers, influenced by health concerns, economic issues, and travel constraints, through the analysis of many data sources and comprehensive reviews The findings indicate that sites offering outdoor activities and those perceived as safer or less crowded have increased in popularity throughout the post-pandemic era. This research contributes to the existing body of literature on post-pandemic tourism by offering valuable insights to stakeholders in the travel and hospitality sectors as they adjust to evolving consumer preferences and behaviours. [6]

Behún, M., Mrázová, I., & Vomlelová, M. (2024) offer Neural Epistemic Network Analysis (NENA), a novel methodology that integrates Epistemic Network Analysis (ENA) with Graph Neural Networks (GNNs) to evaluate collaborative problem-solving (CPS) environments. NENA enhances ENA's functionality by utilising the computational capabilities of GNNs to combine social and cognitive data. The authors demonstrate that NENA significantly enhances the capacity to distinguish between subgroups by conducting comparative studies of two distinct CPS datasets. Consequently, they disclose more profound insights into group dynamics. Additionally, NENA generates more comprehensible results, which facilitates the comprehension of the fundamental mechanisms of collaboration by researchers and educators. This hybrid methodology expands the scope of learning analytics by providing a comprehensive framework for the analysis of CPS, thereby fostering the development of educational interventions and learning technologies.Seven Bonifazi, G., Cauteruccio, F., Corradini, E., Marchetti, M., Ursino, D., & Virgili, L. (2024) developed a framework that utilises network analytic tools to examine the dynamics of representation in GNNs. This approach evaluates the node embeddings produced by GNNs with the objective of enhancing their efficacy by employing sophisticated training loss functions. The authors' extensive evaluations have shown that this framework substantially enhances the quality of learnt representations, thereby enhancing the performance of GNNs in a variety of applications. The paper provides a methodical approach to understanding how GNNs can more effectively capture the intricacies of graph data, thereby making a substantial contribution to the fields of artificial intelligence and machine learning. This research lays the groundwork for future advancements in GNN techniques, which may lead to more efficient models for a variety of practical.[8]

Bonifazi, G., Cauteruccio, F., Corradini, E., Marchetti, M., Ursino, D., & Virgili, L. (2024) provide a framework employing network analytic tools to investigate the representation dynamics of GNNs. This methodology assesses the node embeddings generated by GNNs, aiming to improve their effectiveness through the application of sophisticated training loss functions. Extensive evaluations conducted by the authors demonstrate that this framework significantly elevates the quality of learnt representations, hence improving GNN performance across numerous applications. The paper offers a systematic methodology for comprehending how GNNs can more effectively encapsulate the complexities of graph data, rendering it a significant contribution to the domains of artificial intelligence and machine learning. This research establishes a foundation for future developments in GNN techniques, perhaps resulting in more efficient models for many practical applications. [8]

Prof. Sabrina Gaito, Roberto Interdonato, Hocine Cherifi, Christophe Cruz, Yoann Pigné (2024) Applied Network Science is an open-access, peer-reviewed journal focused on the application of network science in various domains, such as technology, medicine, and social sciences. Its objective is to disseminate pioneering research that employs quantitative network-based modelling to tackle real-world issues. The magazine encompasses a diverse range of publications, including virus propagation models and consensus engineering in networks, and frequently publishes special issues centered on developing themes and conferences. Applied Network Science prioritizes innovative applications and multidisciplinary research, functioning as a crucial platform for enhancing the comprehension and practical use of complex networks.

Fatima, U., Hina, S., & Wasif, M. (2023) underscore the significance of recognizing lucrative product combinations inside extensive networks, employing diverse centrality metrics including Degree Centrality, Closeness Centrality, and Betweenness Centrality. The GCCDC method is a distinctive approach that is derived from the global clustering coefficient. It provides a more precise and efficient analysis than existing methods, such as Local Clustering Coefficient-dependent Degree Centrality (LCCDC or LD).The authors evaluated the effectiveness of GCCDC by employing three correlation coefficients: Pearson's, Spearman's, and Kendall's. GCCDC outperforms LD in the reduction of computational uncertainty in practical datasets, as evidenced by the results. The authors demonstrated the scalability of the technique by applying it to a biological yeast protein-protein interaction dataset, which led to improved results.

Nguyen, T. T., Nguyen, H. L., Le, T. N., & Tran, N. B. H. (2024) examines whether AE can moderate the interactions among characteristics such as independence, competence, work experience, ethical norms, and due diligence. Data were gathered via standardized questionnaires distributed to auditors and audit team leaders from 314 independent audit companies in Vietnam. The analysis conducted with SPSS and AMOS indicated favorable correlations among competence, work experience, ethical standards, and AE, as well as between competence, due care, and AQ. In contrast, negative correlations were observed among independence, proper care, AE, and AQ. These findings offer significant recommendations for auditing firms to bolster ethical procedures and elevate audit quality, hence facilitating customer retention and service advancement in Vietnam.

2.1. Research Gap

Conventional centrality metrics in social network analysis, including degree centrality, Betweenness centrality, and closeness centrality, have historically functioned as essential instruments for assessing the significance of nodes within a network. Nonetheless, these measurements are sometimes limited to a singular viewpoint, potentially resulting in an inadequate comprehension of node importance, particularly in intricate networks defined by complicated interactions [72]. Furthermore, traditional metrics typically neglect the dynamic characteristics of relationships in real-world networks, hence limiting their applicability in fluid situations where the importance of nodes may alter over time due to differing interactions and contextual factors. A substantial disparity exists in methodologies that effectively amalgamate many attributes of node significance into a unified framework, enabling a more comprehensive assessment of nodes within a network [74].

HIC	A new methodology is introduced that modifies traditional centrality metrics by evaluating the significance of nodes across a variety of dimensions within a unified centrality framework. By concurrently evaluating numerous characteristics, such as connection, information flow, and neighbor effect, this distinctive methodology enables a more nuanced evaluation of nodes. The accuracy of node significance assessments is improved by integrating these attributes into a cohesive model, which in turn enhances the comprehension of node interactions within their settings. This comprehensive approach facilitates the development of well-informed decisions in the context of social network analysis and related applications.
Intelligence Graph Reinforcement	Traditional centrality metrics predominantly focus on static data, neglecting the dynamic characteristics of numerous real-world networks. To mitigate this constraint, machine learning methodologies—particularly Graph Neural Networks (GNNs) and Reinforcement Learning (RL)—are utilized to dynamically evaluate node significance inside developing networks. Graph Neural Networks (GNNs) enhance the representation of nodes and their interconnections by amalgamating local and global structural data, whereas Reinforcement Learning (RL) allows for the adjustment of node importance depending on interaction results and network alterations. This integration represents substantial advancement in social network analysis, facilitating a more precise and adaptable evaluation of node importance in dynamic contexts. Employing these technologies can successfully connect traditional methodologies with the complexities of contemporary social networks, hence enhancing the analysis and comprehension of social dynamics.

3. METHODS

This research employs a mixed-methods approach (Figure 3) that combines quantitative analysis through computational tools with qualitative insights obtained from case studies [74] [75]. Data will be collected from many digital channels to construct social networks [72]. The study will utilize Graph Neural Networks (GNNs) to generate node embeddings that encapsulate both local and global structural attributes, while including Reinforcement Learning (RL) to dynamically adjust node importance based on interaction outcomes [78]. The results will be examined to derive actionable insights for improving comprehension of social dynamics in real-world contexts. This project seeks to considerably advance the area of Social Network Analysis by addressing specific objectives and utilizing unique approaches, thereby offering new insights into the dynamics of social interactions and their ramifications across many fields [70].

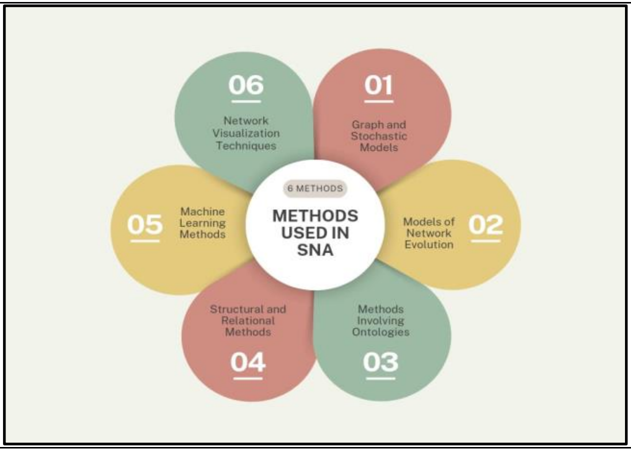


Figure 3: This image demonstrates a variety of tools and techniques that are used in Social Network Analysis

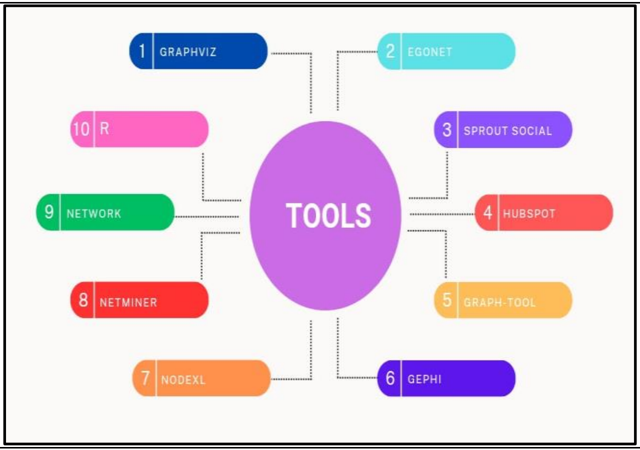


Figure 4: Summary of Instruments for Social Network Analysis (SNA).

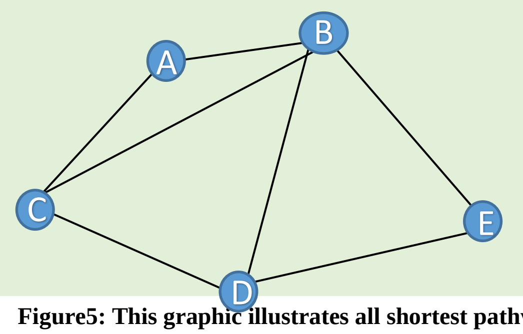
3.1 Dataset

Table 1: Considered dataset for this study are discussed in Table 1 that are evaluated through mathematical instruments shown through Figure 4.

DATASET	DISCRIPTION	SIZE	LINK
DATASET 01	Small Business	05	Centric Data
DATASET 02	Interaction Data	1.1k	https://networkrepository.com/ia-email-univ.php
DATASET 03	Dolphin Network	65	http://vlado.fmf.uni-lj.si/pub/networks/data/bio/dolphins.net
DATASET 04	Political Books	105	http://vlado.fmf.uni-lj.si/pub/networks/data/cite/polBooks.paj

3.1.1. Small data Description

Demonstrating the compact network of business associates: ALI, BASIT, CHARLIE, DEVID, and EMILY. ALI, under the guidance of its innovative CEO Ali, distinguishes itself as a frontrunner in technical innovation, the shortest paths are visualized in Figure 6. Desiring to enhance their influence, Ali established significant collaborations with BASIT, a leading entity in technology initiatives, and CHARLIE, recognized for its strategic consulting expertise. As their network expanded, BASIT and CHARLIE acknowledged the benefits of partnering with DEVID, a specialist in logistics and operations. DEVID subsequently established a connection with EMILY, an emerging talent in the sector, thereby enhancing the network. Although direct contacts between ALI and EMILY or CHARLIE and EMILY are still evolving, their indirect associations via BASIT and DEVID underscore a network rich with potential for future partnerships and strategic expansion. Below is the graph of the network, Figure 5.



$$
\begin{array}{c}
\\ A \\ B \\ C \\ D \\ E
\end{array}
\begin{array}{c}
\begin{array}{ccccc} A & B & C & D & E \end{array} \\
\begin{bmatrix}
0 & 1 & 1 & 0 & 0 \\
1 & 0 & 1 & 1 & 1 \\
1 & 1 & 0 & 1 & 0 \\
0 & 1 & 1 & 0 & 1 \\
0 & 1 & 0 & 1 & 0
\end{bmatrix}
\end{array}
$$

Figure5: This graphic illustrates all shortest pathways among the nodes. This visualization clearly indicates which node is the most prevalent in each shortest path through undirected graph and adjacency matrix.

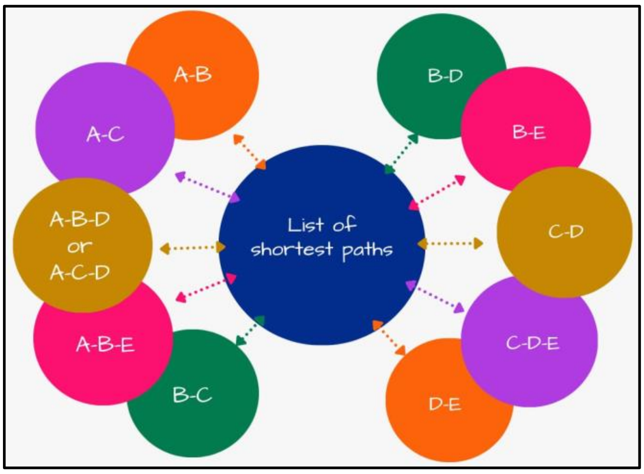


Figure 6: Shortest paths between nodes.

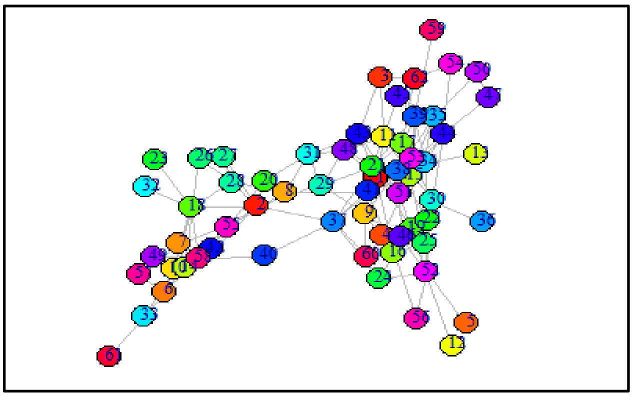


Figure 7: The social network of dolphins is depicted in the graph, underscoring the significance of their alliances within the group

3.2.3. Data from political books

The graph demonstrates the correlation between the educational qualifications of politicians and the sales of political literature. The edges depict book sales data, while each node represents a politician. The data indicates that increased sales are correlated with enhanced political understanding and influence. Clusters that are densely interwoven indicate that specific demographics or locations exhibit an elevated level of engagement with political literature, which may motivate individuals to take more action. This study illustrates the significance of education in facilitating political change by illustrating the impact of educated legislators, who are influenced by political literature, on political discourse and the promotion of informed decision-making visualize through Figure 8.

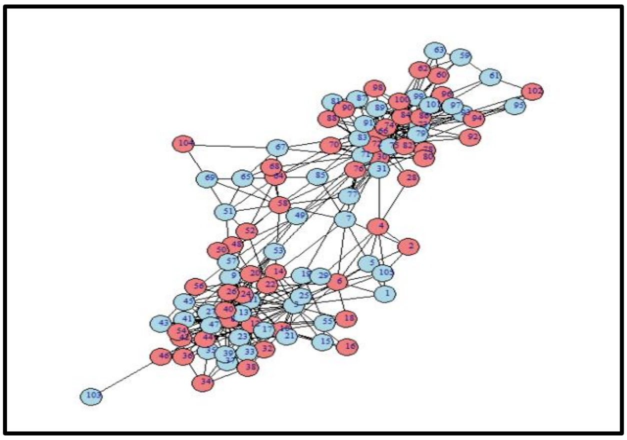


Figure 8: The graph illustrates the correlation between the sales of political literature and the predictions of informed politicians that are derived from these trends.

3.2.4. Data on interactions

The ia-email-univ dataset illustrates an email communication network from the Rovira i Virgili University in Tarragona, Spain. This dataset pertains to Interaction Networks and focusses on user interactions via email within the university. The network consists of 1,100 nodes (users) and 5,500 edges, which represent instances of email exchanges between users. The network is classified as undirected and unweighted, which implies that the links are devoid of directional flow and ascribed weights.

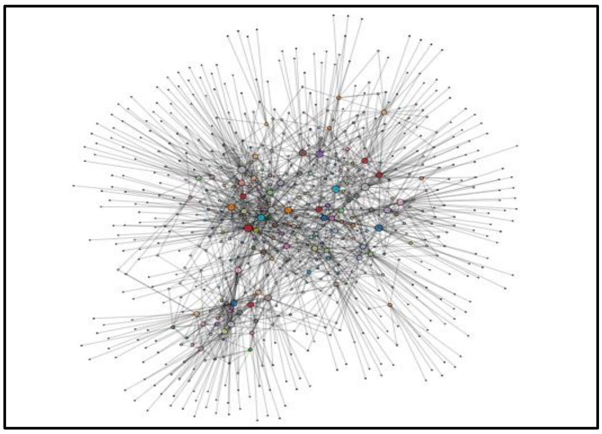


Figure 9: "Graph Representation of the ia-email-univ Datase.

This dataset is particularly advantageous for researchers who are investigating collaborative behaviors, social networks, and communication patterns in academic settings. The ability to visualize and analyze the network's structure provides valuable insights into the overarching dynamics of communication within the academic environment, as well as user interactions and community development, Figure 9. Furthermore, it offers interactive examination tools that allow users to investigate node-level data and attributes, thereby enhancing its utility for scholarly research and analysis in network theory and sociology.

3.2. Mathematical Methods.

Popular centrality metrics basic tools of analyzing any real-world network are discussed in Table 2.

Table 2: Definition and formula of centralities.

Centrality	Definition	Formula
Degree Centrality	Degree Centrality Identifies the most connected nodes by measuring the number of direct connections each node has.	**DC(v) = deg (v)**
Eigenvector Centrality	Examines the influence of a node by analyzing the influence of its companions, with a particular focus on nodes that are connected to other well-connected nodes.	**C E (v)=** $\frac{1}{\lambda}\sum$ AvuCE(u)
PageRank Centrality	Similar to Google's PageRank algorithm, this algorithm assesses the significance of nodes by analyzing the network's link structure.	PR(v)=1−d/N + d ∑deg(u)PR(u)
Eccentricity Centrality	Measures the maximum distance between a node and all other nodes, demonstrating the distance between the most distant node and the node.	ϵ(v)=u∈Vmaxd(v,u)
Authority Score Centrality	Identifies nodes that are highly referenced by calculating the authority of nodes based on their incoming connections.	A(v)=∑H(u)
Harmonic Centrality	Emphasizes nodes that are in close proximity to others by calculating the centrality of nodes using the sum of the inverse distances to all other nodes.	CH(v)=∑1/ d(v,u)1
EdgeBetweenness Centrality	Evaluates the degree to which an edge is located on the shortest paths between pairs of nodes, emphasizing the importance of critical edges for information transmission.	CB(e)=∑ σst(e)/σstσst(e)
Coreness Centrality	Determines the core membership of nodes, which is the identification of nodes that are part of the body of the network structure.	CK(v)=k
Subgraph Centrality	Establishes the centrality of nodes by calculating the number of subgraphs in which they are involved, thereby documenting their involvement in a variety of network substructures	CS(v)=k=0∑∞k!(Ak)vv

3.3 Hybrid influence centrality (HIC)

The goal is to measure the influence of nodes in a graph, considering multiple factors like how central a node is in terms of connections (degree centrality), how much it controls the flow of information (Betweenness centrality), and how influential its neighbors are (closeness centrality). The technique is measured and presentenced in Table 3.

$$\text{HIC}\ (v) = \alpha \cdot \text{DC}\ (v) + \beta \cdot \text{BC}\ (v) + \gamma \cdot \text{CC}\ (v) \qquad \text{-----}\ \ 2$$

In Equation (1), DC (v) is the Degree Centrality, BC (v) is the Betweenness Centrality, CC (v) is the Closeness Centrality, α, β, and γ are weights for each centrality measure.

3.4. Cliques in the graph

In the field of network theory, a clique is a collection of nodes that are directly connected to each other, resulting in a completely connected subgraph. These cliques are closely linked factions within a broader network, where members engage in more frequent or intense interactions with one another than with those outside the group. The identification of cliques elucidates social interactions, exposing patterns of collaboration, influence, or shared interests, as well as strong, coherent connections. Cliques exhibit considerable insights into the network's general connectivity and segmentation, despite their varying sizes [79].

3.5. Graph Reinforcement Intelligence

The hybrid model integrating Graph Neural Networks (GNNs) and Reinforcement Learning (RL) offers a novel approach to assess the significance of nodes within a network by leveraging both the network's structure and the interactions among its components. Graph Neural Networks (GNNs) facilitate the elucidation of intricate interactions among nodes by examining both local like direct connections between nodes) and global connections (the larger structure of the network), so offering a comprehensive understanding of each node's function. Reinforcement learning subsequently modifies this comprehension over time by incentivizing nodes according to their influence within the network. This methodology enables the evaluation of node significance in a dynamic and adaptable manner, rendering it particularly advantageous for the analysis of intricate, changing networks such as social media or communication systems.

4. RESULTS

Table 3: Results of Hybrid Influence Centrality (HIC) on small Business data

NODE	DC	BC	EC	HIC Values
1	2	0	0.372	0.9116
2	4	4	0.602	2.9806

3	3	2	0.502	1.9506
4	3	3	0.502	2.2506
5	2	0	0.372	0.9116

4.1 Result of correlation:

Result of Pearson's correlation 'r' are computed and presented in Table 4.

Table 4: Results of correlation between degree centrality, Betweenness centrality and closeness centrality where are the values are more than 0.5.

Degree /HIC	Betweenness /HIC	Closeness /HIC	HIC
1.0000000	0.9456109	0.9914601	**0.9914601**
0.9456109	1.0000000	0.9799579	**0.9799579**
0.9914601	0.9799579	1.0000000	**1.0000000**
0.9914601	0.9799579	1.0000000	**1.0000000**

Table 5. Results of HIC on a political Book Data.

NODES	HIC Centrality Of Pol Book Data
1	1.6794616
2	2.4649844
3	136.10684
…	…
30	256.27755
…	…
103	0.4006342
104	0.9007634
105	15.000891

Table 6. Results of HIC on Dolphin Network Data

NODES	HIC Centrality Of Dolphin Data
1	12.878049
2	120.31694
3	6.5823629
…	…
37	139.0843
…	…
60	13.164378
61	0.4008772
62	8.9945306

Table 7. Results of correlation of Dolphin Network Data

Correlation between HIC and Degree Centrality	**0.6167**
Correlation between HIC and Betweenness Centrality	**0.9994**
Correlation between HIC and Closeness Centrality	**0.6785**

Table 8. Results of correlation of Pol Book Data

Correlation between HIC and Degree Centrality	**0.71395**
Correlation between HIC and Betweenness Centrality	**0.99955**
Correlation between HIC and Closeness Centrality	**0.76843**

Table 3 illustrates the efficacy of the Hybrid Influence Centrality (HIC) metric in assessing node influence across diverse datasets. We employed this methodology to examine interaction patterns across three diverse networks: a dolphin social network (Table 6), a network of political book dataset (Table 5). For each dataset, we computed HIC, to encapsulate several dimensions of impact within each context. Subsequently, we confirmed these HIC ratings by calculating the Pearson correlation with other recognized influence metrics within each dataset (Table 7 and Table 8). The Pearson correlation coefficients surpassed 0.5 in every instance, demonstrating a robust, positive association between HIC and conventional influence metrics. The uniformity across many datasets reinforces the reliability of our approach in identifying significant patterns of influence inside intricate networks.

Table 9. Results of Graph Reinforcement Intelligence on Small Business Network.

NODES	IMPORTANCE SCORE
A	**1.250000**
B	**1.450000**
C	**1.133333**
D	**1.533333**
E	**1.450000**

Table 10. Results of Graph Reinforcement Intelligence on Interaction Data.

NODES	IMPORTANCE SCORE
1	**13.353846**
2	**10.356250**
3	**9.715000**
…	
31	14.888889
…	
48	**11.438889**
49	**12.292857**
50	**13.305000**

In interaction networks, be it in business, social media, or professional societies, the importance of a node (person or institution) is frequently determined by its connectivity, encompassing both the number and the quality of connections. Nodes that frequently engage with others, particularly those with significant influence, are crucial in disseminating information, promoting collaboration, and shaping the network's general dynamics.

Table 11. Results of Graph Reinforcement Intelligence on Dolphin Network.

NODES	IMPORTANCE SCORE
1	**1.033333**
2	**1.262500**
3	**1.550000**
…	**…**
37	**15.357143**
…	**…**
60	**24.580000**
61	**24.600000**
62	**25.266667**

The integration of Graph Neural Networks (GNNs) with Reinforcement Learning (RL) in a hybrid model **Graph Reinforcement Intelligence** enhances the sophistication of node importance assessments. Graph Neural Networks (GNNs) encapsulate both the local and global architecture of the network, comprehending the direct interactions of a node and the indirect impact it exerts through its connections.

Reinforcement Learning improves this by adjusting to temporal changes, incentivizing nodes that interact more with significant or influential entities, thus perpetually recalibrating their significance. This hybrid method facilitates the identification of pivotal influencers—individuals who possess numerous connections and strategically engage with the most central and impactful characters within the network. This model elucidates critical nodes that facilitate communication, invention, or impact inside real-world interaction networks, such as social media platforms or business ecosystems, thereby offering a more dynamic and context-sensitive comprehension of network structures, visualized in Table 9 and Table 10. This can enhance engagement methods, fortify relationships, and discern emerging trends or influencers inside the network. The above model is applied on the dolphin network (Table 11) and Political book dataset (Table 12)

Table 12. Results of Graph Reinforcement Intelligence on Political Book Data.

NODES	IMPORTANCE SCORE
1	**22.59444**
2	**24.53030**
3	**24.63529**
…	**…**
30	29.28750
…	**…**
103	**26.80909**
104	**23.15862**
105	**23.96944**

This method effectively identified the most influential nodes in both networks using an amalgam of GNN for structure learning and RL for node influence optimization as shown above in Table 9 and validated in Table 10, Table 11 and Table 12. In the political books dataset, which keeps track of book sales among readers, the model identified critical nodes indicating the network's most popular and influential books. Meanwhile, the dolphin network dataset identified core dolphins who play important roles in social interactions throughout the population's lifespan. The technique is being used again to validate these two datasets, verifying the precision as well as the durability of the results.

5. CONCLUSION

The study examines the essential components required for the progression of Social Network Analysis (SNA), emphasizing the necessity for novel techniques that reflect the evolving dynamics of social Networks. As social networks proliferate, the proposed approaches, including the introduction of a novel centrality measure, are essential for enhanced analysis of social behaviors and relationships, hence facilitating a more profound comprehension of society structures and their implications. The research presents a novel centrality measure that evaluates the significance of nodes across multiple dimensions within a singular outcome. Furthermore, it introduces the Graph Reinforcement Intelligence technique, which amalgamates graph neural networks and reinforcement learning to ascertain the most influential node inside dynamic datasets. This methodology can be utilized on any dataset to identify significant influential nodes. The study investigates the essential components required for the progression of Social Network Analysis (SNA), emphasizing the necessity for novel approaches that reflect the continually evolving nature of social networks. As social networks proliferate, the proposed approaches, including the introduction of a novel centrality measure, are essential for enhanced analysis of social behaviors and relationships, hence facilitating a more profound comprehension of society structures and their implications. The research presents a novel centrality measure that evaluates the significance of nodes across multiple dimensions within a singular outcome. Furthermore, it introduces the Graph Reinforcement Intelligence technique, which amalgamates graph neural networks and reinforcement learning to ascertain the most important node in dynamic datasets. This methodology can be utilized on any dataset to identify significant influential nodes.

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