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A Methodological Review of Communication Network Analysis (CNA)

Asyam Ahmad Fathin[a], Suciana Wijirahayu[b*]
[a*]Akademi Kepolisian Republik Indonesia, Semarang, Indonesia
[b*]Universitas Muhammadiyah Prof. DR. HAMKA, DK Jakarta, Indonesia

*Correspondence: sucianawijirahayu@uhamka.ac.id

Abstract

This study reviews the application of Communication Network Analysis (CNA) as a research method. CNA is a theoretical approach and a set of research techniques that focus on mapping the relationships between actors within a social structure. It is crucial because it can visually map out social structures. Studying CNA is crucial because it can visually map out social structures, identify the central players in an issue, and reveal the influential figures working behind the scenes. While it may seem more straightforward than quantitative statistical analysis, CNA presents its own unique challenges. Researchers may find it difficult to identify a network relevant to the research's urgency. In addition, CNA can serve as a foundation for studying various social-economic sub-sectors, including anthropology, politics, linguistics, and history, applied in accordance with the knowledge acquired by the academic community. In its application, CNA presents information in the form of graphs or visualizations of a network, various centrality calculations of actors in the network, which generally include closeness centrality, between centrality, and eigenvector centrality. From the whole network sector, it includes calculations of average degree, density, and reciprocity. Other challenges include difficulty in meeting with high-ranking officials or obtaining data from respondents who consider their relationships to be private. Therefore in this study that CNA is a highly relevant methodology to be applied for various social science purposes, especially in describing social structures where persuasive science can be combined with an understanding of the networks studied, particularly key actors who have been successfully mapped.

Keywords:

Communication Network Analysis, communication studies, social science, methodological review

1. Introduction

In the contemporary era, higher education has become a fundamental necessity for national development, especially at the postgraduate level. This commitment to advanced learning is a key priority for many governments, including the Indonesian administration (Wijirahayu & Syarif, 2021). As highlighted, the government is committed to drastically increasing the low ratio of citizens with master's and doctoral degrees, which currently stands at just 0.45% of the productive-age population (Novianto, 2024). This national push underscores the need for postgraduate graduates to possess advanced practical and academic skills, particularly in research and development (Wijirahayu, 2024). Meeting this high-level national goal requires social science researchers capable of diagnosing and solving complex, multi-stakeholder problems—a task that demands sophisticated methodologies. For this purpose, Communication Network Analysis (CNA) has emerged as a key, and often required, research tool in many graduate programs. CNA is uniquely suited to visualize and quantify the complex communication structures that define policy implementation, innovation diffusion, and organizational effectiveness, thereby directly supporting the national research and development agenda. This paper provides a methodological review of CNA, exploring its application as a means to understand the complex communication structures that shape social and organizational dynamics.

To effectively utilize CNA, researchers must be familiar with the fundamental metrics used to characterize both individual actors (nodes) and the network as a whole. Understanding these concepts is crucial for translating network structures into meaningful social or organizational insights.

While Communication Network Analysis (CNA) has become an established and widely applied methodology across the social sciences, a significant gap remains in the existing literature. Much of the scholarly work on CNA tends to focus on its application within specific disciplines, or it presents a generalized overview that may not address the practical and methodological complexities faced by researchers today. Critically, the rapid proliferation of digital communication platforms has created new data sources and analytical challenges that are not comprehensively synthesized in a single, updated review (Jeong et al. 2022). This gap is further compounded by the evolving ethical considerations of using digital traces for research, a topic that demands a dedicated and critical examination (Wijirahayu, Farischa & Fathin, 2025). Despite the many advantages of network analysis, there are several practical limitations and challenges that researchers should be aware of. Based on the author's experience in conducting network analysis (Fathin, 2022), these are some of the key application-based drawbacks: (1) Difficulty in Establishing Research Urgency: It can sometimes be challenging to find a compelling and academically significant research question, especially for theses and dissertations that rely on big data-based network analysis. Researchers must ensure that their questions not only can be answered with network analysis but also contribute meaningfully to the field. (2) Challenges in Respondent Access: When network analysis research focuses on topics related to policy or regulation, gaining access to key respondents, such as officials or legislators, can be extremely difficult. Without this access, the necessary data to build an accurate network may be impossible to obtain, which can significantly limit the scope and validity of the study. (3) Relational Data Privacy Concerns: Some respondents may view their relational data as highly sensitive and private.

When this occurs, they may be reluctant to participate or provide accurate information, complicating the data collection process and potentially compromising the completeness of the constructed network. Therefore, a need exists for a comprehensive, contemporary, and practice-oriented methodological review that not only synthesizes traditional CNA concepts but also critically evaluates new methods, tools, and the ethical frameworks required to navigate the digital era of network analysis. By addressing these oversights, this paper aims to provide a unified and practical resource for postgraduate students and scholars, guiding them through the full lifecycle of a CNA study, from data collection to interpretation.

2. Method

The foundation of any Communication Network Analysis (CNA) study lies in its ability to accurately and systematically capture the relational data that exists between individuals or groups. The selection of a research method is not a trivial matter, as it fundamentally shapes the type of network that can be analyzed and the conclusions that can be drawn. The methodological landscape of CNA is diverse, encompassing both traditional and contemporary approaches. This section provides a review of the primary data collection methods used to construct communication networks.

1. Surveys and Questionnaires

The most traditional and direct method for collecting network data is through the use of surveys and questionnaires. This approach, often referred to as sociometric data collection, involves asking individuals to identify their communication partners within a defined group. Researchers can use a name generator or a roster-based method where participants select from a predefined list of individuals. This method provides explicit data on perceived relationships and intentions, but it is susceptible to recall bias and the limitations of self-reported information.

2. Archival and Digital Trace Data

The advent of digital communication has revolutionized CNA by providing an abundance of passive, unobtrusive data. This method involves the collection of pre-existing records generated through routine interactions. Examples include analyzing email exchanges, call logs, co-authorship records, or interactions on social media platforms like Twitter. The primary advantage of this method is the ability to analyze large-scale networks with high fidelity, as the data is a direct record of behavior rather than a self-report. However, this method raises significant ethical and privacy concerns and may lack the rich context that accompanies direct communication.

3. Observational Methods

In some cases, especially within smaller groups or specific contexts, researchers may opt for direct observation to capture communication patterns. This method involves a researcher systematically observing interactions and manually recording who is communicating with whom, the frequency of their interactions, and the nature of the communication. While this approach is labor-intensive and can be affected by the observer's presence, it yields highly contextualized, qualitative data that can capture nuances and non-verbal cues often missed by other methods. This can be particularly useful for understanding informal communication networks that are not documented elsewhere.

To effectively utilize CNA, researchers must be familiar with the fundamental metrics used to characterize both individual actors (nodes) and the network as a whole. Understanding these concepts is crucial for translating network structures into meaningful social or organizational insights.

A. Centrality Measures (Individual Level) Centrality metrics identify the most influential or critical actors within a network. The three primary types are:

1. Degree Centrality: Measures the number of direct connections an actor has. In communication terms, this reflects how active an actor is—the more connections, the more frequently they send or receive information.
2. Betweenness Centrality: Identifies actors who lie on the shortest path between other pairs of actors. These actors serve as 'gatekeepers' or 'brokers,' controlling the flow of information across different parts of the network.
3. Closeness Centrality: Measures how quickly an actor can reach all other actors in the network. Actors with high closeness centrality are strategically positioned to disseminate information efficiently.

B. Group and Structural Measures (Network Level) These metrics describe the overall properties and cohesion of the network structure:

1. Density: Represents the proportion of actual connections in the network relative to the total possible connections. A high density suggests a highly integrated and cohesive group where information spreads rapidly.
2. Cliques and Components: A clique is a subset of actors where every actor is directly connected to every other actor in that subset. A component is a maximal set of actors who can reach each other, even if indirectly. These concepts help identify functional subgroups within the larger structure.

The procedural integrity of CNA is paramount for ensuring valid and reliable network representations. The following steps outline the essential lifecycle of relational data collection:

1. Define the Network Type and Research Tie: Clearly articulate the communication behavior or relationship being measured (e.g., 'sharing policy advice,' 'professional friendship') and specify the network boundaries (socio-centric or ego-centric).

2. Select Data Elicitation Method: Based on the network type and resource constraints, choose the appropriate method (Survey, Archival, or Observation).
3. Raw Data Acquisition: Implement the chosen method, rigorously collecting the raw relational information (e.g., distributing surveys, executing API calls, or conducting observation logs).
4. Data Transformation to Adjacency Matrix: Convert the raw data into a structured format usable by network analysis software. The standard format is the Adjacency Matrix, where rows and columns represent actors, and the cell value indicates the presence (1) or strength (weight) of a tie (0 indicates no tie).
5. Data Cleaning and Verification: Review the matrix for anomalies, missing data, and potential errors arising from self-report bias or technical collection failures. This step is critical to ensure the network accurately reflects the real-world communication structure

3. Results and Discussion

3.1 Results

Communication Network Analysis

Communication Network Analysis (CNA) is a powerful research method used to describe the relationships between actors—which can be individuals, organizations, institutions, or other entities—within a social structure (Eriyanto, 2014:5). Complementing this, Smiraglia (2015:84) explains that network analysis is a set of research techniques based on network theory, which was originally developed from computer science to describe the power and structure of social networks.

The study of CNA is crucial because it allows researchers to map out the key players within a network. This mapping can reveal who holds influence over a particular issue and, more broadly, who is driving a particular narrative or agenda. For example, in a political context, CNA can be used to identify the main accounts or individuals behind the virality of a specific prediction, such as the names of cabinet ministers for an incoming government. Similarly, it could be used to determine the most influential actors involved in drafting a new human rights law, thereby revealing who needs to be engaged in policy discussions. Through quantitative network analysis, these insights can be studied and accounted for with scientific and academic rigor.

Methodological Distinction and Tools

One of the key advantages of CNA is that its data processing is generally less complex than traditional statistical quantitative methods. Unlike statistical research that relies on structured data from samples and often requires extensive validity testing, quantitative CNA focuses on relational data. Because network analysis is concerned with the relationships between every actor in a defined population, it does not require the same type of statistical validation. This streamlined approach also means that many scientific articles using CNA do not need to include complex formulas for every calculation.

While traditional social quantitative research typically uses software such as Excel, SPSS, SEM AMOS, or PSPP, network analysis relies on specialized tools. Gephi, VOSviewer, and Ucinet are among the most common software applications used to process the relational data central to CNA studies. The final output of this quantitative research typically includes a relational map or graph of the network, accompanied by a table of key network metrics and components.

Graph and Visualization

A graph, or network map, serves as the primary visual output in Communication Network Analysis (CNA), providing an intuitive and powerful representation of relational data. A graph is composed of two main elements: nodes and edges.

Nodes are the graphical symbols that represent the actors in the network (e.g., individuals, organizations, institutions). The visual default for nodes can vary depending on the software used for analysis. For example, in Gephi, the default node symbol is a circle, while in Ucinet-Netdraw, the default is a square.

Edges, more commonly referred to as ties within this field, are the thin lines that represent the relationships or connections between actors. These ties are the core of the network, as they show the existence and nature of communication flows (Krishen et al. 2021). In some cases, these lines are accompanied by arrows, which are used to represent the direction of the relationship, illustrating which actor is initiating communication with another. For instance, a tie from Actor A to Actor B with an arrow indicates that A is communicating with B, but not necessarily vice versa. The final appearance of a graph, while representing the same underlying data, can look distinct when processed by different software due to variations in their default visualization and layout algorithms.

Figure 1.

Graph from Ucinet - Netdraw (Source:Asyam Ahmad Fathin document)

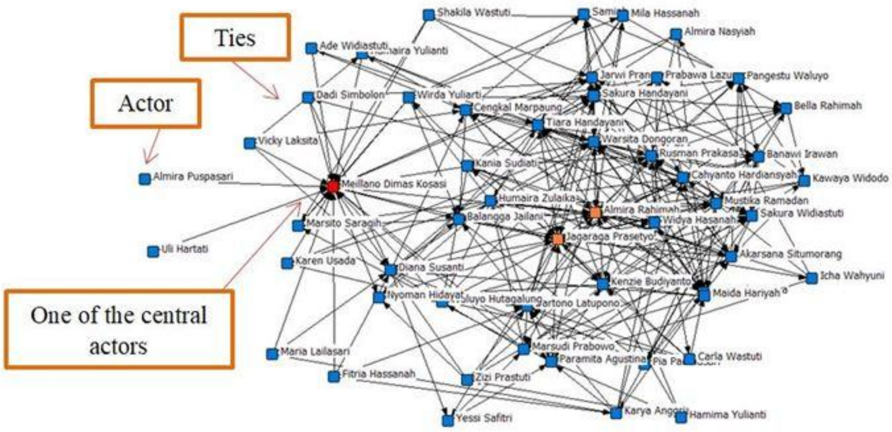
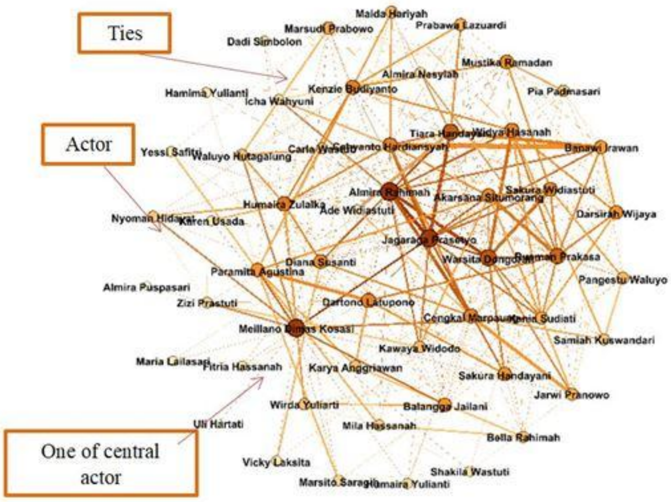


Figure 2.

Graph from Gephi software (Source:Asyam Ahmad Fathin document)



Network Analysis Calculation Components

Network analysis calculations are diverse, and the selection of which metrics to use should align with the specific research questions and the focus of the study. A fundamental calculation that is almost always included in network analysis research is Degree Centrality. This metric measures an actor's popularity within the network. Popularity is calculated by considering the number of actors an individual is contacted by (in-degree centrality**)** or contacts themselves (out-degree centrality). In essence, it measures how many direct ties an actor has within the network (Prell & Schaefer, 2024:27).

Beyond degree centrality, a deeper focus on an actor's specific role within the network can be achieved through other key metrics. It is including Closeness Centrality, Betweenness Centrality, and Eigenvector Centrality.

Closeness Centrality

This calculation measures how close an actor is to all other actors in the network. "Closeness" is determined by the number of steps, paths, or ties it takes for an actor to reach or be reached by others in the network. This metric helps identify actors who can quickly reach everyone else, making them efficient communicators (Perry-Smith & Shalley, 2003: 96-97 in Eriyanto, 2014: 177).

Betweenness Centrality

This metric quantifies an actor's role as an intermediary or bridge. It describes the extent to which an actor can control the flow of information between others by being positioned on the shortest path between them (Ortiz-Arroyo, 2010:28). An actor with high betweenness centrality is crucial for communication between different parts of the network and can therefore be a gatekeeper of information.

Eigenvector Centrality

This calculation goes beyond simple popularity by measuring the importance of the connections an actor has. An actor's eigenvector score is high if they are connected to other actors who also have high scores, meaning they are connected to important people (Bonacich, 1972 in Hupa et al., 2010:325). This is particularly useful for identifying key opinion leaders or influencers whose connections are highly valuable.

In practice, the results of these calculations are typically presented in a table that complements the visual network map or graph. It is shown in Table 1 below.

Table 1

The analysis of Network Centrality from Ucinet Software (Document Asyam Ahmad Fathin)

Rank	Degree Centrality		Closeness Centrality		Betweenness Centrality	Eigenvector Centrality
	Out	In	Out	In		
1	Almira Rahimah (15)	Meillano Dimas Kosasi (29)	Almira Rahimah (127.000)	Jagaraga Prasetyo (85.000)	Meillano Dimas Kosasi (314.048)	Jagaraga Prasetyo (0.327)
2	Meillano Dimas Kosasi (13)	Jagaraga Prasetyo (21)	Dartono Latupono (128.000)	Almira Rahimah (89.000)	Almira Rahimah (314.000)	Almira Rahimah (0.284)
3	Jagaraga Prasetyo (12)	Almira Rahimah (18)	Widya Hasanah (131.000)	Warsita Dongoran (100.000)	Tiara Handayani (218.673)	Warsita Dongoran (0.261)

3.2 Discussion

3.2.1Network Metrics and Interpretation

While network graphs provide a powerful visual representation, the true analytical power of Communication Network Analysis (CNA) lies in its quantitative metrics. These calculations provide a numerical basis for understanding the structure of the network and the specific roles of the actors within it (Park et al. 2023). This section details the most common centrality measures and their practical interpretation.

Centrality Measures: Focusing on Actor Importance

(1)Degree Centrality

Degree centrality measures an actor's popularity, which is calculated based on the number of ties they have. There are two types: in-degree, which counts the number of incoming connections (an actor being contacted by others), and out-degree, which counts the number of outgoing connections (an actor contacting others) (Haye, 2024:122). | Actor Name | In-Degree | Out-Degree | | Almira Rahimah | 5 | 15 | | Meillano Dimas Kosasi | 29 | 10 | | Jagaraga Prasetyo | 12 | 8 |

Interpretation

In the sample data above, Almira Rahimah has the highest out-degree centrality with 15 points, indicating that she is the actor who most frequently initiates communication. Conversely, Meillano Dimas Kosasi has the highest in-degree centrality with 29 points, suggesting he is the most popular or sought-after actor in the network.

(2)Closeness Centrality

Closeness centrality measures how close an actor is to all other actors in the network. Unlike degree centrality, a lower value is better, as it indicates a shorter path or fewer steps are needed to reach all other actors (Eriyanto, 2014:176). This metric identifies the most efficient communicators.

Interpretation

In our sample, Almira Rahimah's out-closeness centrality is 127.000, meaning she needs an average of 127 steps to reach every other actor. Jagaraga Prasetyo's in-closeness centrality of 85 signifies that, on average, it takes 85 steps for all other actors to reach him, making him a central hub for receiving information.

(3) Betweenness Centrality

Betweenness centrality identifies actors who act as bridges or intermediaries between others. A high score suggests that an actor is positioned to control the flow of information between different parts of the network (Ortiz-Arroyo, 2010:28).

Interpretation

Meillano Dimas Kosasi has the highest betweenness centrality at 314.048, indicating that he is the most likely to serve as an intermediary, giving him significant control over the flow of information within the network.

(4)Eigenvector Centrality

Eigenvector centrality measures an actor's influence by considering the importance of their connections. A high score means an actor is connected to other highly connected or important actors (Bonacich, 1972, in Hupa et al., 2010:325). Scores are typically normalized between 0 and 1, where 1 indicates a high connection to other central actors and 0 indicates no such connections.

Interpretation

Jagaraga Prasetyo has the highest eigenvector centrality at 0.327, indicating that his network is composed of other important actors, making him a significant influencer.

3.2.2 Holistic Network Metrics

If the research focus is on the overall system rather than individual actors, the following metrics are used. **Average Degree:** This is the average number of ties per actor in the entire network. **Density:** This metric measures the network's compactness by comparing the number of existing ties to the total number of possible ties. A high density suggests a highly interconnected, cohesive network. **Reciprocity:** This measures the ratio of two-way, or mutual, relationships within the network. A high reciprocity score indicates that actors are more likely to have a mutual relationship. It is shown in Table 2 below.

Table 2.

The Analyissi of Network system from Ucinet Software. (Source:Document Asyam Ahmad Fathin)

Average Degree	Density	Reciprocity
5.547	0.107	0.170

While centrality measures focus on the roles of individual actors, other metrics are used to analyze the network as a whole, providing a holistic view of the system's structure. These metrics include Average Degree, Density, and Reciprocity.

Average Degree

This calculation provides the average number of ties per actor across the entire network. In the example data, an average degree of less than 6 indicates that, on average, each actor has fewer than six connections.

Density

This metric measures the network's compactness by comparing the number of actual ties to the total number of all possible ties. According to Eriyanto (2014:329), a high density is typically considered above 50%, or 0.500. Your network's density of 0.107, or 10.7%, indicates that it is very sparse, with many actors not connected to each other. This suggests a fragmented network with a high number of isolated individuals.

Reciprocity

This metric measures the ratio of two-way, or mutual, relationships within the network. A reciprocity value of 0.170 means that only 17% of the relationships are reciprocal. This low figure suggests that a significant portion of the communication in this network is one-directional.

Methods for Acquiring Network Data

There are three primary methods for acquiring the data needed to conduct network analysis. The choice of method depends on the research question, the available resources, and the type of network being studied (Singh et al. 2025).

Interviews

Through this method, researchers gather information by asking specific questions to identify relationships, such as "Who do you communicate with and how often?" For example, a researcher studying the social impact of an event might interview participants to map the networks that formed afterward. Questions would be designed to uncover who talked to whom, who they discussed the event with, and how frequently they communicated.

Documentary Studies

According to Eriyanto (2014:134), a wide range of documents can be used as sources for network data. This includes media reports, company reports, investigative documents, meeting minutes, court rulings, diaries, and biographies. The goal is to find data that explicitly or implicitly identifies "who contacted whom" to construct the network's ties.

Internet Data

The internet is a rich source of big data for network analysis, with interactions being captured through a process known as scraping or crawling. This method involves programmatically collecting digital interaction data from social media platforms like Twitter, Facebook, and YouTube. Twitter, in particular, is often a prime source for this type of research due to its inherently interactive content format, which makes it an excellent platform for capturing user interactions.

Future Research

The methodological journey of a CNA study, from data collection through interviews, documentary studies, or big data crawling, is not without its challenges. The difficulties in securing research urgency, gaining access to key respondents, and navigating sensitive privacy concerns are significant and must be carefully managed. However, as the digital landscape continues to evolve and generate unprecedented amounts of relational data, the role of CNA becomes even more critical. By embracing a systematic and ethically conscious approach, researchers can leverage these methods to create academically rigorous work and make meaningful contributions to a wide range of fields, from sociology and political science to business and public health. This review, therefore, serves as a guide for scholars to navigate the complexities of CNA, reaffirming its vital role in contemporary social science research.

4. Conclusion

Communication Network Analysis (CNA) is an exciting and highly relevant research methodology for contemporary social science studies. As this chapter has demonstrated, the relative ease of data processing and collection is a key advantage of CNA. However, the author recommends thorough preparation in research planning. This is especially true when the required respondents are individuals who hold important positions within a social structure. Therefore, strong persuasive skills are essential for convincing respondents to provide the relational data crucial for this type of research.

It is an invaluable and increasingly essential research methodology for understanding the complex relational dynamics of social systems. As this review has demonstrated, CNA moves beyond traditional, actor-centric research by revealing the hidden structures and flows of influence that shape communication. From the fundamental visualization of a network graph to the nuanced interpretation of key metrics like centrality, density, and reciprocity, CNA provides a robust toolkit for scholars to gain new insights.

In short, CNA is an effective and engaging tool for mapping the dynamics of relationships between actors. This method is well-suited for application in a variety of academic works, including research articles, theses, and dissertations. CNA not only offers a deep understanding of social structures but also provides a strong foundation for data-driven case studies that can be scientifically validated.

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