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DERLEME MAKALE / REVIEW ARTICLE

Operationalizing Graph Theory and Social Network Analysis in Mixed Methods Research: A Cyclical Integration Model

Karma Yöntem Araştırmalarında Graph Teori ve Sosyal Ağ Analizinin İşlevselleştirilmesi: Bir Döngüsel Entegrasyon Modeli

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Abstract

Graph theory provides a conceptual foundation for social network analysis (SNA) in examining communication patterns. Within this framework, the application of SNA makes it possible to identify key components within the network and measure the types of connections. A review of the existing literature shows that researchers have predominantly adopted a quantitative stance in defining network structures. This study examines the potential of Mixed-Methods Social Network Analysis (MMSNA), which combines quantitative and qualitative approaches within a common framework, from a theoretical-interpretive perspective. In addition, this study presents a fundamental theoretical argument for the development and integration of methodologies that enable the discovery of relationships within network structures. Furthermore, it discusses the capacity of mixed-method research designs to analytically structure social relations. To this end, a systematic conceptual review design was adopted to map the MMSNA literature. Searches conducted in the Web of Science and Scopus databases as of September 2025 were yielded 733 records, which were merged using the R programming language and duplicates removed. Ultimately, 200 international academic publications directly related to the subject were included in the review. As a result of this analysis, an original two-layered conceptual model that integrates methodological and epistemological dimensions is proposed to address the identified gap. First, the Cyclical Integration Model operates

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integration not only at the final stage but also continuously throughout the design, data collection, analysis, and interpretation processes. Second, the Bridge-Builder and Network-Weaver Model emphasizes the researcher's reflective role in the integration process, establishing connections between quantitative "what" questions and qualitative "how/why" questions. In conclusion, the study makes visible the methodological orientations and integration debates in SNA, providing a conceptual basis for the proposed two-layered model. The combination of quantitative and qualitative approaches under mixed-methods research produces more interpretable and valid results in SNA studies, and the operationalization of MMSNA makes an indispensable contribution to the examination of social relationship structures.
Keywords: Graph Theory, Social Network Analysis, Mixed Methods Social Network Analysis, Cyclical Integration, Bridge-Builder and Network-Weaver Model

Öz

Graph teorisi, iletişim kalıplarını incelemede sosyal ağ analizine (SNA) kavramsal bir temel sunmaktadır. Bu çerçevede SNA'nın uygulanması, ağ içindeki önemli bileşenlerin belirlenmesine ve bağlantı biçimlerinin ölçülmesine imkân vermektedir. Mevcut alanyazın incelendiğinde, araştırmacıların, ağ yapılarını tanımlamada çoğunlukla niceliksel bir duruş benimsediği görülmektedir. Bu çalışma, niceliksel ve niteliksel yaklaşımları ortak bir zeminde birleştiren karma yöntemli sosyal ağ analizinin (MMSNA) potansiyelini teorik yorumlayıcı bir perspektifte incelemektedir. Ayrıca, bu çalışma ağ yapılarındaki ilişkilerin keşfini mümkün kılacak metodolojilerin geliştirilmesi ve bütünleştirilmesine dair temel bir teorik argüman sunmaktadır. Bununla birlikte, karma yöntemli araştırma tasarımlarının sosyal ilişkileri analitik biçimde yapılandırma kapasitesi tartışılmaktadır. Bu doğrultuda, MMSNA literatürünü haritalamak amacıyla sistematik bir kavramsal derleme tasarımı benimsenmiştir. Web of Science ve Scopus veri tabanlarında Eylül 2025 itibarıyla yürütülen taramalardan elde edilen 733 kayıt, R programlama dili kullanılarak birleştirilmiş ve yinelenen yayınlar çıkarılmıştır. Nihai olarak, konuyla doğrudan ilişkili 200 uluslararası akademik yayın inceleme kapsamına alınmıştır. Bu inceleme sonucunda, söz konusu boşluğu gidermek amacıyla metodolojik ve epistemolojik düzeyleri bütünleştiren özgün ve iki katmanlı bir kavramsal model önerilmektedir. İlk olarak, Döngüsel Entegrasyon Modeli, entegrasyonu yalnızca sonuç aşamasına bırakmayarak tasarım, veri toplama, analiz ve yorumlama süreçlerinin tamamında sürekli bir mekanizma olarak işletmektedir. İkinci olarak, Köprü Kurucu ve Ağ Örücü Modeli, araştırmacının entegrasyon sürecindeki yansıtıcı rolünü vurgulamakta; niceliksel "ne" ve niteliksel "nasıl/neden" soruları arasında bağlantılar kurmaktadır. Sonuç olarak çalışma, SNA'da kullanılan nicel, nitel ve karma yöntem yaklaşımlarına dair metodolojik yönelimleri ve entegrasyon tartışmalarını görünür kılarak, önerilen iki katmanlı modele kavramsal bir zemin sunmaktadır. Karma yöntemlerin çatısı altında nicel ve nitel yaklaşımların birleşimi, SNA araştırmalarında daha yorumlanabilir ve geçerli sonuçlar üretmekte; sosyal ilişki yapılarının incelenmesinde MMSNA'nın işlevselleştirilmesi ise alana önemli bir katkı sağlamaktadır.
Anahtar Kelimeler: Graph Teori, Sosyal Ağ Analizi, Karma Yöntemli Sosyal Ağ Analizi, Döngüsel Entegrasyon Modeli, Köprü Kurucu ve Ağ Örücü Model

Introduction

Early studies on social networks demonstrate that the structural perspectives of numerous sociologists on social life were instrumental in the development of social network analysis. These approaches, which centered on relational patterns among social phenomena, merged mathematical advances in sociometry and graph theory with the ethnographic contributions of sociologists, thereby transforming SNA into an interdisciplinary field of research. Noted for its rich historical foundations, SNA has gained increasingly widespread application in recent decades, particularly due to advancements in computer software that have significantly facilitated the visualization and mapping of network data.

Owing to its inherently interdisciplinary nature, social network analysis enables the characterization of network dynamics embedded in the structure of social relations through matrices. This approach provides researchers aiming to decipher social reality with a comprehensive set of formal and theoretical tools. The multilayered relationships among human and non-human actors can be effectively analyzed using the mathematical apparatus of graph theory. Graph theory offers a robust theoretical foundation for the examination of communication patterns, and applications within this framework allow for the identification of key network elements and the measurement of connection types. Although the representation of network structures via numerical indicators affords analytical convenience, a review of the extant literature reveals a predominant reliance on quantitative methods, often at the expense of contextual depth.

At this juncture, MMSNA offers a constructive route for addressing this constraint by integrating quantitative precision with qualitative interpretive depth. However, contemporary practices often treat integration as a merely technical and mechanical procedure. This approach tends to focus predominantly on when integration should occur (sequential or concurrent designs), while largely neglecting the epistemological underpinnings of how it should be conducted and the position of the researcher within this framework. As a result, integration frequently remains limited to a side-by-side presentation of findings, thereby failing to capture new forms of knowledge that could emerge from a dialectical interaction between methods.

This study proposes an original two-layered conceptual model that integrates methodological and epistemological dimensions to address this gap. The first layer, the Cyclical Integration Model, conceptualizes integration not as a final-stage activity but as a continuous mechanism permeating all research phases-design, data collection, analysis, and interpretation. It provides a comprehensive methodological framework that interweaves structural (quantitative), semantic (qualitative), and temporal (longitudinal) dimensions through a principle of mutual reinforcement. The second layer, the Bridge-Builder and Network-Weaver Model, positions the researcher as an active and transformative agent who constructs bridges between quantitative "what" questions and qualitative "how/why" questions, generates meta – inferences through a thesis-antithesis-synthesis dialectic, and cultivates new forms of knowledge from this interplay. Thus, social network analysis transcends its role as a purely technical exercise and evolves into an integrated knowledge architecture enabling dynamic transitions among the structural, semantic, and temporal layers of social reality.

Accordingly, the article is structured into four sections. The first section discusses the theoretical foundations and historical evolution of SNA and outlines the methodological contributions of graph theory to the field. The second section evaluates current trends in quantitatively and qualitatively oriented social network research and examines debates concerning methodological integration. The third section systematically reviews existing approaches in the MMSNA literature. The final section introduces the study's original contribution – the two-layered conceptual model – and delineates the methodological and epistemological advancements it offers for future social network research.

Development and Growth of Network Analysis

Network analysis investigates the relationships and patterns that connect social actors, encompassing both human and non-human entities within social networks. These social structures are analyzed concretely and mapped using tools primarily derived from mathematical graph theory. Unlike traditional research, network analysis evaluates the connections between social actors, providing a distinct perspective. Both theoretical and empirical approaches to networks have evolved. According to Wellman and Berkowitz (1988), SNA is neither a method nor a metaphor but an "intellectual" approach to studying social structures. Characterized as structural analysis, social network analysis focuses on linked social relationships. In its early stages, terms like "structural analysis", "structural sociology", and "structuralism" were often used interchangeably with SNA to describe this field (Carrington, 2014).

Before the advent of modern SNA, scholars like Auguste Comte, Emile Durkheim, Ferdinand Tönnies, Herbert Spencer, and Gustave Le Bon conducted studies on families, individuals, interpersonal relationships, social group networks, and crowd dynamics. Georg Simmel later articulated the interaction patterns foundational to modern social network analysis (Freeman, 2004). Simmel (1972) argues that society is formed through the interactions of multiple individuals, which consistently occur driven by specific impulses or aimed at particular objectives. Simmel is regarded as the first scholar to conceptualize social interactions in terms of network dimensions. However, as Wasserman and Faust (1994) note, the term "social network" is often attributed to Barnes (1954). The idea of networks connecting social entities or units radiating from societies has since gained widespread recognition and influence. Building on this perspective, early research on social networks suggests that the structural perspectives of many sociologists on social life laid the groundwork for the development of SNA.

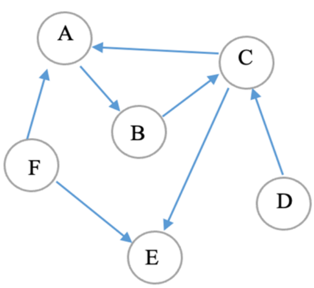
Sociometry, organizational research undertaken at Harvard during the 1930s and 1940s, along with the work of British social anthropologists affiliated with the Manchester School in the 1950s, are widely regarded as foundational conceptual traditions that informed the early development of SNA (Carrington, 2014, p. 38). The strong integration of mathematics in network research arises from its capacity to structure and organize network data. The traditional data structure in network research traces back to Jacob L. Moreno (Leinhardt, 1977). Moreno's book *Who Shall Survive?* (1953) is regarded as a pivotal work in the history of SNA, marking a significant milestone in the field's development. According to Scott (2000), Moreno's (1953) development of the sociogram, a tool for representing the formal features of social configurations, was a significant innovation. Earlier sociologists examined interpersonal connections, collaboration among diverse individuals, and interaction dynamics but did not formalize these network-level relationships into an analytical framework.

Sociology achieves results by employing experimental techniques and quantitative methods to study populations, analyzing their properties mathematically through sociometry (Moreno, 1953). Sociometry focuses on positive and negative relationships within groups, with social network datasets based on emotional ties such as liking, disliking, friendship, and hostility referred to as sociometric. Sociograms are used to visualize interpersonal interactions, even in datasets with many actors. Historically, the use of sociometry to represent social network data increased significantly in the 1940s (Wasserman & Faust, 1994).

Moreno initially applied his sociometric technique to analyze and organize data on interpersonal attitudes within small informal groups (Leinhardt, 1977). Sociometric testing acts as an experimental method to obtain accurate information about group organization. For instance, when participants indicate "which friends they prefer" in a group, their responses are represented by arrows connecting individuals, forming interaction patterns visualized as a sociogram. These arrows, whether one-way or two-way, are then converted into a matrix format, creating a sociomatrix that provides a structured representation of these relationships.

Figure 1

Difference Between Sociogram and Sociomatrix



Sociogram

	A	B	C	D	E	F
A	0	1	0	0	0	0
B	0	0	1	0	0	0
C	1	0	0	0	1	0
D	0	0	1	0	0	0
E	0	0	0	0	0	0
F	1	0	0	0	1	0

Sociomatrix

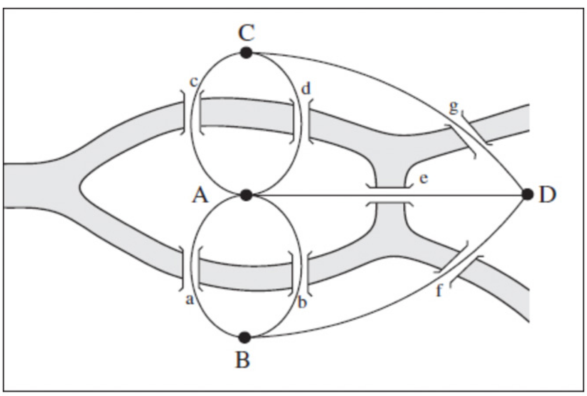
Figure 1 demonstrates intra-group network relationships, with a sociomatrix derived by converting the sociogram's spider web-like graphical data into numerical form. This six–member interaction begins with sociometric testing, followed by mapping. The second figure shows interaction sizes, with outgoing connections represented left-to-right (A-F) and incoming connections bottom-to-top (A-F). These visual and quantitative analyses highlight the network's structure, and Moreno's (1953) quantitative representation significantly influenced network analysis and its integration into graph theory models.

Fundamental Principles of Graph Theory and Its Structural Relationship with Social Network Analysis

From an applied perspective, the centrality measures in SNA rely on the mathematical structure of graph theory, where nodes and edges constitute the basis of calculation. Graph theory offers theorems that can be utilized to investigate the formal characteristics of sociograms. Points are used to represent individuals, while lines are used to show the social ties that exist between points. This is similar to the way sociograms appear. It is possible for graph theory to function straightforwardly on matrices when the data of any network is captured in matrix form. From a mathematical perspective, graph theory can operate directly on matrices when the data of any network is captured in matrix form. Therefore, in processing large-scale datasets, working directly on matrices rather than developing a visual representation provides researchers with a significant advantage (Scott, 2011). It is possible to trace the formation of graph theory back to an intelligence inquiry and the subsequent publishing of the answer to that question. In 1736, Leonhard Euler's intelligence question-based mathematical research concerning the bridges of Königsberg, located in Eastern Europe, led to the development of graph theory.

Figure 2

Simplified Representation of River and Bridge Models in Königsberg



Note. The image is taken from Barabási (2014).

In the year 1736, the mathematician Leonhard Euler examined the Königsberg Bridges puzzle, a mathematical puzzle concerning the city of Königsberg. Positioned along the Pregel River, the city included two islands at its center, connected to the surrounding landmasses by seven bridges, as illustrated in Figure 2. The central question posed was whether it was possible to devise a single path that crossed each of the seven bridges exactly once (Newman et al., 2006). Leonhard Euler developed an innovative theory that a circular walk around the city of Königsberg would not be possible by not using a bridge more than once (Hage & Harary, 1983). Euler demonstrated that the Königsberg graph lacks a route that traverses each link exactly once. He conceptualized the problem as a network of nodes and connections, where the four geographical sections divided by the river were represented as nodes labeled A, B, C, and D (Figure 2). The bridges were depicted as connections linking these nodes. This abstraction formed a graph in which nodes corresponded to landmasses and connections to bridges. Through this framework, Euler provided definitive evidence that no path could cross all seven bridges exactly once.

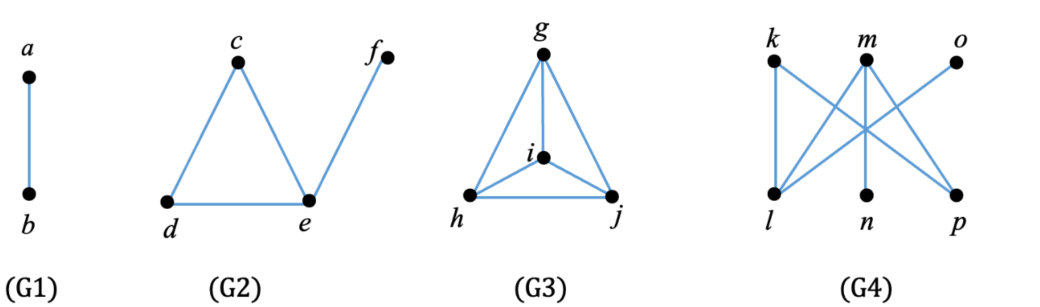
For a path to traverse all bridges, nodes with an odd number of connections must serve as the starting and ending points. Thus, such a path requires exactly two nodes with an odd degree of connectivity. If a graph contains more than two nodes with an odd degree, a continuous path traversing all bridges is impossible (Barabási, 2014; Harary, 1999). In seeking a solution to the Königsberg Bridge problem, Euler established a criterion requiring all connected points to be equal. This approach offered a method for analyzing networks of any scale, including those with large datasets. Through this groundbreaking work, Euler became a foundational figure in the fields of graph-theoretical studies and topology.

In this section, the fundamental principles and methodological approaches of graph theory that contribute to SNA will be discussed. The use of basic mathematical principles and how the mixed methods presented in the following sections will be integrated to analyze relationships within social network structures will also be addressed in line with the study's purpose.

"A graph (G) is an object consisting of two sets called the vertex set (V) and the edge set (E). That is, V (G) is the node set, and E (G) is the connection set of G." A simple graph represents a finite, non-void set of elements referred to as vertices or nodes. The set of edges composed of different and unordered pairs of elements can be empty. On the other hand, these elements are two-element subsets of the vertex set (Litherland, 2009; Trudeau, 1994; Wilson, 1996). The nodes (●) of a graph in any plane and the relationships (⁄) established between these nodes are represented by straight lines. Connections that start from a node and end at the same node are shown as loop (○). In many studies, the concepts of vertice, vertex and node are used as corners or points, and the concepts of edge are used as connections or lines. The corresponding study adopts the use of nodes and edges.

Figure 3

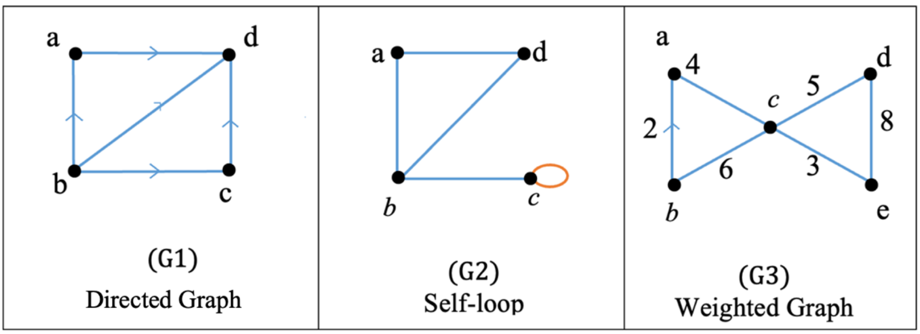
G (V, E) Example Drawings



The figure called G2 in Figure 3 represents a simple graph with a V(G) node set {c,d,e,f} and an edge set E(G) consisting of edges {cd,ce,de,ef}. Since there is no connection between nodes (c) and (f) in the graph, there is no element such as (c,f) in the edge (E) set. The set mentioned is a classical graph's set representation. A simple graph lacks multiple edges and self-loops, unlike complex graphs. Graph types vary based on node connection directions and edge quantities, including directed graphs (digraphs), undirected graphs, graphs with self-loops, multigraphs, subgraphs, regular graphs, complete graphs, weighted graphs, bipartite graphs, tree graphs, edgeless graphs, null graphs, and special graphs.

Figure 4

Illustrations of Directed, Loop, and Weighted Graphs



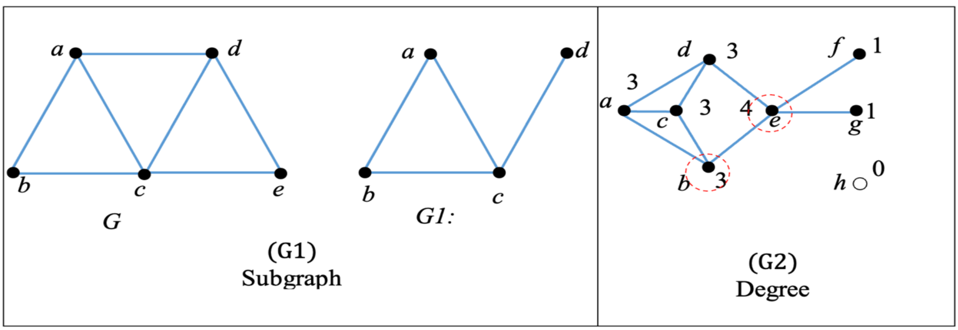
When the edges of a graph have a direction associated with them, the structure is known as a digraph (short for directed graph). A digraph is defined as a graph G=(V, A) with a vertex set V(G) and an arc set A(G). An arc is defined as an ordered pair of vertices. A digraph is composed of a finite vertex set V together with a set E comprising such ordered pairs. The term arc is used instead of edge to distinguish directional and non-directional situations. Therefore, every such pair is referred to as an arc or directed graph. A directed graph is a digraph that does not have a symmetric bidirectional line. In order to draw a directed graph, the drawing starts as in the undirected case but is completed one way towards the edge direction. For instance, in a directed graph, the relationship between a pair of nodes such as u, v is denoted as u→v. In the (u,v) arc, there is a connection from (u) to (v) (Harary, 1999; Jungnickel, 2012; Saoub, 2021). In the directed graph shown in Figure 4 (G1), an arc exists between (b) and (c) in both directions, but no direct arc connects (d) to (b).

In the graphs mentioned so far, there has been no line connecting a point to itself, that is, a loop. If both ends of an edge coincide at a single to each edge, then the vertex constitutes a loop of the edge. The same analysis can also be done for looped graphs (Jungnickel, 2012; Saoub, 2021). In the graph in Figure 4 (G2), node (c) has a loop to itself. The node that serves as the connection's starting point and its ending point is the same.

There are graphs where quantities are examined instead of directions. One of these is a weighted graphs, where a weight is assigned to each edge. A weighted graph G=(V,E,w) is defined as a graph where each edge is assigned a real integer. Each edge in the graph is allocated a non-negative number. The value associated with each edge "E" represents its weight, denoted as "w(e)". The specified value is referred to as the weight and is represented as w(xy) for the xy edge (Saoub, 2021; Wilson, 1996). In this graph, the weight given to the edges can represent many things or measurements between two objects. The weight here could be time, distance, cost, or the number of retweets. The specified weight function is optional and can vary depending on the context. In the graph example with weights written on the edges (G3) in Figure 4, it takes 2 units to go from (a) to (b).

Figure 5

Examples of Subgraph and Graph Degree Representations



The subgraph is used to discuss smaller sections, especially when examining complex graphs. A subgraph of the graph G shown on the left-hand side in Figure 5 is a graph whose vertices belong to V(G) and each edge belongs to E(G). A subgraph H of a graph G is defined as a graph that comprises a subset of the edges and vertices of G. The mathematical expression of this situation is shown as follows: "$V(H) \subseteq V(G)$ and $E(H) \subseteq E(G)$" (Saoub, 2021; Wilson, 1996). When nodes or connections in a graph are deleted, a subgraph can be obtained. However, given a graph G, H must contain a copy of G as a subgraph. The graph H (G1) shown on the left-hand side in Figure 5 forms the subgraph of G.

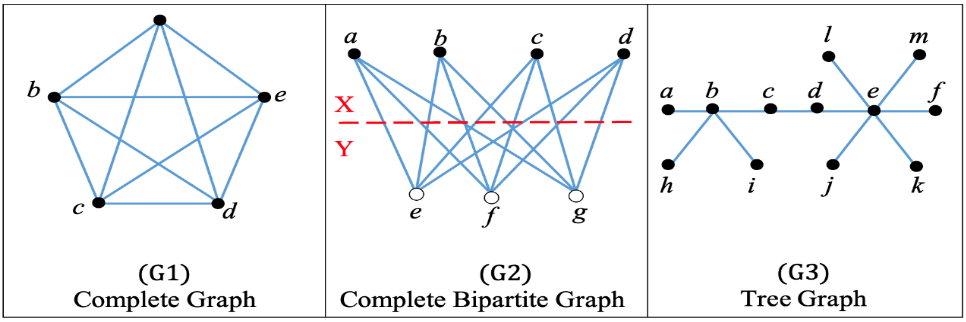
Weighted graphs should not be mistaken for degrees. The degree refers to the quantity of edges originating from each node. Here, check how many neighbors each node has. For instance, when drawing an imaginary circle over node X, the degree of node X is the number of edges it intersects. At this point, the total count of edges in a graph will correspond to the number of items in the set. For example, in regular graphs, all nodes have the same degree. Regular graphs are connected to each other.

The degree of a node denoted by "d(i)" or "deg v(i)" in the graph constitutes the number of straight lines that coincide with "v(i)". The total degree of the vertices in a graph is equal to twice the number of edges. Although the quantity of vertices with odd degrees in every graph is even, a regular graph with degree 0 contains no edges (Harary, 1999). In G2 of Figure 5, node (a) has a degree of

3, node (E) has a degree of 4, and node (h) has a degree of 0. In directed graphs, node degrees are divided into "in-degree" and "out-degree", with the total degree being the sum of these two values.

Figure 6

Sample Drawings of Full Graph, Two-Part Complete Graph and Tree Graph



Complete graphs are defined as simple graphs in which different pairs of vertices are adjacent. An edge defines the relationship between two objects in a complete graph. A complete graph that has n vertices is denoted by Kn, and the equation denoted by $\frac{(n)(n-1)}{2}$ represents the number of edges of Kn (The mentioned expression referred to as an edge refers to the line connecting two corners.) (Wilson, 1996, p. 17). The complete graph shown as G1 in Figure 6 is represented as K5. The degree of each node in Kn is calculated by (n-1). According to the expression mentioned, the degree of node "a" in K5 is 4 units. The $\frac{(n)(n-1)}{2}$ formula of Kn gives the number of edges. In this regards, graph G1 in Figure 6 has K5, $\frac{(5)(4)}{2} = 10$ edges. If the vertices of a graph (x-y, v1, v2, or A, B) can be divided into two subsets, that graph has a bipartite structure. Binary graphs can be used to show the relationship between different types of objects (Saoub, 2021). When a complete graph is divided into two parts, (X) and (Y), each node in (X) will be connected to each node in (Y) by only one edge. That means all edges alternate between two groups, and one of these edges must belong to (X) and the other must belong to (Y). Thus, two vertex groups can be obtained. If two edges are located in a graph denoted as (Y), the structure of the bipartite graph will be distorted. The two-piece complete graph structure is shown as an example in G2 in Figure 6. A node must be connected to all nodes in the other group in this graph. Node A, B, C, D is connected to nodes E, F, G in the other cluster.

A tree graph is the simplest graph type among the important graphs. In a connected graph, each edge forms a tree graph as a bridge. Trees are characterized by the number of edges between connected graphs. A graph with (N) vertices does not contain a loop and has (n-1) edges. To put it another way, each edge serves as a bridge, and there is one less edge than node. There are distinct connections between any two nodes (Wallis, 2006). There is only one path connecting two nodes in tree graphs. There is no path back to node A when starting from node (A). A graph G3 in Figure 6 is shown as an example of a tree graph.

There are a number of definitions, such as loops, walks, and paths, in graph theory. In a graph, a route that does not pass through the same node twice and returns to the node it started from is called a loop. There may be repetition of edges and nodes during the walk term. For instance, to go from node (A) to node (C), one passes through node (B). A walk starting from node (A) continues in the form of ab, bc, cd,.. yz. A path, however, requires traversing different edges without repetition. Some problems focus on finding routes that traverse each edge or node exactly once, with Euler's path and Hamilton's path being the most notable examples. See Bollobás (2012) and Litherland (2009) for more information.

Solutions to graph-related problems are influenced by the specific properties of each graph, as exemplified by the Königsberg problem. In the Königsberg graph, four nodes have an odd degree, making it mathematically impossible to traverse every bridge in single pass and finish at the initial vertex. This conclusion is firmly rooted in the principles of graph theory. Beyond solving such theoretical problems, graph theory's mathematical models and formulas have played a substantial role in shaping SNA, offering tools to study complex relational structures.

Centrality Measures in Social Network Analysis

SNA, as an interdisciplinary field, bridges various domains to provide formal and conceptual frameworks for understanding the complexities of the social world. It focuses on embedded relationships, encompassing both human and non-human actors. From an applied perspective, the centrality measures used in SNA rely on the mathematical structure of graph theory. Therefore, centrality calculations are directly based on the concepts of nodes and edges.

Social network analysis relies on two key components: objects and their relationships. Objects are expressed as "nodes" while relationships between them are illustrated as "lines" or edges. Together, nodes and edges form mathematical models of network structures. In real – world applications, nodes can represent entities such as individuals in a social network or web pages on the World Wide Web, while edges signify connections or links between them. Researchers may focus on analyzing a single social actor (ego network analysis) or the relationships among all actors in the network (whole network analysis). By utilizing graph theory and network data analytics, SNA offers an analytical basis for examining and interpreting complex social configurations.

Social network analysis, often referred to as network science, has developed various indicators and metrics to evaluate the structural properties of networks. Once a network's topology is defined, specific metrics can be calculated to identify key features. One of the most significant measures is centrality, which assesses the relative significance and impact of a node across the overall network (Newman, 2010). Centrality encompasses multiple concepts, focusing on different aspects of what it means to be central in a network. For this study, focusing on degree, closeness, and betweenness centrality, which are among the frequently employed measures in SNA research, will suffice to achieve theoretical saturation.

Freeman (2004) identified three primary centrality measures: “degree”, “closeness”, and “betweenness”. Degree centrality, which measures the number of direct connections a node has, plays a key role in analyzing communication and interaction patterns within a network. Nodes with high degree centrality are regarded as important, as they often act as critical hubs, facilitating the flow of information or communication and influencing the general configuration and functioning of the network.

An actor’s importance within a network can be assessed through point centrality, which evaluates their role in information flow. This metric distinguishes between out-degree, indicating how extensively an actor disseminates information, and in-degree, representing how much information an actor receives from others (Pryke, 2012, p. 90).

In the basic degree metric, a vertex’s degree in a network is defined as the number of edges connected to it. This reflects the total connections a node has within the network. For example, in a social friendship network, an individual’s degree equals the number of friends they have. Nodes with the highest degree and the most connections play a critical role in maintaining the network’s functionality (Newman, 2010). In an undirected network, if node (x) has edges connecting to nodes (y) and (z), its degree is two. However, in a directed network, this scenario introduces three distinct degree measures: “in-degree”, “out-degree”, and “total degree”.

Closeness centrality measures the distances between two specified points in a network. This metric, reflecting an actor’s independence and efficiency, is noted for its complexity (Pryke, 2012). According to Newman (2010), the issue with closeness centrality lies in its limited measures. Distances between vertices tend to be shorter in smaller components, resulting in higher closeness centrality values compared to those in larger components. This often leads to the assumption that vertices in smaller components are better connected than those in larger ones. Therefore, Newman (2010) suggests that such vertices should be assigned lower centrality values to address this discrepancy. Closeness centrality indicates the extent to which a node maintains direct proximity to all other nodes within a network. It is defined as the “average number of hops” required for a node to access all other nodes. For instance, if node (x) has a connection with node (y), and (y) is linked to node (z), it takes two hops for (x) to reach (z).

Betweenness centrality indicates the degree to which a node is located along the shortest routes between other nodes within a network. It captures a node’s role as an intermediary or conduit, reflecting how often it connects two other nodes. Essentially, betweenness centrality indicates how a node facilitates interactions between other actors within the network, serving as a crucial link between users.

An individual with high betweenness centrality holds substantial influence over information circulation across the network, often functioning as a gatekeeper (Pryke, 2012, p. 90). In a social network, messages, news, information, and rumors are transmitted between individuals. Nodes with high betweenness centrality perform a key function in shaping the flow of this information. These nodes, through which a significant volume of messages pass, hold a strategic position in the network. By observing or facilitating the delivery of these messages, they can leverage their position to gain power. Conversely, the removal of nodes with the highest betweenness can disrupt communication, as their absence breaks the pathways connecting other nodes, leading to a fragmentation of the network (Newman, 2010). Betweenness centrality highlights distinct relational dynamics compared to other centrality measures. It assesses the relevance of a node's links in enabling access to other vertices. A node can act as a critical conduit, linking separate clusters within the graph.

Social network analysis represents a mathematical structure of nodes and links, typically derived from interactions. SNA techniques can be applied to networks with varying node and connection properties, employing graphical methods to measure data networks. Users within these networks are categorized based on various variables, with roles in information flow reflected through measures like centrality, degree, and interconnection. While these metrics offer insights into information flow among users, SNA calculations provide a comprehensive summary of the network's structural properties. This summary is often visualized through graphs or interaction matrices, revealing the relationship networks embedded within the social structure.

Quantitative and Qualitative Focused Social Network Analysis

SNA has the capacity to summarize the dynamics of a network on social media in matrix form. It is seen that researchers mostly choose one of the quantitative or qualitative methods when looking at the existing literature on SNA. Wellman and Berkowitz (1988) describe network analysis as an intellectual tool for examining social structures, rather than a metaphor or method. According to the authors, the basic idea of network analysis is not to look at network society. It is to see relationships as the basic units of social structure. Rather than starting with a theory of groups or societies, network analysis proceeds by looking at the density and texture of connections and relationships among nodes that include states and other societies. These connections consist of structures that can be measured, modeled, and visualized. Visualizations created from basic data are a useful tool for understanding important structural features of a network. While debates persist regarding whether social network analysis should be classified as quantitative or qualitative, it can also be effectively positioned within mixed research methods, combining elements of both approaches.

Crossley (2010a) argues that the quantitative instruments of SNA create an abstract, formal, and structural representation of the complexities of social existence. This approach enables investigations that are otherwise unattainable by filtering key aspects of social life and standardizing observations, often concealing tangible details. It reveals hidden structures and allows for precise and reliable measurement of their properties. Quantitative SNA is especially appropriate for analyzing large-scale social media data, as it efficiently summarizes key aspects of complex networks into relational data tables, addressing the limitations of traditional methods, which often struggle with the collection, recording, and processing of such relational data (Cooray, 2021).

Many researchers consider social network analysis as a quantitative research technique due to its mathematical foundation. However, the relationships between nodes remain a central aspect of this approach. As Scott (2000, p. 3) suggests, network analysis combines quantitative and statistical evaluations of relationships with qualitative assessments of network structure. This integration enables researchers to conduct detailed analyses of the social topology within networked societies.

Researchers utilize both quantitative and qualitative approaches in studying SNA and social media analytics. Quantitative approaches focus on analyzing social media groups, while qualitative methods provide insights into the social processes within and between these groups. Although the analyst's role is often overlooked, their subjective perspectives can influence both quantitative and qualitative analyses. Therefore, a mixed-methods design that combines SNA with qualitative techniques is recommended (Cooray, 2021).

Martínez et al. (2003) proposed a hybrid evaluation methodology combining social network analysis, quantitative metrics, and digital data records within a qualitative case-based framework. Social network analysis tools, such as indices and sociograms, are particularly valuable for examining collaborative patterns. This mixed-method strategy offers researchers a more efficient way of examining social network data compared to methods that rely solely on qualitative analysis. In this regard, quantitative network analysis provides valuable insights into social structure but may fall short in capturing the complexity of social dynamics and relationships.

Nooraie et al. (2017) integrated quantitative themes and patterns into their study to enhance and expand the outcomes of their empirical analysis. The results derived from quantitative and qualitative phases were integrated within the framework of network analysis. The study concluded by being recommended that quantitative SNA be supplemented with a qualitative exploration of participants' perspectives and experiences.

Social network analysis has increasingly incorporated mathematical methodologies, including formal models and analytical tools. As a result, many researchers equate the approach with quantitative methods, leading to the perception that social network analysis is primarily a quantitative approach within the social sciences (Teddlie & Tashakkori, 2009). According to researchers, data on cliques and isolates, which are key criteria in social network analysis, cannot be effectively visualized using quantitative sociomatrix alone. For this reason, authors preferred to call social network analysis a mixed data analysis technique by nature. Researchers aim to generate both quantitative and qualitative outputs derived from a single data source before data collection begins, a process referred to as "combined data analysis." Bazeley (2003) describes this as involving the twin processes of unification and transformation. Mixed-form data can be analyzed through parallel or sequential methods using software tools, enabling the incorporation of quantitative data into qualitative analysis or the conversion of matrices derived from qualitative coding into formats suitable for statistical analysis. This approach allows researchers to not only merge data from different sources but also use the same data in interconnected ways to gain a more holistic insight into the issue under examination.

In both social movements and network analysis, there has been a notable increase in the study of networks and social relations often overlooked by quantitative methods. While quantitative approaches are invaluable for network analysis, certain features are better explored through qualitative methods. Qualitative approaches can uncover hidden complexities within quantitative studies, offering deeper insights. Although it is impossible to fully understand every link in a network, qualitative data, especially historical information, can help clarify the meaning of specific ties (Edwards & Crossley, 2009). Researchers advocate for integrating advanced qualitative analysis techniques with complex quantitative methods in network analysis. This combined approach allows qualitative and quantitative techniques to work in a complementary manner. As a result, the binary assumption that relationships simply exist or do not exist is "deconstructed," enabling the exploration of their history, phenomenology, context, and variability.

Analyzing qualitative data in large social network datasets with traditional methods is challenging. However, structural features of a network that are not immediately apparent through quantitative methods can be further explored through qualitative analysis. Quantitatively, a network consists of nodes and edges, with their interconnections represented numerically. Yet, a network extends beyond these numerical abstractions. Qualitative analysis shifts the focus to the networked subjects themselves, emphasizing the interactive and relational dynamics of the network rather than reducing them to mere numerical values.

As Crossley (2010b) points out, qualitative analysis is not a universal solution to all problems but serves as a valuable tool for researchers due to its flexibility and lower level of abstraction compared to quantitative methods. It allows researchers to focus on unique cases, features, and content, providing access to concrete details. Unlike the mathematically driven aspects of SNA, qualitative approaches can uncover the narrative of the network by connecting various elements. Complementing quantitative analysis, qualitative tools enable direct engagement with interpretive meanings, identity constructions, contextual definitions, and narrative accounts. It is further emphasized that quantitative and qualitative analysis are inherently interconnected and should be used together.

Mixed Methods Social Network Analysis (MMSNA)

Historically, SNA developed through the quantitative tools provided by sociometry and graph theory; however, today this foundation is increasingly complemented by qualitative approaches (Edwards, 2010). As Peter Carrington (2014) noted, the increasing mathematization of SNA has rendered network concepts applicable across a wide range of academic disciplines, contributing to its widespread application (Hollstein, 2014). Consequently, a quantitative perspective is commonly adopted in SNA studies for defining and analyzing network structures.

Social networks, commonly studied in quantitative research, are much more than a collection of nodes and the relationships linking them (Crossley, 2010b). Peter Carrington (2014) asserts that, in contrast to other studies, SNA cannot be classified as quantitative or qualitative, nor as a simple combination of both, but should instead be understood as inherently structural.

It appears that some features of network structures cannot be easily accessed through quantitative approaches. Relying solely on quantitative or qualitative research techniques with SNA may lead researchers to miss critical aspects of the network's narrative. Therefore, it is essential to focus on the potential of mixed-method research designs that combine both approaches. Mixed-method research involves multi-stage designs, where quantitative and qualitative data are applied either simultaneously or sequentially. By using mixed-method research designs, studies gain a systematic perspective on the research problem, questions, and hypotheses across different disciplines.

In mixed-methods research, quantitative and qualitative strategies are employed to support data collection, analysis, integration of findings, and drawing inferences (Tashakkori & Creswell, 2007). Mixed-methods studies provide researchers with unique opportunities to enhance data quality and explanatory power. This approach facilitates a deeper understanding of social phenomena across broader contexts (Greene et al., 1989). Mixed-methods research designs provide a structured framework for systematically integrating quantitative and qualitative procedures in order to meet research objectives (Creswell & Plano Clark, 2018). This approach, referred to in international literature as "mixed methods social network analysis (MMSNA)," combines the strengths of both methodologies to enhance the depth and scope of analysis.

Mixed-method social network analysis integrates quantitative and qualitative approaches to provide insights into individual actors within social structures. These approaches complement each other in exploring actors' perceptions and choices regarding their interactions with others. Quantitative data reveals whether relationships exist, while qualitative data explains the reasons behind these relationships (Pantic et al., 2023). MMSNA addresses the limitations inherent in social network studies by combining quantitative and qualitative methodologies within a single framework, providing a more holistic interpretation of network structures (Baker-Doyle, 2015). Froehlich and Brouwer (2021) describe SNA as inherently a mixed-methods framework.

Qualitative techniques will concentrate on comprehending the significance individuals ascribe to these relationships and interaction processes. Qualitative approaches offer contextual insights into diverse situations, shedding light on shared norms, identity formations, and preferences that influence a particular social setting as well as the dynamics of individual interactions (Crossley, 2010a). While quantitative methods are predominantly employed to measure network properties, qualitative methods are essential for complementing and enriching networks, particularly in determining the central axis positions of the research design. By integrating methods in this way, quantitative approaches can concentrate on analyzing relational frameworks and the roles of participants within these structures.

Quantitative (sociometric) methodologies explore the structure of social interactions, while qualitative approaches investigate the mechanisms that create networks, their perception, significance, and evolution over time (Edwards, 2010). Qualitative methods enable researchers to uncover the relational content within networks that cannot be identified through quantitative approaches alone.

SNA is frequently characterized as an "analytical" approach. The use of visual representations in network analysis indirectly influences other aspects of the research process. To effectively guide such inquiries, network analysis necessitates a complex conceptual model (Hilpert & Marchand, 2018). Crossley (2010b) emphasizes the importance of integrating both methodologies in social network research. While qualitative methods lack a structured framework for recording, presenting, and explaining social structures, quantitative approaches often oversimplify and abstract the social dimensions of networks. Consequently, quantitative methods generate measurements that are difficult for researchers to interpret due to their detachment from the social context.

The distinct applications of quantitative and qualitative approaches each hold value, yet each is subject to inherent constraints. Quantitative SNA methodologies translate the complexities of networks into numeric representations, potentially oversimplifying intricate structures. Conversely, qualitative approaches often fall short in fully explaining complex network configurations. By combining these methodologies, numerical data can reveal detailed structural features of the network, while qualitative insights enrich the analysis, providing context and depth to the objective numerical representation of reality (Crossley, 2010b). Sociologists are increasingly studying networks within the context of social worlds, recognizing the interplay between form and content. Both quantitative and qualitative approaches are indispensable, as they mutually shape and influence each other (Crossley, 2010b).

Mixed-methods research facilitates the mapping and measurement of network properties, the structure of ties, their reproduction, variability, dynamics, and the exploration of the meanings those ties hold for individuals (Edwards, 2010). By integrating quantitative and qualitative social network data, the comprehensive effects of networks can be more fully realized. This integration creates a reciprocal relationship where both methods enhance and reinforce one another, offering mutual advantages in social network research (Thomas et al., 2020). Mixed-methods approaches, like many others, bring significant value to social network research. Qualitative methods enhance this research by providing contextual insights that help researchers interpret network maps and their implications (Edwards, 2010). Consequently, social network research increasingly relies on mixed-method approaches to produce empirical results (Froehlich et al., 2020).

The current methodological orientation in social network analysis has largely been shaped around quantitative approaches. Techniques from both paradigms – whether the structural generalization power of quantitative methods or the contextual depth of qualitative approaches – remain insufficient on their own to fully grasp the multilayered nature of social networks. Nevertheless, the complementary potential of these approaches provides a strong rationale for integrating mixed-method research designs into the field. Accordingly, penetrating the complex reality of networks becomes possible only by bringing together structural patterns and contextual meaning within the same analytical framework.

Although there is broad consensus in the literature on the necessity of such integration, how it should be achieved – that is, the epistemological and methodological principles guiding integration and their reflection in research processes – remains a significant uncertainty. It is precisely this gap that the present study aims to address by proposing an original model offering a theoretically and practically grounded framework for integrating quantitative and qualitative approaches within SNA.

Method

This study adopted a systematized conceptual review design to map the literature on mixed-method social network analysis. The Web of Science Core Collection and Scopus databases were selected as data sources, with searches conducted in September 2025 across title, abstract, and keywords fields. The search strategy employed the following key queries: *"mixed method" AND "social network analysis"*, *"quantitative" AND "social network analysis"*, *"qualitative" AND "social network analysis"*, and *"MMSNA"*. The search was restricted to articles published in English within the social sciences category.

Table 1

Search Fields and Key Queries Used in the Study

Search Fields	Key Queries
Title, Abstract, and Keywords	"mixed method" AND "social network analysis"
Title, Abstract, and Keywords	"quantitative" AND "social network analysis"
Title, Abstract, and Keywords	"qualitative" AND "social network analysis"
Title, Abstract, and Keywords	"MMSNA"

The initial search yielded 733 records, which were merged and deduplicated algorithmically using the R programming language and the tidyverse package to create a unified dataset. For the final selection, inclusion criteria encompassed studies that employed social network analysis as a method, explicitly addressed the "MMSNA" approach, or discussed the integration of quantitative and qualitative methods. After screening titles and abstracts based on these criteria, 200 publications were included for in-depth review. Methodological trends and prominent debates were identified through an analysis of these publications. The insights gained from this process directly informed the development of the original conceptual model presented in this study.

Conceptual Framework: A Two-Layered Model of Cyclical Integration and the Bridge Builder-Network Weaver Approach

The literature on mixed-method social network analysis has largely focused on the timing of integration (e.g., sequential, convergent) but has insufficiently addressed the question of what kind of epistemological mindset should guide this process. This study proposes an original, two-layered conceptual model that complements existing approaches. The model provides not only technical procedures for integration but also a comprehensive framework that encompasses the researcher's epistemological transformation throughout the process (see Figure 7).

Philosophy and Originality of the Model

This model conceptualizes integration not merely as a technical procedure but as a process of "building bridges" between two distinct epistemological worlds (quantitative – qualitative) and "weaving new networks of meaning" across these bridges. Unlike existing models, which emphasize when integration occurs, this model emphasizes how integration is undertaken. It aims to reposition the researcher from a passive data collector to an active "bridge builder" and "network weaver".

Methodological Layer: The Cyclical Integration Model

This model treats integration as a continuous and transformative component, not restricted to the final stage of research but operating across design, data collection, analysis, and interpretation. At each stage, quantitative and qualitative methods mutually inform and reframe one another.

Research Design: Research questions are formulated to simultaneously capture quantitative (e.g., network density, centrality) and qualitative (e.g., meaning of ties, actor experiences) dimensions. This stage functions as the blueprint for building epistemological bridges.

Data Collection: Quantitative data (surveys, digital traces, matrices) guide qualitative sampling and data strategies, while qualitative insights refine and contextualize quantitative measures. This process resembles constructing the foundations of a bridge from both ends.

Data Analysis: Quantitative analysis reveals structural properties of the network, while qualitative analysis uncovers the meanings behind them. Through joint displays and integrative matrices, a dialectical interplay is established. The researcher continually moves between quantitative metrics and qualitative narratives, fostering a dynamic dialogue.

Interpretation and Inference: Structural, semantic, and temporal insights are integrated dialectically to generate meta-inferences. These meta-inferences go beyond the simple juxtaposition of data, creating a third form of knowledge that emerges from the interplay. Thus, social network analysis is expanded from mapping mathematical structures to revealing the meanings and transformations of ties.

Epistemological Layer: The Bridge Builder and Network Weaver Model

Beyond the methodological framework, this model articulates the mindset and role transformation that researchers must embrace during integration. The Epistemological Layer represents the intellectual dimension behind the cyclical methodological process.

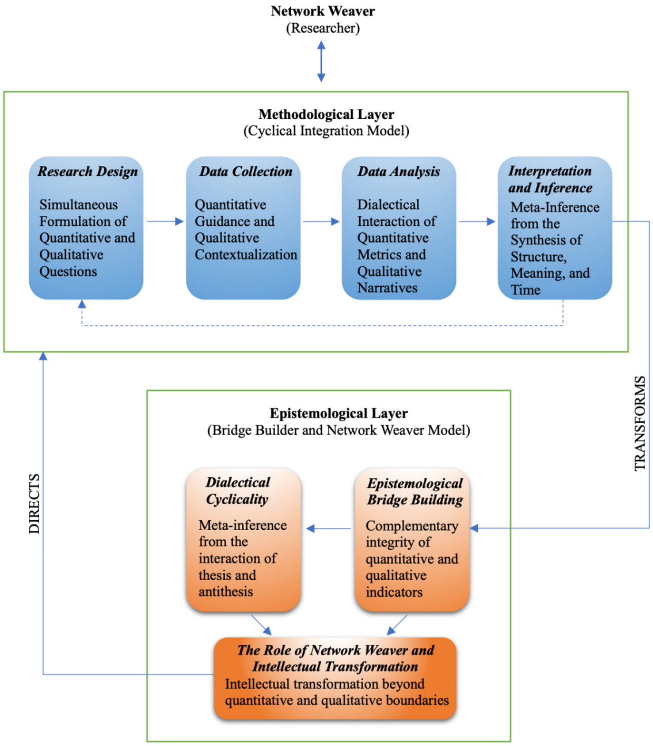
Epistemological Bridge Building: Quantitative data serve as a map for exploration, while qualitative data act as the legend explaining its symbols. These elements are regarded not as mutually exclusive but as complementary and transformative.

Dialectical Cyclicality: Integration is not a simple feedback loop but a thesis – antithesis-synthesis process. Quantitative findings propose a thesis, qualitative insights challenge or enrich it as an antithesis, and the interplay generates a synthesis/meta-inference that transcends both data sets.

The Role of Network Weaver and Intellectual Transformation: The researcher weaves together structure and meaning to construct a new network of understanding. The outcome is not only empirical findings but also the researcher's own intellectual transformation, moving beyond the boundaries of quantitative and qualitative paradigms.

Figure 7

A Two-Layered Model of Cyclical Integration and the Bridge Builder-Network Weaver Approach



This study makes the often-overlooked epistemological dimension visible in the MMSNA literature by offering an integrative perspective at both methodological and cognitive levels. At the methodological level, the Cyclical Integration Model embeds integration throughout the research process, fostering reciprocal enrichment between methods. At the epistemological level, the Bridge Builder-Network Weaver approach repositions the researcher from a passive data collector to a reflective actor engaged in a dialectical dialogue between structure and meaning. In doing so, the proposed two-layered model elevates social network analysis from a purely technical application to a holistic framework for capturing the multilayered nature of social reality.

Conclusion

Graph theory and social network analysis serve as fundamental theoretical and methodological tools for examining questions within social systems. These approaches provide a precise and formal framework by making it possible to systematically measure and map specific aspects of social relations. Methodologically, social network analysis has largely been dominated by quantitative approaches; however, ongoing debates on methodological choices remain (Borgatti et al., 2013; Carrington et al., 2005; Edwards, 2010; Freeman, 2004; Wasserman & Faust, 1994). Standardized tools are frequently used to formalize network structures through numerical and quantifiable values. Nevertheless, elements such as "content, context, process, change, and awareness" fall outside the scope of quantitative methods and thus cannot be uncovered through these approaches alone. To enhance the explanatory power of social network analysis, these elements must be integrated into the research process. While quantitative methods reveal the structure of networks through mathematical models and numerical data, they cannot fully explain the meaning, context, and dynamics of relationships. At this point, qualitative methods assume a complementary role. Content can be revealed through interviews, document analysis, and observations; context can be explained through fieldwork or case studies exploring the cultural, organizational, or environmental factors; the process dimension can be examined by long-term data collection that captures the evolution of relationships over time; and awareness can be assessed through surveys or in-depth interviews to understand how actors perceive their positions and influence in networks. Addressing these dimensions through mixed methods provides a more holistic view of both the structural and relational aspects of networks.

Different research questions require different methods; therefore, measuring and mapping social relations should not be confined to a single category. Although SNA is characterized as an analytical approach, the visual representation of data indirectly influences additional dimensions of the research process. Highlighting the contextuality of social actions in network research requires qualitative conceptual models that guide inquiry and reveal complexities otherwise obscured in quantitative discussions (Emmel, 2008; Emmel & Clark, 2009; Heath et al., 2009; Pahl & Spencer, 2004; Trotter, 1999).

Single-method social network analysis studies cannot fully contribute to understanding the nodes, ties, or relational bonds within a network. Quantitative social network analysis, while useful for measuring and visualizing networks through computer programs, cannot capture the strength of ties or whether interactions between actors are "positive" or "negative." Quantitative approaches reduce social relations to numerical data, focusing only on whether ties exist. These data are visualized and mapped, but human and non-human actors, their relationships, and the unconscious mechanisms beyond the reach of quantitative methods require qualitative tools for deeper analysis. Consequently, the use of mixed-method research designs must be aligned with the research question. For example, changes in network structures over time can be analyzed by applying or combining methods at different stages, depending on the specific requirements of the research design. The choice of mixed-method designs allows researchers to explore networks in greater depth, focusing on fundamental elements such as nodes and ties. Depending on the epistemological, ontological, and theoretical assumptions, researchers can integrate a variety of tools within mixed-method social network analysis. This approach goes beyond the mere combination of methods, enabling a deeper and more nuanced understanding of networks.

The two-layered conceptual model developed in this study provides an inclusive analytical framework that overcomes the limitations of single-method approaches and enables the integrated examination of both the structural and semantic dimensions of social networks. Its primary contribution lies in shifting mixed-method debates from a technical question of integration timing ("when") to a deeper inquiry into the epistemological mindset guiding the process ("how"). The Cyclical Integration layer ensures continuous interaction between quantitative and qualitative methods throughout all stages of research, while the Bridge Builder-Network Weaver layer positions the researcher as an active agent who builds bridges between structure and meaning. Ultimately, this model eliminates the need to choose between "counting ties" or "interpreting meanings," instead combining both approaches in a dialectical relationship that makes it possible to achieve a more holistic and explanatory social network science.

Discussion and Recommendations

This approach has revealed complex structures within social issues that researchers might otherwise overlook. Through centrality measures, concrete details of network structures have been identified, enabling the standardization of social network analysis and allowing key aspects of social life to be reliably measured across diverse contexts worldwide.

Throughout this study, the potential of Mixed-Method Social Network Analysis has been discussed within a theoretical and interpretive framework. While methodological gaps have been addressed both in previous studies and in this article, certain concerns raised during the implementation phase are expected to provide useful guidance for analysts.

Although social network analysis rests on a strong theoretical and epistemological foundation, it also presents certain limitations. First, contemporary social structures are increasingly based on large-scale datasets. Therefore, sample groups composed of small components should not be generalized to entire relational structures. Particularly due to the nature of centrality measures, short path lengths between nodes and ties in small networks may artificially inflate ratios, leading to misleading results.

Another issue in the practice of SNA is the subjectivity and methodological competence of the analyst. Since this approach is grounded in the mathematical foundations of graph theory, analysts are expected to possess a certain level of mathematical proficiency. Although software packages now facilitate social network analysis, analysts remain responsible for accurately identifying and interpreting data within network structures – particularly qualitative or relational data.

Furthermore, although mixed-method social network analysis seeks to combine the advantages of quantitative and qualitative techniques while minimizing associated limitations, its implementation often entails challenges related to resource demands and time management. Compared to single-method studies, researchers must devote significantly more effort and time.

In addition, in social network analyses that incorporate qualitative methods, the lack of standardized metrics for measuring contextual meaning within network clusters may expose the analyst to criticisms of subjectivity. For this reason, it is essential that researchers adopting mixed-method social network analysis maintain a holistic and objective perspective.

Two directions are particularly important for future research. First, the Cyclical Integration and Bridge Builder-Network Weaver Model proposed in this article should be empirically tested across different disciplines, datasets, and contexts to enhance both its validity and flexibility. Second, the incorporation of advanced techniques, including artificial intelligence and machine learning, into MMSNA could reduce resource demands in processing large-scale datasets, strengthen analytical depth, and provide a more flexible and scalable methodological framework for social network analysis.

Author Declaration

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