Original article

ARTIFICIAL INTELLIGENCE AND ONA: TRANSFORMING PROJECT MANAGEMENT PRACTICES

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Abstract: Organizational Network Analysis (ONA) examines communication patterns and interactions within organizations to identify key individuals, optimize knowledge flow, and boost performance. Based on Social Network Analysis (SNA) concepts like centrality, weak ties, and structural holes, the study uncovers hidden relational structures essential to success. Objectives include identifying key employees, detecting bottlenecks, supporting leadership development, and enhancing project management. A mixed-method approach integrates quantitative data from digital communication records with qualitative organizational interviews. Tools such as Neo4j, Gephi, and a custom console application streamlined data processing. The research advances project management by embedding ONA methods, offering AI-driven real-time insights and predictive capabilities. Practical contributions include tools for monitoring workloads, fostering collaboration, promoting innovation, and improving management effectiveness.

Keywords: Organizational Network Analysis (ONA); Social Network Analysis (SNA); Project management; Network clustering; Employee collaboration; Organizational performance.

1. INTRODUCTION

In an era where organizations increasingly rely on collaboration across departments and teams to drive innovation and performance, understanding internal communication networks has become essential. Organizational Network Analysis (ONA) offers a sophisticated approach to uncovering the relational structures that support organizational success. By analyzing how individuals and teams interact, ONA helps identify key personnel, optimize knowledge flow, and improve both strategic decision-making and project execution (Cross & Parker, 2021).

ONA builds upon key principles of Social Network Analysis (SNA). Foundational concepts such as centrality (Freeman, 1978), weak ties (Granovetter, 1973), and structural holes (Burt, 1992) are integral to understanding how influence, communication, and collaboration operate within organizations. Centrality metrics enable the identification of influential employees who maintain efficient communication networks, while weak ties provide access to novel information and diverse perspectives, often crucial for fostering innovation (Granovetter & Burt, 2022). Burt's concept of structural holes highlights how individuals or teams positioned as brokers between disconnected groups can facilitate knowledge transfer and organizational agility (Burt, 1992).

Tools such as Neo4j and Gephi support large-scale data storage and visualization, while AI-powered solutions enable real-time insights and predictive analytics (Lee & Park, 2023). For example, AI algorithms can dynamically

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monitor workload distribution and predict employee turnover risks, enabling timely interventions (Chen & Wu, 2023). These innovations make ONA a powerful strategic tool for human resource management, project coordination, and organizational development (Johnson & Patel, 2023).

The analysis of communication records and other digital interactions must adhere to strict data protection standards such as the General Data Protection Regulation (GDPR). Ethical concerns related to transparency, consent, and employee trust must be addressed to ensure the sustainable use of these technologies (Carter & McKinley, 2022; Nguyen & Chen, 2023).

This research contributes to both scientific and organizational practice. From a scientific perspective, the study advances the theoretical understanding of network dynamics within organizations by integrating SNA and ONA concepts with AI-driven methodologies. It extends the application of established theories - such as centrality and weak ties - by demonstrating their relevance to real-time organizational decision-making in project management. Furthermore, it introduces a methodological framework for dynamic network analysis, which bridges traditional SNA metrics with predictive modeling capabilities. From a practical perspective, the research offers organizations tools to enhance their performance management and project execution.

2. LITERATURE REVIEW AND BACKGROUND

The study of ONA has its roots in Social Network Analysis (SNA), which investigates how individuals within a network connect and interact (Scott, 2017). SNA uses graph theory as its mathematical foundation, where individuals are represented as nodes and their relationships as edges (Freeman, 1978). The development of network analysis progressed through the 20th century, with key contributions from researchers such as Moreno, who introduced sociograms to visualize social interactions (Moreno, 1934). The concept of centrality emerged as a crucial metric in network analysis, helping to identify influential individuals within a network. Granovetter's concept of the strength of weak ties revolutionized network theory by showing how less frequent but more diverse connections could foster innovation and access to new information (Granovetter, 1973). Burt's theory of structural holes further emphasized the strategic advantages gained by individuals who bridge disconnected clusters within a network (Burt, 1992). These theories have proven fundamental in understanding how information spreads.

Cross and Parker (2021) examines the impact of social networks on organizational innovation and efficiency. The authors emphasize the role of bridging structural holes and fostering diverse connections to drive innovation and knowledge transfer. The study done by Granovetter and Burt (2022) explores how weak ties contribute to organizational flexibility and innovation. The authors provide empirical evidence from longitudinal studies showing that organizations leveraging weak ties outperform competitors in adaptability and innovation.

The principles of clustering and homophily have also been central to network analysis. Clustering occurs when nodes form tightly connected groups, enhancing trust and efficient communication (Watts & Strogatz, 1998). Homophily refers to the tendency of individuals to associate with others who share similar characteristics, fostering network stability but potentially limiting access to diverse perspectives (Scott, 2017). Borgatti and Halgin (2021) introduce innovative tools for visualizing and interpreting network data.

Wasserman and Faust (2020) research provides an exploration of SNA's theoretical foundations and applications. It discusses statistical models, graph theory, and data analysis techniques used to study organizational networks. Barabási (2021) explores the role of network theory in understanding success within organizations and individuals.

2.1 ONA Applications and Advancements with AI

Technological advancements have further advanced ONA by enabling large-scale data processing and network visualization. Tools such as Neo4j and Gephi have become

essential for network analysis, while artificial intelligence (AI) has introduced predictive modeling and real-time network adjustments (Watts & Strogatz, 1998). These advancements have expanded ONA's applicability, making it a strategic tool in organizational development and performance management.

ONA offers a wide range of applications in human resource management. It can be utilized for silo analysis (teams that do not communicate), diversity and inclusion analysis, predicting employee turnover risk, organizational development, talent management, communication analysis during and after mergers or acquisitions, workspace optimization, onboarding, promotions, knowledge management, identifying weak and high-performing teams, change management, and leadership development (Bersin, 2018).

Researches demonstrated that a bank used ONA to identify the causes of drastic performance differences between branches. This insight led to implementing changes that increased sales by 11% in underperforming branches (Garfield, 2018).

The research of Smith and Taylor (2022) explores the use of ONA to improve employee performance through better collaboration and knowledge sharing. By applying ONA in various case studies, the authors demonstrate how mapping communication patterns can identify key influencers and reduce silos within organizations.

Lee and Park (2023) analyze the role of artificial intelligence (AI) in advancing ONA. The paper discusses how AI-powered tools enable real-time monitoring and predictive analytics of organizational networks. The authors argue that combining AI with ONA enhances decision-making processes and improves organizational agility. Johnson and Rivera (2022) demonstrate how network metrics can reveal underrepresented groups and foster inclusive communication patterns. The research provides actionable recommendations for HR professionals to use ONA in designing interventions that promote equity and belonging. Chen and Wu (2023) present a novel approach to predicting team performance using network metrics and AI. Their research integrates ONA data with AI models to forecast team success across various industries. The results show that network centrality and density are key predictors of high-performing teams.

The global company Genpact analyzed communication patterns over several months using message metadata (information about messages, not their content). The analysis statistically demonstrated that specific communication behaviors directly correlate with business performance. By leveraging employee communication data and deep learning models, Genpact accurately identified high-performing employees or "rising stars" with 74% precision, based on their activity in email, Slack, Skype, and other communication channels (Bersin, 2018).

2.2 Ethical considerations

Transparency, consent, and secure data handling are essential to maintaining trust and ensuring compliance with legal frameworks (Scott, 2017). Carter and McKinley (2022) explore the ethical challenges of implementing ONA in workplace settings, particularly regarding employee monitoring. They discuss the importance of transparency and informed consent when collecting and analyzing communication data.

Nguyen and Chen (2023) examine privacy risks associated with ONA, particularly in the context of compliance with regulations like GDPR. The research provides practical recommendations for anonymizing data and securing sensitive employee information.

Harris and Johnson (2022) focus on how organizations can build employee trust when implementing ONA. They argue that transparency and clear communication about data collection and usage are critical to gaining employee buy-in. The research provided by Lee and Zhang (2023) discusses the ethical dilemmas that arise from combining AI with ONA. They analyze scenarios where predictive models could unintentionally reinforce biases or invade employee privacy.

The paper of Brown and Wilson (2022) addressing employee concerns about ONA.

They argue that early engagement with employees, clear communication, and robust data protection measures are essential for mitigating resistance.

2.3 ONA and project management

Johnson and Patel (2023) explore the dynamic nature of networks in project-based organizations, focusing on the use of ONA to improve coordination and decision-making. The paper highlights how ONA identifies network bottlenecks and enhances cross-functional collaboration. The authors provide case studies demonstrating how organizations have used ONA to accelerate project delivery timelines and improve stakeholder engagement.

Davis and Carter (2022) emphasize how ONA helps project managers identify key team members who facilitate communication and collaboration. By analyzing network structures, the authors show how project performance can be optimized through better resource allocation and conflict resolution. Practical examples highlight ONA's role in enhancing project success rates.

Taylor and Wilson (2022) demonstrate how ONA metrics like betweenness and closeness centrality improve team efficiency and information flow in agile environments. The paper provides actionable insights into how project managers can use ONA to build adaptive and resilient teams, ensuring faster response to project changes.

Chen and Zhang (2023) analyze how ONA helps project managers identify key individuals within teams who influence project outcomes. By focusing on roles such as brokers and connectors, the study illustrates how these actors facilitate effective communication and coordination. The findings provide a framework for project managers to structure teams strategically to maximize success. High out-degree centrality often contributes to better project performance, as team members initiating communication help resolve issues faster and improve activity coordination (Toomey, 2012).

Miller and Adams (2022) highlight how ONA reveals communication patterns and collaboration gaps in virtual teams. Their findings demonstrate the importance of leveraging ONA to build cohesive and productive teams across geographic locations. The paper examines the use of ONA in managing distributed project teams, particularly in remote work scenarios.

Virtual teams are rapidly emerging across various sectors and geographic regions, further accelerating progress. It is crucial for leaders to empower teams to deliver projects while giving them autonomy to decide how to achieve this. Leaders must assemble the best people for the job—those motivated and inspired by clients rather than managers - fostering psychological safety and collective commitment to shared goals and excellent, innovative outcomes (Fisk, 2021).

3. METHODOLOGY

3.1 SNA and graph theory

Key theoretical foundations include graph theory. Graph theory provides a mathematical framework for representing networks through nodes (representing individuals or entities) and edges (representing relationships or interactions). These theoretical foundations enable Social Network Analysis (SNA) using formal methods and algorithms, contributing to the understanding of the organization and functioning of social networks in real-world conditions. A graph is an abstract mathematical concept that depicts relationships and connections between objects. It contains nodes and edges between those nodes, which can be either directed or undirected. A simple graph G consists of a non-empty set V, called the vertices (or nodes) of G, and a set E of two-element subsets of V. Members of E are called edges (connections) of G, and it is written as G= (V, E) (Lehman, Thomson Leighton & Meyer, 2010).

To operationalize the research, key concepts from SNA were applied, including centrality measures, clustering, structural holes, and weak ties. The methodological approach also integrates Granovetter’s theory of weak ties, emphasizing how indirect connections foster access to novel information and opportunities (Granovetter, 1973). Burt’s structural holes theory highlights the strategic advantage of occupying network positions that bridge

disconnected clusters, granting greater access to diverse resources (Burt, 1992). Additionally, concepts such as clustering and homophily were considered to explore how tightly connected groups and similar individuals form cohesive sub-networks (Watts & Strogatz, 1998).

3.2 Data collection and analytical process

Primary data was gathered through structured surveys and digital communication records, while qualitative insights were obtained from organizational interviews. Data Collection Process is as follows in Figure 1.

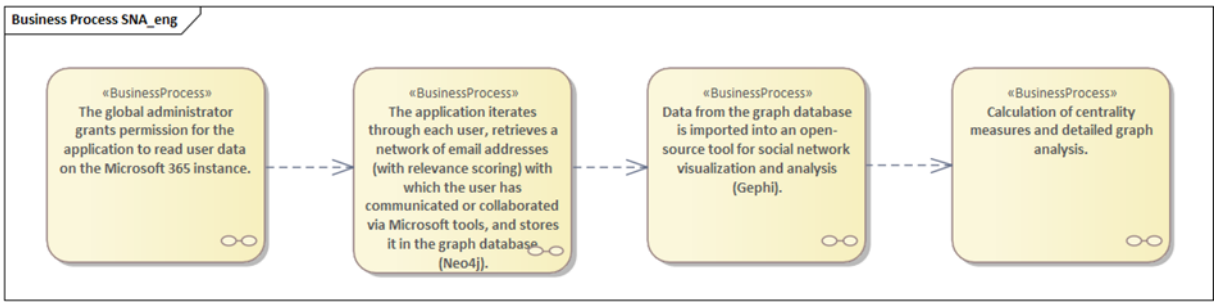

Figure 1: Data collection process (BPMN annotation)

Before being stored in the graph database, the data undergoes a processing phase, shown in Figure 2.

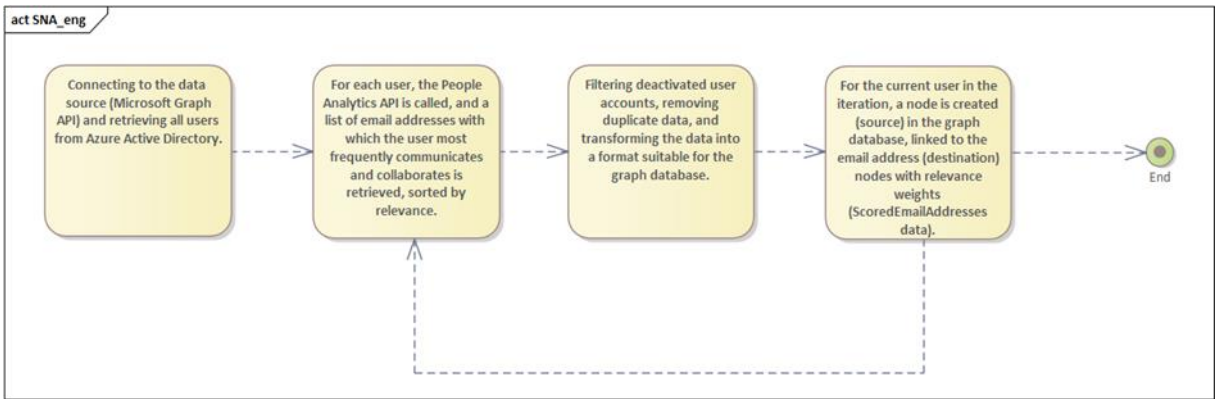

Figure 2: Logic execution flowchart for data retrieval and transformation in a .NET application

The data is then stored in the Neo4j graph database. A console application that collects all the necessary information for creating a social network was developed using open-source .NET technology.

Figure 3 represents the main command that saves data into the Neo4j graph database.

```
MERGE (source_p:Person {address: $sourcePersonEmail, isExternal: $sourceIsExternal,
jobTitle: $sourcePersonJobTitle, department: $sourcePersonDepartment })

MERGE (target_p:Person {address: $targetPersonEmail, isExternal: $targetIsExternal,
jobTitle: $targetPersonJobTitle, department: $targetPersonDepartment})

MERGE(source_p)-[r:KNOWS {relevance: $relevance}]->(target_p)
```

Figure 3: Command for setting a relationship (with weight) between two nodes in the network

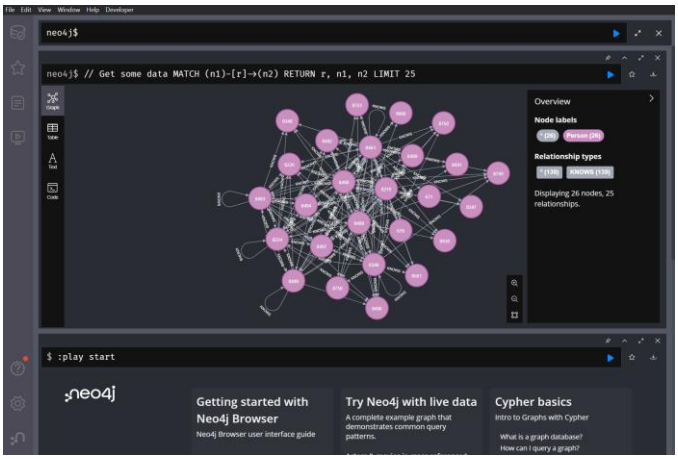

Figure 4: View of the Neo4j database interface where node and connection data are stored

Neo4j (Figure 4) is a graph database known for its ability to model, store, and analyze connected data in a more natural and efficient way compared to traditional relational databases.

For visualizing the organizational network and performing statistical calculations for Social Network Analysis (SNA), Gephi is used.

3.3 AI assistant development

As part of this study, an AI assistant based on the ChatGPT-4 model was developed to facilitate decision-making within business organizations. The AI assistant uses data on nodes and their centrality measures, exported from Gephi, to provide managers and human resource professionals with quick and easy access to key information about the structure and dynamics of the organizational network.

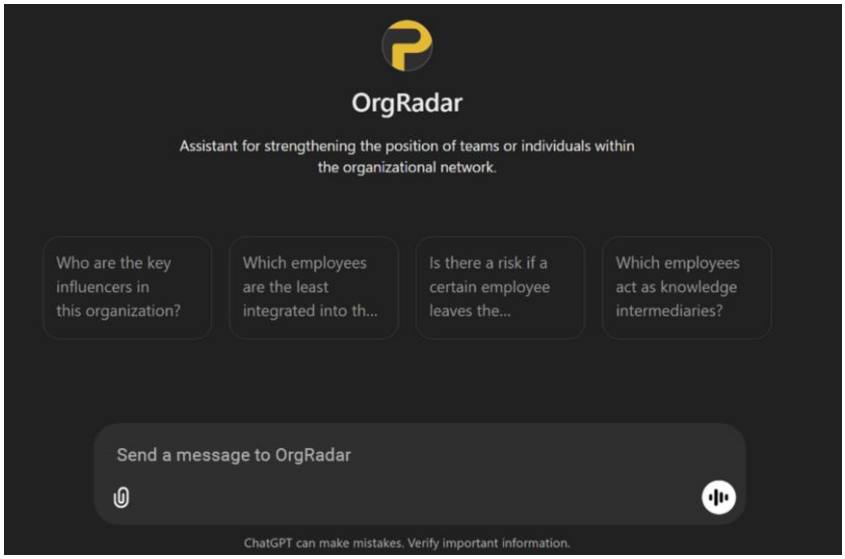

Figure 5: Interface of the developed AI assistant

Figure 5 illustrates the interface of the AI assistant designed to analyze and interpret organizational network data. The assistant identifies key individuals influencing communication flows, knowledge intermediaries, and employees who are the least integrated within the network.

The business purpose of this AI assistant is to provide insights into organizational dynamics, identify risks associated with potential employee turnover, and support efforts to strengthen the position of teams or individuals. By leveraging these insights, managers can effectively plan and implement human

resource management strategies, relying on objective and reliable data analyzed by the AI assistant.

4. CASE DESCRIPTION AND RESULTS

4.1 Case and analysis description

The analysis presented in this paper is based on the example of an IT company facing challenges in strengthening its organizational culture and gaining a comprehensive overview of the level of collaboration among individuals.

The first analysis focuses on the organizational network, which is limited to internal communication between employees and concentrates on the internal structure and flow of information. The second analysis includes external collaborators, partners, and industry members with whom the company works.

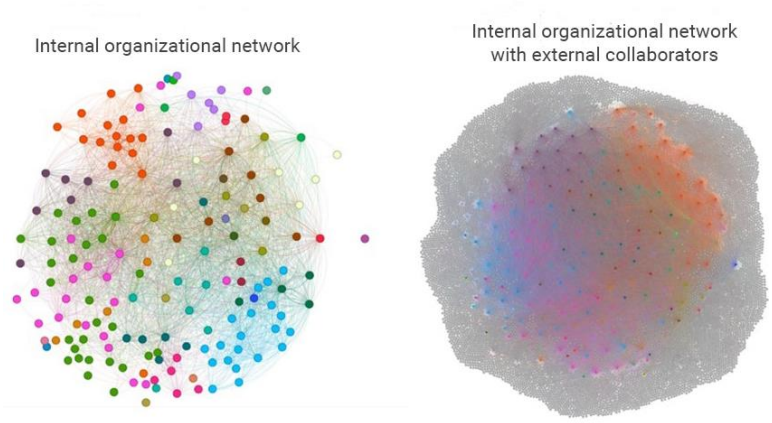

Figure 6: Internal organizational network (left) and a network where nodes are connected to external collaborators (right).

The first network (Figure 6 left) refers to communication and collaboration among employees within the observed organization, where the color of the node represents the organizational unit to which they formally belong. The network on the right illustrates internal communication and collaboration among employees, as well as communication between employees and external collaborators and partners outside the organization. Both networks are of a directed type, meaning that the connections between nodes have a clearly defined direction, allowing for the observation of asymmetrical dynamics of relationships.

4.2 Results

The basic data presented in Table 1 indicate that the internal network encompasses only 2% of the nodes in the network that includes external collaborators, which means that employees have significant external collaboration.

Table 1: Basic data of the internal network and the network with added external collaborators

Attribute	Internal organizational network	Internal organizational network with external collaborators
Number of nodes	165	8187
Number of edges	5067	40 295
Network type	directed	directed
Attribute for node color	organizational unit	organizational unit
Network diameter	4	4
Network density	0,187	0,001
Average path length	1,886	2,125

A network that includes external collaborators has an average path length of 2.125, meaning that, on average, any node in the network can reach any other node in the network through

two individuals. While this indicates good network connectivity, caution is necessary when drawing such a conclusion, especially if certain paths are heavily reliant on one or more nodes that facilitate the connection. This is indicated by the extremely low network density value (0.001), which quantifies the level of connectivity among nodes within the network relative to the total possible number of connections. The internal network has an average path length of 1.886, meaning that, on average, any node can reach any other node in the network through slightly less than two individuals. The density of the internal network is 0.187, indicating that it is not overly connected but is more connected than the network with external collaborators.

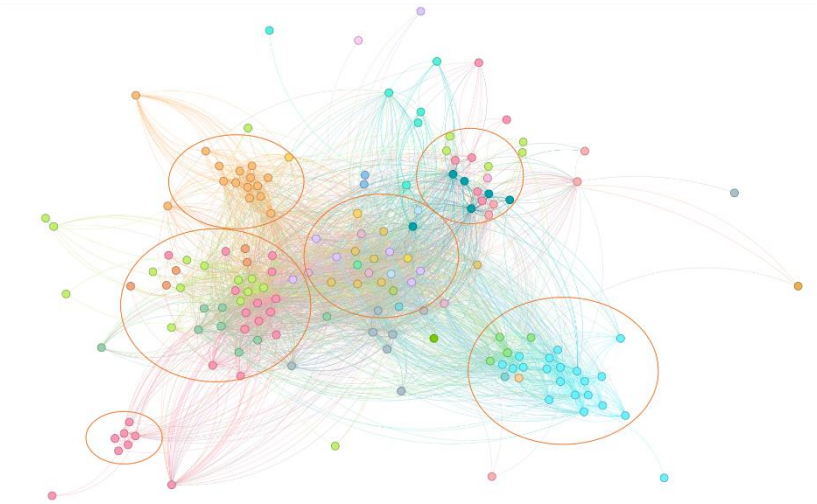

Figure 7: A representation of the labeled strong ties within an organization.

One of the important relationships in any organization concerns the collaboration between accounting, legal, and sales departments. Figure 7 depicts this connection with a central circle, symbolizing the frequent and strong interaction between employees from these departments.

It can be concluded that accounting, legal, and sales departments are naturally interconnected due to their roles in ensuring basic business activities, while teams working on different products are often isolated due to the specific tasks they perform. Figure 8 shows nodes representing individuals whose weighted degree centrality value is greater than three standard deviations, or whose value is greater than 2046.

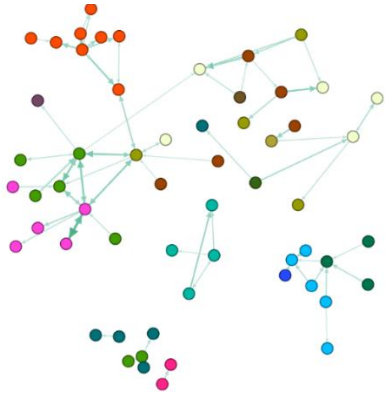

Figure 8: Display of individuals with strong ties.

These nodes represent employees who are very strongly connected to others within the organization. In this type of analysis, such individuals can be considered key employees

due to their role in maintaining the social network within the company. Strong ties indicate a high level of trust and collaboration among employees, which can reduce the risk of employee turnover (Burt, 2004).

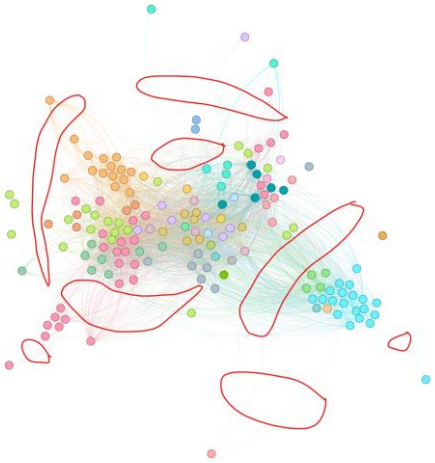

Figure 9: Representation of an organizational network with structural holes marked

Figure 9 illustrates the weak ties discovered that could serve as indicators for stimulating innovation.

Figure 10: A representation of prominent employees who have a strong prestige within the organization (dark green)

Figure 10 highlights employees based on two different prestige measures: in-degree prestige and rank prestige. The visual representation clearly shows that several of the same employees dominate both prestige measures. Identifying employees with high prestige within an organizational network helps recognize key figures who possess important information and can influence other members of the organization.

Figure 11: Highlighted nodes with highest betweenness centrality in the network

Figure 11 provides a visual representation of the employee network in the organization analyzed. The largest node in the center of the network indicates the employee who has the best position in the network.

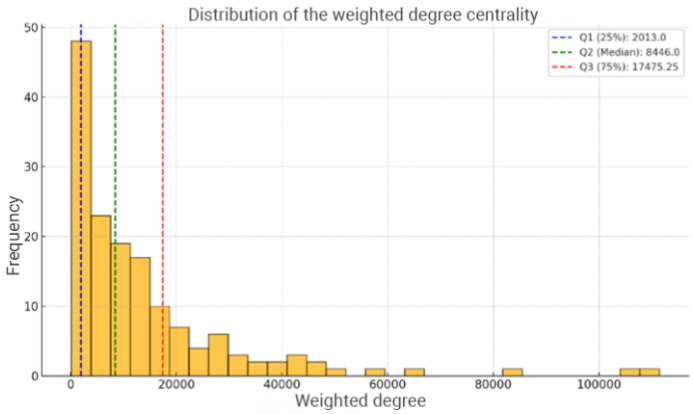

Figure 12: Distribution of the weighted degree centrality in the communication and collaboration network among employees.

An analysis of the distribution of weighted degree centrality values within the internal employee network, as shown in Figure 12, reveals a power-law distribution, characteristic of social networks.

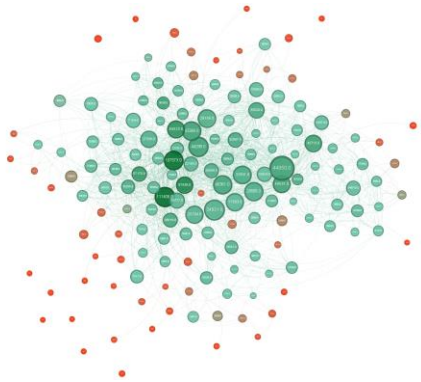

Figure 13: Employee network with highlighted weighted degree centrality

Figure 13 displays an employee network where central nodes are marked in dark green, and isolated ones, whose weighted degree centrality is within the first quartile, are marked in red. Such employees may possess specific information or technical knowledge, such as data work, software skills, or customer preference information, which they can transfer to other members of the network as needed.

4.3 AI Assistant

The business purpose of an AI assistant is to provide insights into organizational dynamics, identify risks associated with potential employee leaving, and support the strengthening of the positions of teams or individuals. In this way, managers can effectively plan and implement human resources management strategies, relying on objective and reliable data that the AI assistant analyzes.

For example, if a medium-sized IT company plans to introduce new technological tools to improve efficiency between its development and sales teams, the human resources manager can use an AI assistant to analyze the network of communication connections within the organization and identify influential employees within the development and sales teams and determine whether they act as knowledge brokers between departments. Based on this information, the manager can involve these employees in the initial phase of implementing

new tools because their role in the organizational network will enable a faster transition to the new system. In addition, the assistant can alert the manager to several employees who are less integrated within the network, allowing the manager to target them for training and adaptation programs. This reduces the risk of their exclusion or potential leaving.

Using an AI assistant allows managers to accurately select change ambassadors who will play a key role in implementing new technologies or strategies. These employees, as influencers within the network, can help overcome employee resistance, making the implementation of changes faster and more efficient.

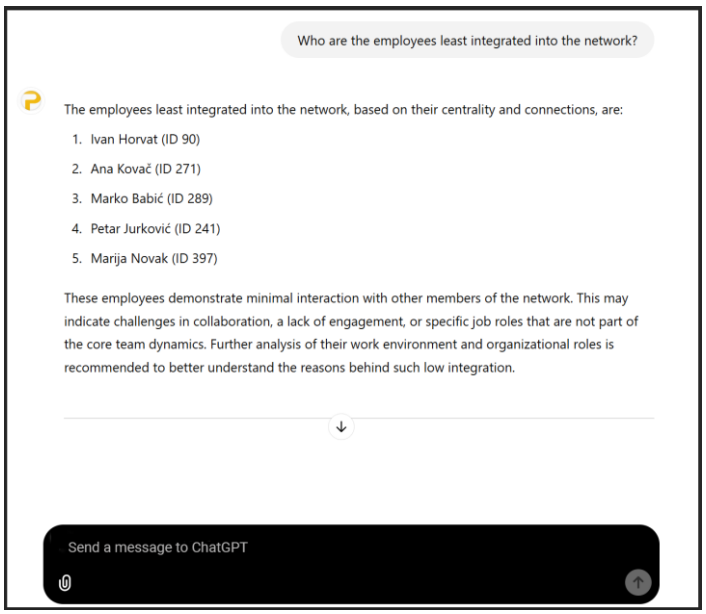

Figure 14: Example of communication with an AI Assistant

Figure 14 presents an example of communication between a user and an AI assistant specialized in analyzing organizational networks. The user poses a specific question to which the assistant responds by providing detailed data. The response includes a list of employees identified as the least integrated, along with their identification numbers and metrics that confirm this. The names are fictitious for illustrative purposes. Additionally, the assistant provides context for the answer, stating possible reasons for weaker integration, such as challenges in collaboration, lack of involvement, or structural positions that exclude them from the center of team dynamics. Beyond the basic answer, the assistant suggests further steps for the user, such as conducting a detailed analysis or implementing measures to improve employee integration. This example illustrates how the AI tool enables informed decision-making based on objective data, helping managers understand the dynamics within the organization and plan targeted interventions to increase team connectivity and efficiency.

5. DISCCUSSSION OF RESULTS AND FUTURE RESEARCH

This study contributes to the evolving field of ONA by demonstrating its practical and scientific value in improving organizational performance and project management. By leveraging foundational theories, such as centrality metrics (Freeman, 1978), weak ties (Granovetter, 1973), and structural holes (Burt, 1992), this research builds on existing literature while offering innovative extensions through AI-driven insights and real-time analytics.

The results support prior studies highlighting the importance of identifying central figures in an organization. As shown in the analysis, individuals with high betweenness and eigenvector centrality were pivotal in maintaining efficient communication flows.

These findings are consistent with Freeman's (1978) and Borgatti and Halgin's (2021) conclusions, which underscore the role of central actors in enhancing team cohesion and knowledge distribution. However, this research extends these insights by applying advanced AI algorithms, which enable predictive identification of critical individuals, thereby mitigating risks associated with employee leaving or overload in real-time.

Similarly, the identification of weak ties as channels for innovation aligns with the work of Granovetter (1973) and more recent empirical evidence provided by Granovetter and Burt (2022). The results show how less frequent but strategically valuable interactions across departmental boundaries foster diverse perspectives and innovation. The discovery of isolated teams within the organization reflects concerns raised in Johnson and Patel (2023) regarding network bottlenecks, emphasizing the need for proactive interventions to integrate marginal groups.

A unique contribution of this study lies in the integration of AI-powered tools for analyzing structural vulnerabilities, such as collaborative overload. Collaborative overload, where a few individuals carry an excessive share of the tasks of team coordination, was identified as a significant risk factor. This aligns with findings by Lee and Park (2023), who demonstrated the necessity of tools capable of dynamically assessing workload distribution.

Furthermore, the use of AI-driven visualization tools like Neo4j and Gephi allowed for the detailed mapping of internal and external networks. The ability to visualize connections between internal employees and external collaborators provides actionable insights into how organizations can optimize their external relationships while maintaining robust internal collaboration. This dual focus on internal and external networks sets this study apart from previous works, which often concentrate solely on internal dynamics (Chen & Wu, 2023).

The identification of knowledge brokers, or individuals who connect otherwise isolated groups, reinforces Burt's (1992) theory of structural holes. The results demonstrate how these brokers enhance the flow of critical information across the organization, ultimately supporting faster decision-making and innovation. This finding resonates with practical applications discussed in Davis and Carter (2022), where knowledge brokers were leveraged to resolve cross-departmental challenges in project management.

The study also validates the use of predictive analytics in ONA, an area previously identified as underdeveloped. For example, the ability to predict turnover risks based on network position represents a novel application of centrality metrics. This aligns with insights from Nguyen and Chen (2023).

In terms of cross-departmental collaboration, the results highlight critical interdependencies between departments such as sales, legal, and accounting.

The research also emphasizes the role of marginal employees, those with fewer connections in the network. While such employees are often overlooked, the findings suggest that they can play crucial roles as specialized experts or as potential areas for improvement through targeted engagement strategies. This understanding aligns with Harris and Johnson's (2022) work on the importance of inclusivity in network structures, while also providing actionable strategies for integrating those individuals into the organizational network.

By using AI to simulate network changes, such as the impact of losing a key employee, the research demonstrates how organizations can proactively adapt to potential disruptions. This dynamic approach extends beyond traditional static network analyses discussed in earlier studies, offering a forward-looking perspective that is essential for modern organizations operating in volatile environments.

From a practical perspective, the study equips managers with tools and methodologies to address common organizational challenges, such as siloed communication and inefficient resource allocation. For example, the AI assistant developed in this research enables managers to identify influencers and marginalized employees quickly, ensuring that interventions are timely and targeted. This capability aligns with calls for more practical

tools in ONA applications, as noted by Taylor and Wilson (2022).

From a scientific perspective, this study advances the theoretical understanding of ONA by applying complex network metrics through AI-enhanced tools. It bridges static and dynamic analyses, providing empirical evidence for the applicability of theories such as structural holes and weak ties in large-scale organizational settings. The research above all presents a new methodological framework on how to use organization data together with ONA to support better organization performance and project management execution.

Tools like the developed AI assistant enable managers to proactively mitigate risks associated with employee overload or turnover. These insights directly enhance organizational resilience, collaboration, and innovation. This is the key practical contribution of this study.

Related to limitation of this work, the data collection relied on digital communication records, which may not capture informal or face-to-face interactions crucial to network dynamics. Additionally, while the use of AI enhances analytical depth, the algorithms depend on the quality and scope of the input data, which might exclude certain network details.

Future research could expand on this work by exploring to include qualitative data from interviews or ethnographic observations to complement digital data analysis and capture informal dynamics more comprehensively.

Exploring deeper implications of data privacy and ethical AI usage in ONA, aligning with the concerns raised by Carter and McKinley (2022), and Nguyen and Chen (2023) regarding transparency and employee trust is a perspective that should be considered in future extension of this research. Possible extension of the research could be development of advanced AI algorithms to simulate and optimize network structures dynamically, enabling organizations to adapt more effectively to real-time challenges.

By addressing these areas, future research can build on this study's foundation to further advance both the theoretical and practical applications of ONA in modern organizational and project management contexts.

6. CONCLUSION

This study has successfully demonstrated the integration of Organizational Network Analysis (ONA) with advanced analytical tools and artificial intelligence, highlighting its scientific and practical contributions to organizational development and project management. By bridging gaps in the literature and operationalizing theoretical constructs such as centrality, weak ties, and structural holes, this research has provided a comprehensive framework for improving communication flows, collaboration, and strategic decision-making in modern organizations.

The scientific contributions of this study are twofold. First, it advances the theoretical understanding of organizational dynamics by incorporating AI-driven analytics, enabling organizations to move from static to dynamic network analyses. Second, it validates the applicability of network theories to large-scale organizational settings, offering methodological framework that supports their relevance in diverse operational contexts. The practical tools developed, including real-time network visualizations and predictive capabilities, provide organizations with actionable insights to address collaborative overload, retain key employees, and foster innovation.

From a practical perspective, the findings underscore the value of identifying key employees, understanding network structures, and mitigating risks associated with collaborative overload. The study equips project managers and organizational leaders with the tools and knowledge to optimize team composition, enhance cross-functional communication, and strengthen stakeholder relationships. Additionally, the ability to predict and address network vulnerabilities ensures resilience and adaptability in rapidly changing environments.

This research also opens new ways for leveraging ONA in project management. The integration of network analytics into project workflows facilitates improved resource allocation, risk mitigation, and innovation. Project managers can now address challenges such as communication silos and team isolation proactively, ensuring alignment with organizational goals.

This study provides a robust foundation for the continued exploration and application of ONA in organizational and project management contexts. By combining theoretical insights with practical methodologies, it gives the way for a more connected, collaborative, and efficient future in organizational operations and project execution.

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