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BEHAVIOURAL DATA MINING FOR ORGANIZATION NETWORKS: OPTIMIZING KNOWLEDGE SHARING AND COLLABORATION

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Purpose: This study utilizes behavioural data mining techniques to analyze knowledge sharing and cooperation dynamics within the organizational network. The article focuses on understanding network composition through employee digital interactions, analyzing communication patterns and factors affecting effectiveness, developing a predictive behavioral model, and proposing strategic data-driven recommendations for knowledge management. The article aims to enhance organizational understanding and strategic decision-making.
Design/methodology/approach: By utilizing a mixed-method approach, this study seeks to leverage behavioural data for improved insights and choices. The method uses digital data mining to extract conversational, informational, and knowledge-consuming patterns from organizational platforms. Key actors and structural barriers are then identified through creating and analyzing organizational knowledge networks using social network analysis. Digital footprints are used in this method to comprehend the corporate knowledge network. Knowledge management principles and social network theory are part of the theoretical framework.
Findings: The study seeks to uncover knowledge brokers and bottlenecks, uncover patterns of behaviours associated with successful information sharing, and provide guidance for adaptation techniques aimed at improving collaboration and knowledge sharing inside organizations. The results will guide suggestions for process improvement by offering a data-driven understanding of the behaviours, important participants, and roadblocks in the knowledge network.
Research limitations/implications: The research acknowledges the fundamental limitations of concentrating on digital data. It also identifies significant implications to further the field of knowledge management by offering a basis for data-driven strategies and proposing significant avenues for future study, such as addressing ethical concepts.
Practical implications: This study offers strategies and insights from examining existing digital activities. They are context-specific, encourage collaboration, and enable adjustments to technology for better business outcomes.
Social implications: The article estimates significant effects on society, including improved innovation, problem-solving, inclusive knowledge access within organizations, positive public perception indirectly, and better Corporate Social Responsibility practices related to environmental issues.
Originality/value: The study applies behavioural data mining techniques to organizational knowledge management, offering a new approach to optimizing knowledge networks. It provides empirical evidence for using data-driven insights to enhance knowledge sharing and cooperation. By integrating qualitative insights with behavioural data mining and network

analysis, it offers a comprehensive understanding of organizational knowledge networks. Additionally, it provides practical guidance for researchers and practitioners.
Keywords: Behavioral data mining, organizational networks, knowledge sharing, collaboration optimization, social network analysis, machine learning.
Category of paper: Literature study publication.

1. Introduction

In the competitive landscape of the twenty-first century, according to Grant (2021), knowledge is a crucial asset for businesses, shifting from traditional structured processes to more informal communication methods due to digital tools and remote work. Behavioural data, generated through individual interactions, plays a vital role in enhancing knowledge-sharing practices within organizations (Alavi, Leidner, 2001). This data includes: email logs, instant messages, collaborative documents, and other forms of communication within the organization. Analyzing this data allows for the identification of hidden patterns and dynamics in knowledge flow, providing organizations with insights that were previously difficult to capture.

The research motif lies in the interest of understudying the increasing use of digital communication tools that generate vast amounts of behavioral data, often untapped for optimizing organizational performance. Despite the abundance of information, organizations struggle to use this data effectively to enhance collaboration and knowledge sharing. As organizations become more dependent on digital tools and networks, it is crucial to understand how these tools facilitate or hinder knowledge exchange. This study explores how data mining can enhance knowledge-sharing practices within organizations and predict outcomes of collaborative efforts, addressing a gap in the existing literature on these topics. The findings could significantly benefit organizations that utilize digital communication tools like email, Slack, and Microsoft Teams for internal collaboration. The study analyzes data from these platforms to identify temporal trends and behavioral patterns within the organization. The scope of this study is limited to internal organizational networks and does not address external collaboration (such as interactions between organizations or with customers). The findings will be contextualized to the tools and platforms used within the organizations under investigation.

1.1. Importance of Knowledge Sharing in Organizations

Effective knowledge sharing enhances collaboration, problem-solving, and decision-making among employees, which in turn boosts an organization's collective intelligence and innovation. This is essential for businesses aiming to remain creative and competitive in a rapidly evolving global landscape. (Nonaka, Takeuchi, 1996). Knowledge sharing can occur in both formal and informal settings within organizations. Formal mechanisms of knowledge sharing according to Davenport & Prusak (1998), include structured processes such as: training programs, workshops, and knowledge management systems (KMS), where knowledge is deliberately transferred between individuals or groups Informal knowledge sharing, however, often happens through casual conversations, emails, and social interactions among employees. Informal networks are often more effective in facilitating knowledge exchange compared to formal ones. According to Muhammed & Zaim (2020), informal interactions in the workplace foster a comfortable atmosphere for employees to share valuable insights that aid in problem-solving and creativity. As also illustrated in Figure 1, effective information sharing relies on company culture, trust, and social dynamics, as employees are more inclined to contribute when they feel valued and supported, unlike in competitive or privacy-focused environments.

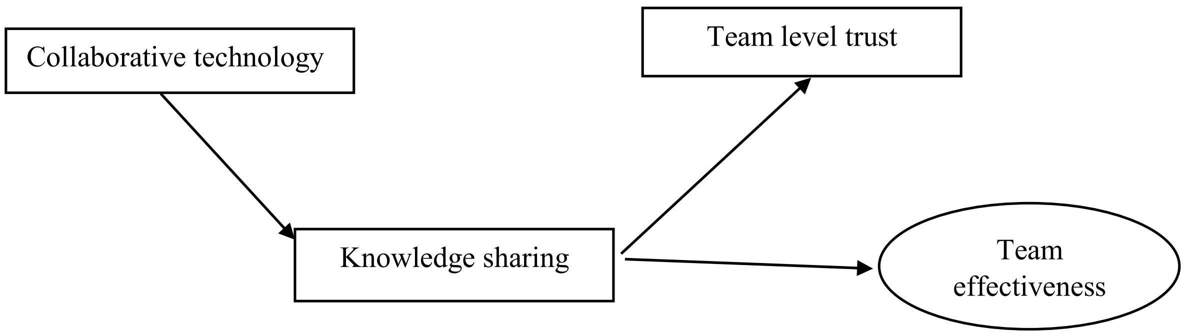

Figure 1. Illustration of the preliminary virtual team effectiveness: The role of knowledge sharing and trust in an organization.

Source: (illustration by the author based on Alsharo et al., 2017).

Digital technology has transformed the sharing of both formal and informal information through tools like email and collaboration platforms, enhancing communication and increasing the volume of behavioral data in organizations, as opined by McAfee et al. (2012). This shift is crucial for organizational performance, innovation, and learning. In summary, the importance of knowledge sharing in organizations cannot be overstated. It is integral to organizational learning, performance, and innovation. As organizations continue to adopt digital communication tools, understanding how knowledge flows within these networks and how it can be optimized using behavioral data mining is becoming a central research priority.

1.1.1. Organizational Knowledge Sharing

Effective knowledge management is crucial for businesses navigating a competitive landscape, with knowledge sharing occurring through explicit and tacit forms. While explicit knowledge is easily documented, tacit knowledge, which is more personal and complex, has been shown to significantly enhance innovation and problem-solving within organizations. (Nonaka, Takeuchi, 1996). Figure 2 breaks down the knowledge process of tacit and explicit knowledge on organizational impacts, given that research by Grant (2021) has shown that tacit knowledge sharing is often more valuable for organizations, driving innovation and enhancing problem-solving capabilities. However, its intangible nature makes it difficult for organizations to formalize and disseminate effectively.

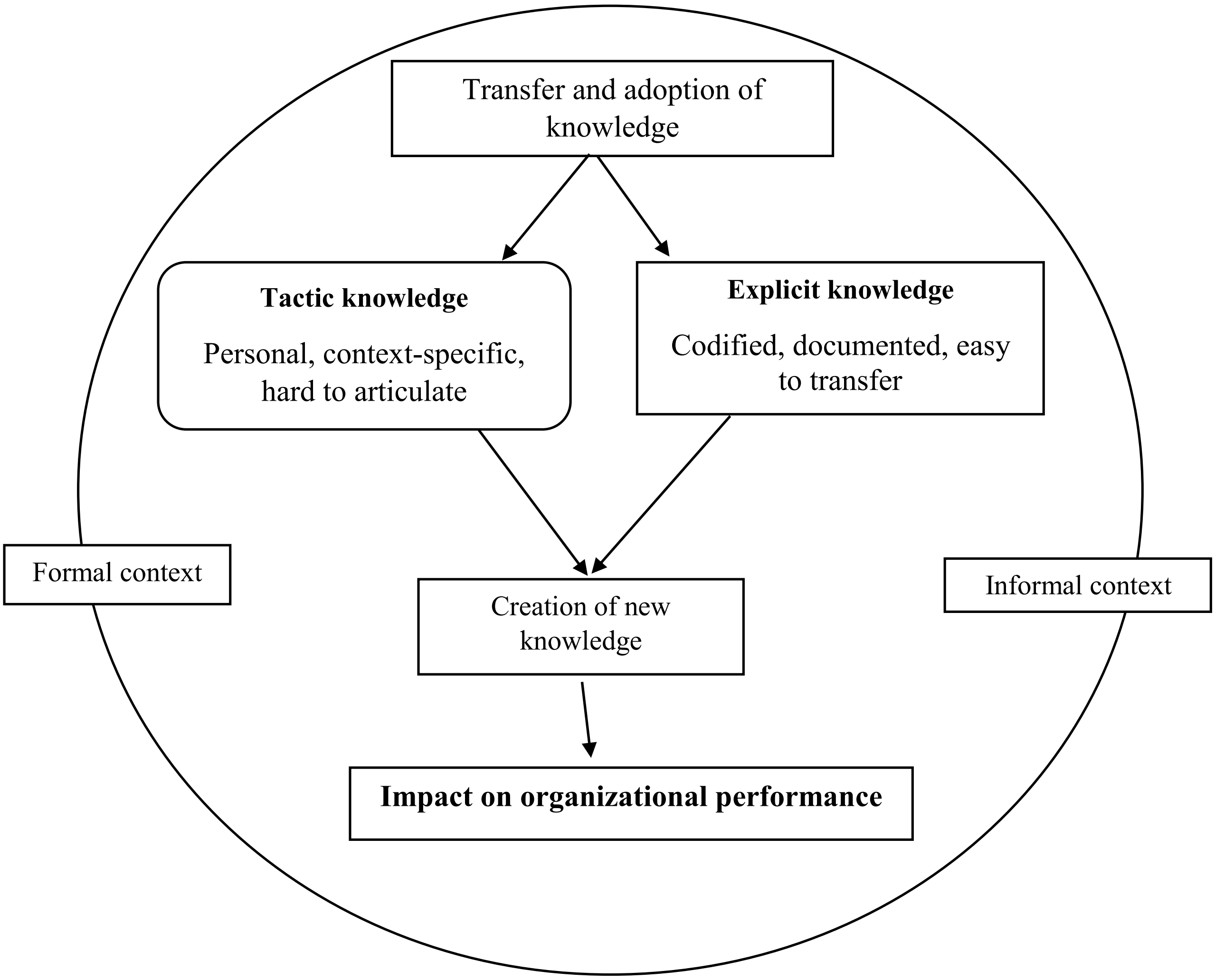

Figure 2. Knowledge processes of tacit and explicit knowledge.

Source: (Illustration by the author, 2025).

The performance of an organization is directly impacted by the efficient exchange of knowledge. Effective knowledge-sharing procedures enhance innovation, productivity, and decision-making in organizations, as highlighted by Muhammad and Zaim (2020). However, as Figure 3 also illustrates, the process is complex and influenced by factors such as organizational culture, beliefs, and available technology, with research indicating its link to increased market share and consumer satisfaction (Davenport, Prusak, 1998).

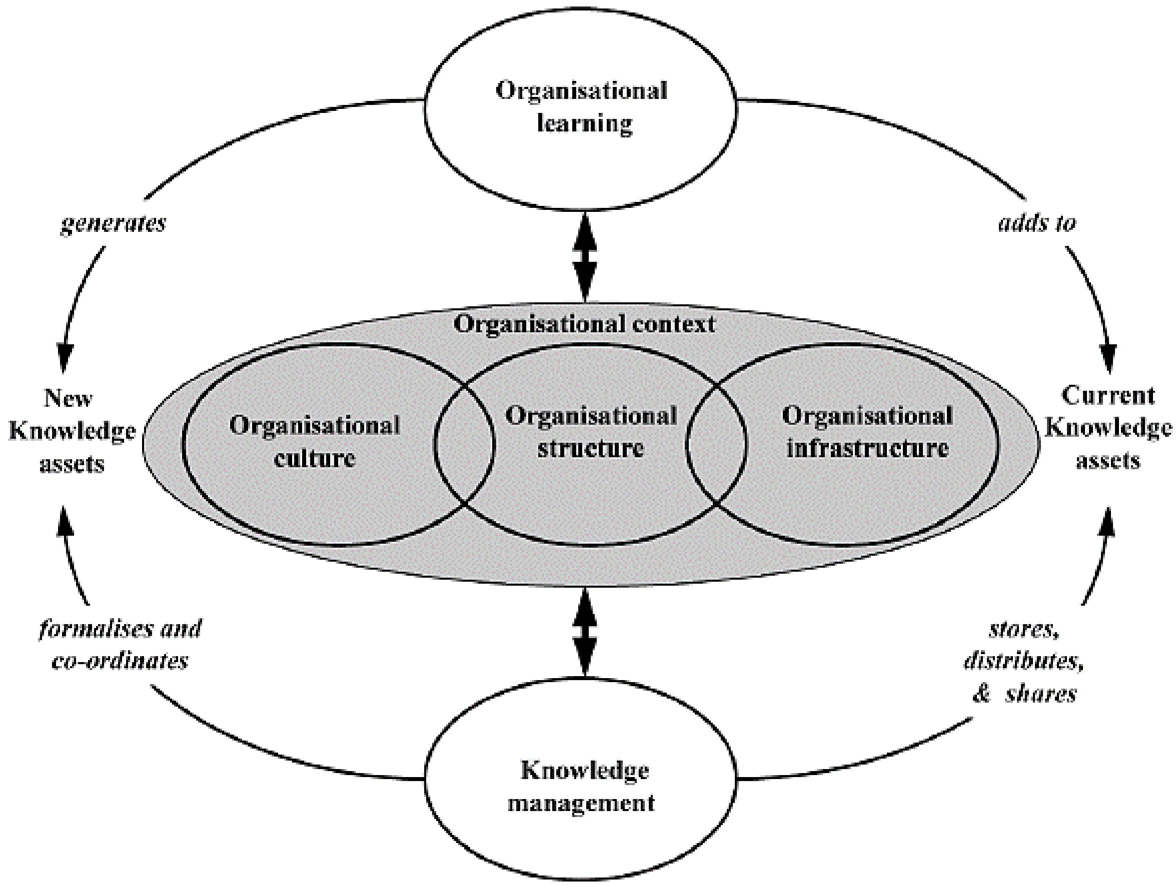

Figure 3. The relationship between organizational learning and knowledge management.
Source: (illustration by the author based on Stonehouse and Pemberton, 2000).

1.2. Collaboration Networks and Social Capital

Collaboration networks in organizations enhance the sharing of skills and expertise by leveraging social capital, which Table 1 highlights, which also includes trust and information access, to facilitate effective collaboration and innovation (Nahapiet, Ghosal, 1988; Garcia-Sanchez et al., 2019). Recent studies by Reus et al. (2023) indicate that individuals in brokerage positions within these networks are more adept at improving the quality of information shared by bridging instructional gaps.

Table 1.
Forms of social capital and their influence on knowledge sharing

Dimension of social capital	Definition	Influence on knowledge sharing
Structural	Network ties and patterns of connection	Provides access to diverse knowledge sources
Relational	Trust and norms among members	Encourages open sharing and reduces knowledge hoarding
Cognitive	Shared language, goals, and mental models	Enhances understanding and relevance of shared knowledge

Source: (table by the author, 2025).

Remote individuals within a network may struggle with communication, hindering innovation, which highlights the need for an inclusive environment that encourages collaboration. As highlighted by Lee & Han (2024), a learning-oriented culture, combined with strong social capital, enhances knowledge sharing and overall organizational performance by fostering mutuality and shared goals. Behavioural data knowledge management (BDKM) emphasizes the importance of behavioral data, like interactions and decision-making patterns, in understanding and improving knowledge management within organizations. By analyzing how information flows through formal and informal networks, BDKM helps streamline knowledge sharing and enhances organizational efficiency.

Formal roles in the organizational hierarchy, managers, supervisors, and department leads, play a central role in decision-making and directing knowledge flow, as depicted in Figure 4. Guo et al. (2023), confirms informal roles, such as connectors, influencers, and knowledge brokers, often emerge based on individual actions, interactions, and personal networks these individuals may not have formal authority, but their behavior and interaction patterns allow them to facilitate or hinder knowledge sharing within the organization. Organizations can leverage behavioral data analysis to identify key players in their collaboration networks and uncover knowledge gaps. By examining interaction patterns, they can enhance data sharing practices and promote effective knowledge exchange among staff.

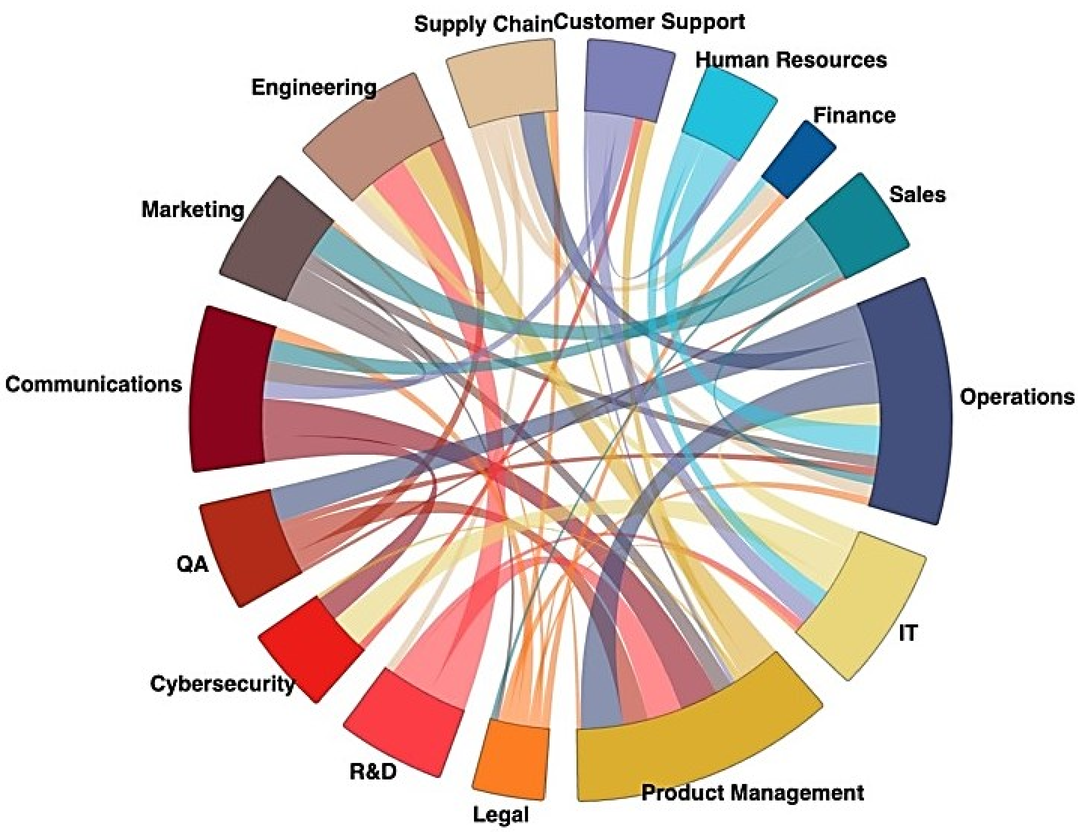

Figure 4. Illustration of the dynamics of organizational hierarchy collaboration networks.
Source: The Organizational Network Analysis (ONA) diagrams (2025).

Behavioural data can help improve organizational collaboration by identifying gaps in knowledge exchange and assessing the effects of information sharing on decision-making. Guo et al. (2023). Helms & Buijsrogge (2006) opined those inefficiencies in information flow often led to problems in cooperation networks, particularly when gatekeepers become overwhelmed, hindering effective knowledge sharing. By analyzing information flow and identifying delays, organizations can pinpoint overworked employees and assess their role in key interactions, as well as detect barriers to knowledge sharing stemming from both structural and behavioral factors. This approach helps in improving knowledge management by addressing obstacles that hinder effective collaboration. Using behavioral data analysis, organizations can take proactive steps to address these bottlenecks by redistributing knowledge flows or by encouraging behaviors that foster collaboration and efficient information transfer, as highlighted by Borgatti & Halgin (2020).

1.3. Behavioral Data in Organizational Settings

Behavioral data refers to the information about roles, interactions, and communication within an organization, largely generated by digital technologies. Analyzing this data can reveal communication patterns and challenges, highlighting issues like isolated individuals in the network that may hinder information sharing according to Wang et al. (2019). Understanding the emotional tone of communication is essential for predicting team cooperation and outcomes, as positive emotions often lead to higher engagement and better teamwork. Teams that communicate positively tend to perform better since members are more likely to rely on each other and collaborate effectively, as Figure 5 shows a clear flow of the behavioural data mining process, highlighting key areas and interchanges.

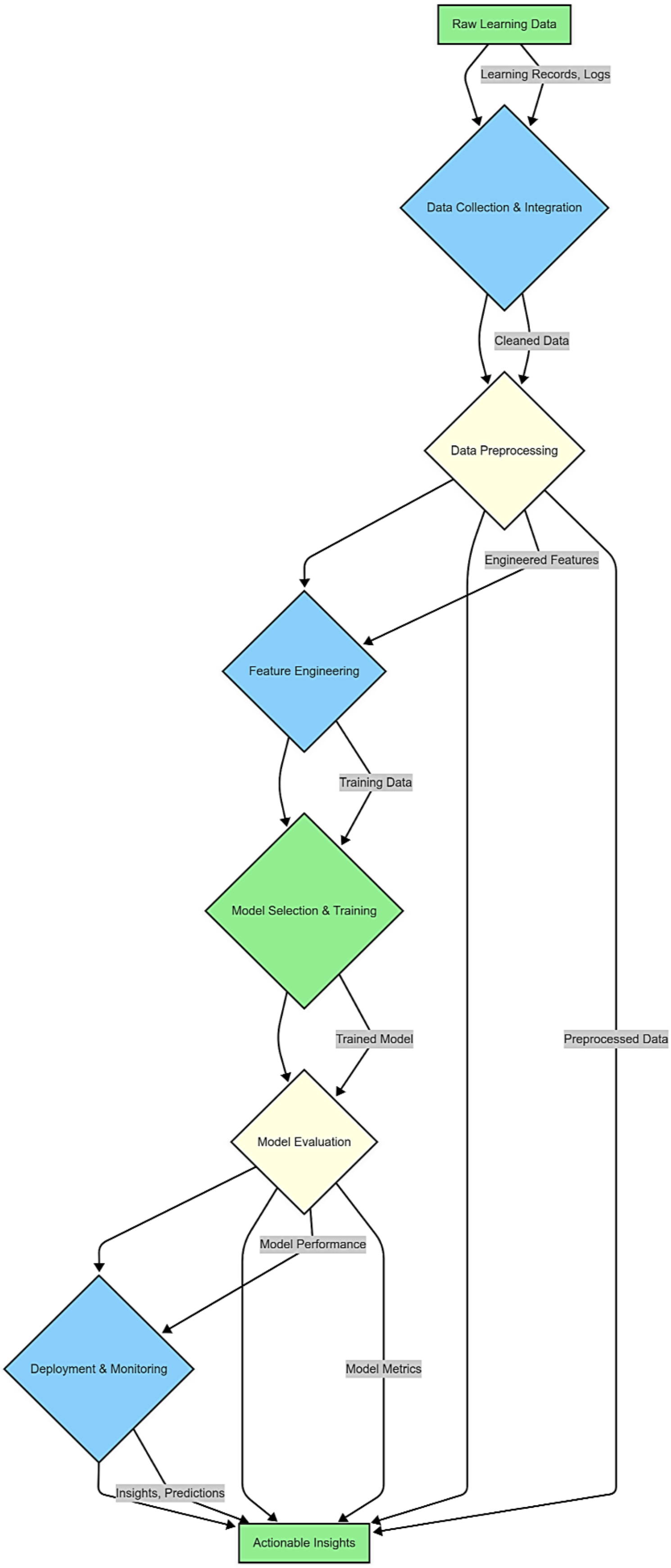

Figure 5. A behavioral data mining and processing flowchart.

Source: (illustrated by the author, 2025).

As described in Table 2, the various behavioural data types can be utilized to better understand and enhance knowledge sharing within an organization. These data types are derived from employee interactions. It classifies the information, explains its meaning, and discusses how it might be used in a knowledge-sharing setting.

Table 2.
Types of behavioral data and their use in organizational research

Type of behavioral data	Description	Application in knowledge sharing
Communication patterns	Frequency and channels of communication (e.g., email, meetings, instant messages)	Identify key influencers, and collaboration bottlenecks
Response times	Time taken for individuals to respond to messages or requests	Assess the responsiveness of teams and departments
Sentiment	Emotional tone of communication	Predict collaboration success, improve team dynamics

Source: (table by the author, 2025).

2. Methodology

The study employs a mixed-method approach to strengthen the validity and reliability of the findings using the data triangulation covered in subsequent subcategories.

2.1. Research Design and Strategy

A discovery sequence mixed-method design was utilized to collect and analyze quantitative data. The quantitative phase involves behavioural data analysis from digital platforms to map and examine the organizational knowledge network's structure via social network analysis. To understand subject experiences better, a more comprehensive insight into the study problem was undertaken.

2.1.1. Data Sources

Quantitative data for the study was gathered from various digital platforms used within organizations, including email logs showing communication patterns, project management tools like Asana and JIRA for task details and collaboration insights, and associate platforms like Slack and Microsoft Teams for channel usage and information flow. SharePoint, Confluence, and similar systems offer insights on document usage, changes, sharing, and contributions, showing the utilization of formal knowledge assets.

2.1.2. Data Collection

The following data were gathered for the study:

Digital interaction data: This covered how often and how strongly people interacted with one another on different digital platforms. The encounter was recorded using this "pre-physical behavior data" before any in-person contacts.

Communication pattern: Data on people's digital communication methods showed their distinct conversational philosophies.

Emotional ratings: Information on emotional indicators or feelings was gathered via online conversations.

Network Matrix: Information was gathered to create a matrix that included the digital interaction network's structure and features, including the degree of interpersonal connection.

Historical behavior data: To serve as a foundation for forecast model training, a broad collection of historical behavior data was gathered.

Collecting data meticulously was essential to understanding collaborative dynamics within the organizational knowledge network.

2.1.3. Data Processing and Analysis

The analysis of the data acquired followed a comprehensive multi-step procedure, principally making use of the methods of supervised machine learning to generate actionable insights.

1. **Data Preprocessing and Feature Engineering:** Initially, raw digital interaction data was preprocessed, converting communication logs into structured data. Network metrics such as centrality, density, and clustering coefficients were then calculated, providing insights into the organizational knowledge network structure. Communication patterns, volume, and emotional ratings were assessed to create features for future machine learning models.
2. **Defining Outcome Variables:** The study established outcome factors to predict team performance, including quantitative measures like project success, efficiency metrics, and performance ratings. Factors such as onboarding speed and technology adoption rates were used to assess knowledge transfer effectiveness, forming the "ground truth" for supervised learning.
3. **Supervised Machine Learning Model Training:** Various supervised machine learning techniques were used for model training with finalized features and predetermined outcome variables. The training involved providing historical behavioral data and engineering facilities to teach algorithms the complex relationships between digital contacts, communication styles, emotional phases, and real team performance or knowledge transfer outcomes. Regression and classification models were employed to predict both continuous outcomes, such as a display score, and categorized outcomes, such as team performance or knowledge transfer success.
4. **Feature Selection Techniques:** The model's effectiveness was enhanced by carefully selecting the most relevant traits from various network measurements and emotional assessments, reducing noise and preventing overfitting to ensure focus on significant behavior indicators.

5. **Model Performance Evaluation:** The metrics assessed the performance and dependability of trained models, mainly through accuracy and misses. Misses were crucial when all instances of a specific outcome mattered. These evaluations ensured the models' robust future-predicting abilities before their deployment.

The processing of the data showcased supervised machine learning in action, emphasizing meticulous analytical methods. It illustrates the creation of network measurements and emotional evaluations from raw digital interaction data, and also establishes outcomes for knowledge transfer and team performance, while training regression and classification models.

3. Findings

3.1. Behavioural Data Mining Models

This section explains the data mining models developed to analyze the organizational knowledge network. These models are crucial for providing insights into knowledge sharing and cooperation adaptation during the data collection and preparation stages.

3.1.1. Network Construction from Behavioural Data

This study created a knowledge network within an organization by studying how individuals interact digitally before even meeting in person. Think of it this way: each individual is a dot (node) connected by lines (edges) based on their digital interactions. The frequency with which they communicate using different digital tools and platforms determines the strength of these connections, or the "weight" of lines as Wasserman & Faust (1994) described. For instance, email exchanges between two people will determine one's advantage in the email network; co-participation and shared tasks will impact the project cooperation network; engagement with documents weighs the edges in the documents access network. Different network layers can be created for various interactions, such as separate networks for email communication, project collaboration, etc. According to Szell et al. (2010), analyzing these layers individually or using multiple network analysis approaches can help understand how different interaction modes shape the organization's knowledge network overall. Understanding the organization's knowledge flow structure is based on this network.

3.2. Identifying Key Influencers and Bottlenecks

After creating the knowledge network, various social network analysis matrices were used to identify key accomplishments and challenges. As Scott (2024) emphasized, people with many direct connections, known as hubs, play a vital role in communication networks. Those with intermediate centrality connect different subgroups, facilitating information flow. People with high eigenvector centrality are influential and connect with other significant individuals. Targeted interventions were used to leverage these key individuals' central positions to promote information sharing within the network. Network nodes with restricted information flow were pinpointed by identifying individuals or groups connecting dense groupings and lacking central links, which is a bottleneck. Figure 6 also depicts communication bottlenecks, and recognizing such barriers was essential for designing interventions to boost network connectivity and knowledge sharing, visually identified using network visualization tools.

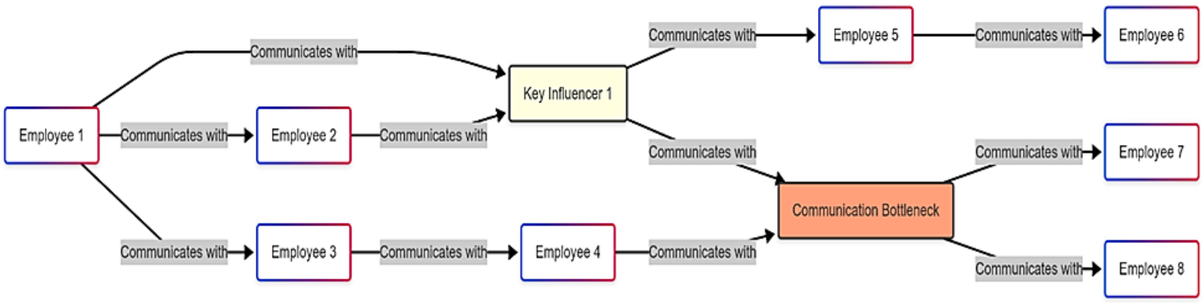

Figure 6. illustration showing the connections between employees in an organization, highlighting key influencers and communication bottlenecks.

Source: (illustration from the researcher, 2025).

3.3. Sentiment and Communication Analysis

Communication content on the network provided insights into collaboration and knowledge. Text data underwent NLP analysis, including information from communication platforms and emails when ethically appropriate. According to Liddy (2001), a key component of behavioral analysis is examining the emotional tone of communication. Negative emotions can imply obstacles to sharing information, while positive emotions encourage cooperation. Emotional states of project teams or communication channels may unveil dynamics for time series analysis. In communication analysis, subjects, queries, and responses are examined to identify main topics and knowledge domains using subject modeling technology. According to Blei et al. (2003), analyzing question and answer flows, knowledge gaps, and subject-matter specialists can be identified, along with assessing accessibility and inclusivity in knowledge-sharing through language variety in group conversations.

3.4. Machine Learning for Predicting Collaboration Outcomes

Using machine learning methods, future models for cooperative outcomes can be developed based on behavior attributes as outlined by Bishop (2006). Project success is measured by stakeholder satisfaction, budget management, and on-time completion. Innovation output is gauged by the development of new concepts, patents, and new products/services. The team's work was evaluated based on reviews and outcomes, and knowledge transfer progress was measured using technology rates and onboarding speed. Computer programs, including regression and classification models, were trained with historical behavior data to forecast outcomes utilizing network measures, trends, and emotions. Facilities selection methods were employed to improve behavior predictions for collaborative results. Model performance was assessed using metrics like recall and accuracy to identify individuals or groups with poor collaboration potential and suggest remedies based on behavior patterns.

4. Discussion

This section highlights research findings, discusses their implications on organizational design and management, and acknowledges the organizational knowledge network in behavioral data mining applications.

4.1. Implications for Organizational Design and Management

This shows how businesses can structure, manage knowledge assets, and engage in activities.

- Mapping and analyzing organizational knowledge networks using behavioural data helps managers understand interaction patterns and knowledge flow. This informs decisions on collaborations, placements, and structure modifications to enhance knowledge exchange. Identifying key knowledge brokers and addressing structural gaps are crucial for optimizing relationships among groups.
- Insights from behavioural data mining can drive more tailored and successful knowledge management interventions for organizations, helping them adjust tactics to their unique knowledge network needs. For example, focusing training on communication and conflict resolution for teams showing negative communication patterns can be beneficial. Taking further action, like team coaching or procedure adjustments, can be based on machine learning predictions of potential project failure due to cooperation issues.

- By understanding factors for successful collaboration and innovation from a machine learning model, organizations can design platforms and rules to enhance creativity through cross-functional contact and various channels. Fostering interactions in communities of practice around specific knowledge areas discovered through subject modeling can advance innovation.
- Identify individuals with strong knowledge-sharing and networking skills for leadership roles or relevant projects. Help those who are isolated in the network by facilitating connections and integration strategies.
- Behavioural data acts as an objective measure to evaluate the effectiveness of a data mining knowledge management initiative. Monitoring changes in network density, emotion scores, communication patterns, and centrality metrics over time can help assess the intervention's impact on promoting information sharing and collaboration, with future collaborative outcomes serving as a key performance metric for the organizational knowledge network.

At the end of the day, organizations benefit from this approach by gaining a data-driven framework to enhance knowledge management, optimize team structure, allocate resources effectively, and implement targeted interventions through behavioural data and analytics.

4.2. Limitations and Critical Considerations

Despite behavior data mining's impressive capacity to understand and personalize the organizational knowledge network, it is important to recognize the various restrictions and critical considerations in place.

- Data bias and perfection are evident in digital platform data, restricting analysis without informal contact or implicit knowledge. Incomplete networks may result from this limitation, influenced by individual preferences, technical expertise, or corporate policies, skewing tool patterns and network representation.
- When collecting and analyzing behavioural data, it is essential that Organizations address privacy and ethical concerns. They should implement strong protection measures, obtain consent from employees, and maintain transparency. Additionally, they must be cautious about misinterpreting or misusing the data.
- Analyzing behavioral data can highlight strong associations, but establishing clear causation can prove challenging due to complex underlying factors, necessitating careful evaluation and intervention planning.
- Knowledge networks in organizations constantly evolve due to changes like personnel, projects, or structure, making continuous monitoring crucial for accuracy.
- Data mining can uncover complex patterns, but translating them into actionable insights for business improvement and intervention creation requires clear communication and a deep understanding of organizational context and technical analysis.

- "Human Factors" such as faith, culture, inspiration, and social mobility influence cooperation and knowledge exchange. Behavioural data provides insights, but cannot capture all the nuances of human interaction.

In organizational contexts, addressing ethical and crucial concepts is key for successful behavioural data mining applications. A well-rounded strategy blending data-operated insight with qualitative understanding and moral concepts is essential for maximizing information sharing and collaboration adaptability.

4.3. Roles and Importance of Artificial Intelligence

In addition to highlighting the important role of AI, particularly in real-world applications in organizations, the article focused on the systematic development of organizational knowledge networks and analytical abilities. AI played a crucial role in this work by converting unprocessed behavioural data into insightful knowledge, especially supervised machine learning techniques like regression and classification models. This study highlights how AI is crucial for implementing solutions in businesses by excelling in identifying patterns and generating insights in complex datasets. AI's machine learning algorithms excel at uncovering intricate relationships among network measurements, communication patterns, emotional ratings, and collaboration solutions, allowing for the detection of subtle behavioral cues that manual analysis may miss. The study emphasized AI's predictive and prescriptive capabilities by using prediction models to anticipate future collaboration problems and provide data-driven remedies. Organizational processes are transformed using this AI approach because problems are tackled early on, and this provides scalable and effective analysis. When AI and human capital management are combined, organizations can make effective data-driven decisions, as evidence-based insights are available, thereby reducing reliance on anecdotes. Machine Learning's (ML) recurrent nature ensures that continuous model improvement is made. This demonstrates AI's critical role in organizational growth through continuous learning by enabling more effective solutions and precise projections based on behavioral data and intervention outcomes.

The design of the study acknowledged that behavioral data alone was not enough. In order to improve organizational cooperation, information sharing, and future forecasting, deep analysis was made possible in large part by artificial intelligence (AI). It would be extremely difficult to provide intelligent answers in a dynamic situation without artificial intelligence.

5. Summary and Recommendations

The conclusion section of the study provides key findings and practical suggestions for companies looking to utilize behavioural data mining. It also includes adoption recommendations, primary contributions, research significance assessment, and suggestions for future studies.

5.1. Strategic, Operational, and Technical Recommendations

The study's conclusions have led to the following recommendations being made:

1. Strategic Recommendations: Organizations should adopt a data-led knowledge management approach, integrating data analytics into their strategy. Also, create a culture of moral consciousness and data literacy, emphasizing ethical use of behavioral data and promoting trust. They can also align knowledge management objectives with professional goals to enhance collaboration and support organizational objectives.
2. Operational Recommendations: Use ongoing network monitoring to analyze changes in network structure, communication styles, and collaboration efficacy. Craft targeted interventions based on communication patterns, key players, and obstacles. Incorporate network insights into performance management for rewarding knowledge sharing and cooperation. Encourage knowledge repositories and collaborative platforms through digital tools and user-friendly integration.
3. Technical Recommendations: Invest in a robust data infrastructure for data collection and analysis. Implement technology to collect, store, process, and analyze behavioural data from various digital platforms. Make use of advanced behavioral data mining models, such as machine learning and network analysis. Develop internal expertise in network analysis and data science through hiring or training.

Implementing these recommendations can enhance organizational performance and flexibility by optimizing knowledge flow in today's digital world.

5.2. Guideline for Organizational Adoption

Organizations looking to adopt a behavioural data mining approach for their knowledge networks should consider these key guidelines: Start with clear objectives, engage stakeholders on data privacy, initiate pilot projects, iterate the approach, blend quantitative and qualitative data, focus on actionable insights, and continuously evaluate and adapt strategies.

5.3. Summary of Key Points

This study identifies behavioural data mining's role in understanding and modifying organizational knowledge networks. Insights from the study include: analyzing behavioural data from digital platforms helps create and analyze organizational knowledge networks; social network analysis of these networks uncovers significant influences on information transfer; studying communication and emotions reveals interaction quality; machine learning algorithms predict support outcomes based on behavior patterns; integrating quantitative and qualitative data provides a comprehensive view of knowledge sharing dynamics.

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