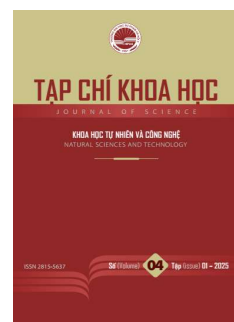




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Big Data and business network analysis: applications in management and optimization

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Abstract

Big Data has significantly transformed business operations, enabling deeper insights and more informed decision-making. Its impact is particularly evident in business network analysis, where companies can now dissect and understand complex supply chains and distribution systems like never before. Businesses can uncover hidden patterns and relationships by analyzing vast datasets, improving efficiency and decision-making processes. This paper explores the applications of Big Data in business network analysis, focusing on how it enhances supply chain visibility, risk management, and demand forecasting. It also addresses challenges like data privacy, security, and managing large datasets. Finally, the paper highlights potential future research directions, emphasizing areas for further development that could drive more innovation in using Big Data for business networks. Through this examination, the paper aims to clarify how Big Data is reshaping business networks and offer insights into this critical field's continued evolution.

Keywords: Big Data, network, analysis, business, supply chain, system

1. Introduction

The advent of Big Data has transformed the business landscape, offering new opportunities for analysis and optimization. Business networks, encompassing supply chains, distribution channels, and inter-company collaborations, are crucial for operational efficiency and competitive advantage. This paper examines how Big Data can be leveraged to analyze and optimize these networks, providing actionable insights business insights [1]–[3].

Big Data refers to large and complex datasets that traditional data processing software and methods cannot handle. These datasets come from various sources such as social media, sensors, transactions,

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and more. Big Data requires advanced analytical techniques and technologies to derive meaningful insights and make data-driven decisions.

Big Data is often characterized by five key attributes, commonly known as the 5 Vs: Volume, Velocity, Variety, Veracity, and Value. These characteristics presents unique challenges and opportunities in data management and analysis.

Volume refers to the massive amounts of data generated every second. The scale of data is immense, measured in terabytes, petabytes, or even exabytes. Managing such large volumes of data requires scalable storage solutions and powerful processing capabilities. Large datasets can provide comprehensive insights that small datasets cannot, revealing critical trends and patterns for decision-making. Velocity pertains to the speed at which data is generated, processed, and analyzed. It emphasizes the need for real-time or near-real-time data processing. High-velocity data streams necessitate quick processing and analysis to derive timely insights. Traditional batch processing methods may not suffice. Real-time data processing enables businesses to respond promptly to emerging trends and events, enhancing operational efficiency and competitiveness [4]–[6].

Variety refers to the different types of data that are generated. This includes structured data (e.g., databases), semi-structured data (e.g., XML, JSON), and unstructured data (e.g., text, images, videos). Integrating and analyzing diverse data types require flexible and advanced data management techniques. The ability to analyze varied data sources enriches the analytical perspective, providing a more holistic view of the subject matter. Veracity denotes the quality and trustworthiness of data. It addresses the uncertainties and inconsistencies in data [5].

Value is the potential worth that can be derived from data. It represents the actionable insights and business intelligence that data analysis can provide. Extracting value from Big Data requires sophisticated analytical tools and skilled personnel to interpret the results correctly. When effectively harnessed, Big Data can drive innovation, improve operational efficiency, and enhance customer experiences, leading to significant business growth.

Understanding and leveraging the characteristics of Big Data—Volume, Velocity, Variety, Veracity, and Value—is crucial for businesses aiming to capitalize on the wealth of information available in today's data-driven world. By addressing the challenges and seizing the opportunities presented by each attribute, organizations can transform raw data into valuable insights, thereby gaining a competitive edge in the market [7]–[10].

The evolution of Big Data technologies has profoundly impacted how businesses operate and compete. From the initial stages of managing structured data to the current landscape of advanced analytics and real-time processing, businesses continue to harness the power of Big Data to drive innovation, efficiency, and strategic decision-making. As technologies evolve, the focus will increasingly be on integrating AI, ensuring data privacy, and democratizing data access to sustain competitive advantage.

Business networks are vital to modern enterprises, offering a range of benefits from enhanced innovation and efficiency to improved market reach and risk management. By leveraging these networks, businesses can achieve greater agility, resilience, and competitive advantage in an increasingly interconnected and dynamic global market. As digital transformation continues, the importance of robust business networks will only grow, necessitating strategic investment in building and maintaining these critical relationships.

Traditional network analysis methods, including graph theory, social network analysis, epidemiological network analysis, and citation network analysis, have been invaluable in understanding

the structure, dynamics, and interactions within various types of networks. These methods have provided insights into social relationships, disease transmission patterns, scholarly communication, and more, shaping our understanding of complex systems in fields ranging from sociology and public health to bibliometrics and computer science [11]–[15].

However, these traditional methods come with their limitations. Challenges such as data quality issues, scalability concerns, static analysis biases, and disciplinary assumptions can hinder the effectiveness and applicability of these approaches in addressing real-world complexities. As networks become increasingly prominent, dynamic, and interconnected, there is a growing need for innovative methodologies and interdisciplinary collaboration to overcome these limitations and advance the field of network analysis.

Emerging technologies such as machine learning, network science, and big data analytics offer promising avenues for addressing these challenges and unlocking new insights into network structures, behaviors, and phenomena. By leveraging these tools and approaches, researchers and practitioners can continue pushing network analysis's boundaries, uncovering hidden patterns, predicting network dynamics, and informing more effective strategies for intervention, collaboration, and decision-making in diverse domains.

The intersection of Big Data and Business Network Analysis offers organizations unprecedented opportunities to gain actionable insights, drive strategic decision-making, and enhance collaboration within their business ecosystems. By harnessing the power of Big Data analytics and network analysis techniques, organizations can unlock the full potential of their business networks, driving innovation, competitiveness, and value creation in the digital age. However, careful attention must be paid to privacy, ethical, and regulatory considerations to ensure responsible and ethical use of Big Data within business networks [11].

2. Preliminaries

2.1. Data collection

Data collection is the foundational step in any data-driven initiative, encompassing the gathering, processing, and preparing raw data for analysis and decision-making. In today's digital age, organizations have access to a wealth of data from various sources, including transactional data, sensor data, social media platforms, and public databases. Effective data collection requires employing techniques for acquisition and preprocessing, such as ETL (Extract, Transform, Load), data cleaning, and normalization. This article delves into the intricacies of data collection, exploring its importance, sources, techniques, and best practices.

Data collection forms the bedrock of data-driven decision-making, enabling organizations to derive actionable insights, enhance operational efficiency, and gain a competitive edge in the market. By harnessing diverse datasets, organizations can understand customer behavior, optimize processes, and innovate products and services. However, the success of data-driven initiatives hinges on the quality, relevance, and reliability of the collected data. Therefore, meticulous attention to data collection processes is paramount to ensure the integrity and utility of the data for subsequent analysis and interpretation [15]–[17].

Transactional data encompasses records of business transactions, such as purchases, sales, invoices, and financial transactions. This data provides valuable insights into customer preferences, buying

patterns, and revenue streams. Transactional data is typically stored in databases or enterprise systems, making it readily accessible for analysis.

With the proliferation of Internet of Things (IoT) devices, sensor data has emerged as a valuable source of real-time information. Sensors embedded in machinery, equipment, vehicles, and infrastructure capture data on various parameters, such as temperature, pressure, humidity, and motion. Sensor data enables predictive maintenance, asset monitoring, and process optimization across manufacturing, transportation, and healthcare industries.

Social media platforms generate vast amounts of user-generated content, including posts, comments, likes, shares, and interactions. This unstructured data provides valuable insights into consumer sentiment, brand perception, and market trends. Social media analytics tools scrape, process, and analyze social media data to extract actionable insights for businesses, marketers, and researchers.

Public databases, repositories, and open data initiatives offer a treasure trove of structured and unstructured data across diverse domains. These include government databases, research repositories, academic datasets, and public APIs (Application Programming Interfaces). Public databases provide valuable resources for research, analysis, and innovation in areas such as healthcare, education, and urban planning.

2.2. Techniques for Data Acquisition and Preprocessing

In the extraction phase, data is retrieved from various sources, including databases, files, APIs, and web scraping tools. This process involves identifying relevant data sources, extracting raw data in its original format, and transferring it to a staging area for further processing. During the transformation phase, raw data undergoes cleansing, normalization, and transformation to prepare for analysis. This includes removing duplicate records, handling missing values, standardizing data formats, and aggregating or summarizing data as needed. In the loading phase, preprocessed data is loaded into a target destination, such as a data warehouse, data lake, or analytical database. This step involves structuring data for efficient storage, indexing, and querying to support analytics and reporting requirements.

Missing values in the dataset are identified and addressed through techniques such as imputation (replacing missing values with estimated values), deletion (removing records with missing values), or flagging (marking missing values for further analysis). Outliers, or data points that deviate significantly from the rest of the dataset, are detected and removed or corrected to prevent them from skewing analysis results. Data from disparate sources may have varying formats and structures. Standardization involves converting data into a uniform format to facilitate integration, analysis, and interpretation [17]–[19].

Numerical features in the dataset are scaled or normalized to a common range to ensure that they contribute equally to the analysis and prevent bias towards features with larger magnitudes. Categorical variables are encoded into numerical representations using one-hot encoding, label encoding, or binary encoding techniques, enabling them to be included in machine learning models. We give figure 1 on Data Acquisition and Preprocessing as follows.

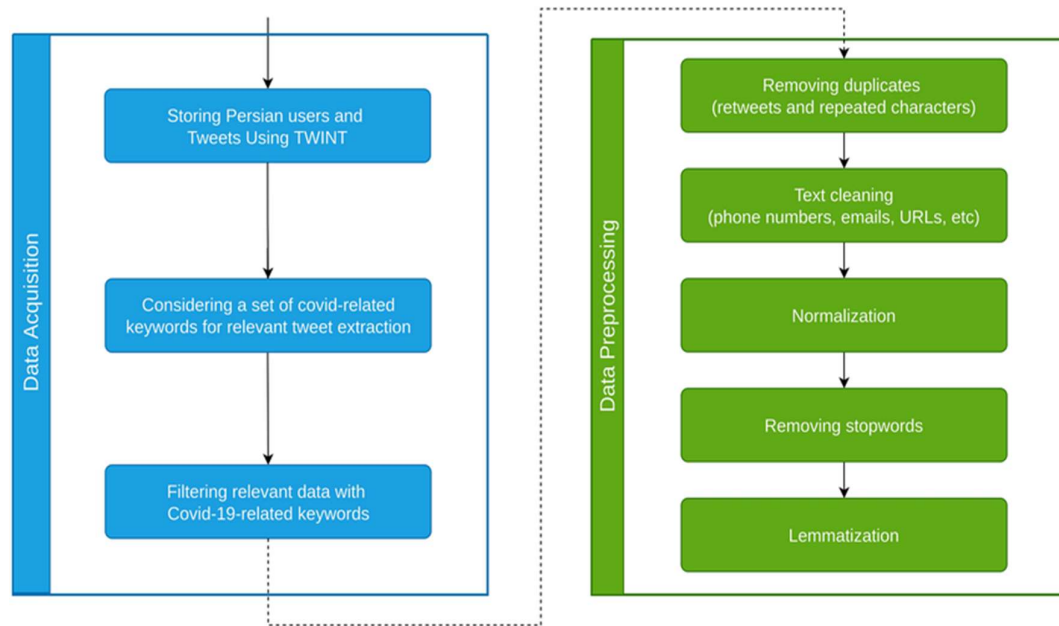


Figure 1. Data Acquisition and Preprocessing scientific diagram (source from: Social Network Analysis and Mining).

2.3. Best Practices for Data Collection

Clearly define the goals and objectives of the data collection effort to ensure that the collected data aligns with the organization's strategic priorities and analytical needs. Implement measures to maintain data quality throughout data collection including data validation, error detection, and quality assurance checks. Adhere to privacy regulations and ethical standards when collecting and handling sensitive data, such as personally identifiable information (PII) and protected health information (PHI). Leverage automation tools, data integration platforms, and ETL frameworks to streamline data collection, preprocessing, and loading tasks, reducing manual effort and minimizing errors. Continuously monitor and evaluate the effectiveness of data collection processes, soliciting stakeholders feedback and incorporating lessons learned to refine and enhance data collection practices over time.

Data collection is a fundamental component of any data-driven initiative, serving as the cornerstone for informed decision-making, innovation, and strategic planning. By tapping into diverse data sources and employing robust acquisition and preprocessing techniques, organizations can unlock valuable insights, drive operational efficiency, and stay ahead in today's competitive landscape. With careful attention to best practices and a commitment to data quality, organizations can harness the power of data to fuel growth, innovation, and success [19]–[21].

3. Results and Discussion

3.1. Data Analysis Techniques

Data analysis techniques play a crucial role in extracting meaningful insights from complex datasets, facilitating informed decision-making and strategic planning within organizations. Among these techniques, Graph Theory, Machine Learning, and Network Visualization stand out as powerful tools for analyzing business networks and deriving actionable insights. We explore each of these techniques as follows.

Graph Theory provides a mathematical framework for representing and analyzing relationships within business networks. Networks are modeled as graphs, where nodes represent entities (e.g., individuals, organizations, products), and edges represent relationships or connections between nodes (e.g., partnerships, transactions). Graph theory metrics such as degree centrality, betweenness centrality, and eigenvector centrality quantify the importance or influence of nodes within a business network. Identifying nodes with high centrality can reveal key players or central hubs in the network. Community detection algorithms partition the network into cohesive groups or communities based connectivity patterns. These communities represent clusters of nodes that exhibit strong internal connections, shedding light on functional units or subgroups within the business network. Specialized graph algorithms, including shortest path algorithms, maximum flow algorithms, and minimum spanning tree algorithms, solve specific optimization or routing problems within the business network. These algorithms help optimize resource allocation, streamline communication pathways, and identify efficient workflows.

Machine learning algorithms are employed to recognize patterns, trends, and anomalies within business networks, facilitating predictive modeling and decision support. Machine learning techniques such as clustering, classification, and outlier detection are used to identify unusual or anomalous patterns within the business network. These anomalies may indicate fraudulent activities, security breaches, or irregular behavior. Machine learning models predict future trends, behaviors, or outcomes within the business network based on historical data and observed patterns. Predictive analytics techniques, including regression, classification, and time series forecasting, enable organizations to anticipate market trends, customer churn, and supply chain disruptions. Machine learning methods, such as node embeddings and graph convolutional networks, learn low-dimensional representations of nodes and edges within the business network. These embeddings capture structural and relational information, facilitating downstream tasks such as node classification, link prediction, and recommendation systems. Network visualization tools and techniques transform complex network data into interactive visualizations, making it easier to explore, interpret, and communicate insights within the business network.

Interactive network visualization platforms allow users to explore and interact with the business network in real time, enabling dynamic exploration of nodes, edges, and network properties. We see that Visualization techniques encode additional attributes such as node size, color, and shape to convey information about entities and relationships within the business network. These visual encodings highlight key insights and patterns, such as node centrality or edge weight. Automated layout algorithms arrange nodes and edges in a visually appealing and informative manner, highlighting structural properties and clustering patterns within the business network. Layout algorithms optimize visualizations for readability, scalability, and aesthetics.

By leveraging Graph Theory, Machine Learning, and Network Visualization techniques, organizations can comprehensively understand their business networks, uncover hidden patterns, identify key players, and predict future trends. These techniques enable organizations to make informed decisions, optimize resource allocation, and drive innovation within their business ecosystem. With the integration of advanced analytics and visualization capabilities, organizations can unlock the full potential of their business networks, fostering collaboration, efficiency, and strategic growth.

3.2. Applications in Management and Optimization

Real-time monitoring tools integrated with Big Data analytics allow businesses to track supply chain activities at every stage, from raw material procurement to product delivery. By analyzing data

streams from sensors, RFID tags, and ERP systems, organizations can identify bottlenecks, streamline processes, and optimize resource allocation in real-time. For example, Walmart utilizes its Retail Link system, which combines sales data, inventory levels, and logistics information in real time to optimize inventory management and replenishment across its supply chain network.

Big Data-driven predictive analytics play a pivotal role in forecasting demand, optimizing inventory levels, and improving supply chain efficiency. Advanced machine learning algorithms analyze historical sales data, market trends, and external factors (e.g., weather patterns, economic indicators) to generate accurate demand forecasts. By anticipating fluctuations in demand, businesses can optimize inventory levels, reduce stockouts, and minimize carrying costs. Amazon, for instance, leverages its vast trove of customer data to predict purchasing behavior and optimize inventory placement in fulfillment centers, enabling faster order fulfillment and reduced shipping costs.

We give some examples as follows. P&G utilizes Big Data analytics to optimize its supply chain operations, reduce costs and improve efficiency. By analyzing data from suppliers, distributors, and retail partners, P&G gains insights into demand patterns, production capacity, and inventory levels. This enables the company to optimize production schedules, minimize stockouts, and enhance customer satisfaction. UPS employs Big Data analytics to optimize its logistics and distribution network, improving delivery routes, vehicle utilization, and fuel efficiency. UPS optimizes its routing algorithms to reduce delivery times and operational costs by analyzing data on package volume, delivery locations, and traffic patterns. Additionally, UPS utilizes predictive analytics to anticipate package volumes during peak seasons, ensuring adequate staffing and resources to meet customer demand.

Big Data analytics enable organizations to analyze distribution channels and identify bottlenecks that impede the flow of goods. Businesses can pinpoint inefficiencies and optimize distribution strategies by analyzing data on transportation routes, warehousing facilities, and inventory levels. For example, FedEx employs data analytics to analyze delivery routes, identify congestion points, and optimize delivery schedules to minimize transit times and costs.

Simulation modeling tools powered by Big Data analytics enable businesses to evaluate different distribution strategies and scenarios in a virtual environment. By simulating various factors such as transportation modes, warehouse locations, and order volumes, organizations can assess the impact of different strategies on key performance metrics such as delivery times, costs, and customer satisfaction. For instance, Coca-Cola utilizes simulation modeling to optimize its distribution network, balancing factors such as transportation costs, inventory levels, and service levels to maximize efficiency and minimize costs.

We give some Examples of Successful Distribution Network Optimization. Walmart leverages Big Data analytics to optimize its distribution network, reduce transportation costs and improve inventory management. Walmart optimizes its transportation routes, warehouse operations, and inventory replenishment processes by analyzing data on customer demand, inventory levels, and supplier performance. This enables Walmart to minimize stockouts, reduce lead times, and enhance supply chain resilience.

Amazon employs Big Data analytics to optimize its distribution network, enabling faster order fulfillment and delivery. Amazon optimizes its fulfillment center locations, inventory placement, and delivery routes by analyzing data on customer preferences, order history, and inventory levels. This enables Amazon to offer same-day or next-day delivery for millions of products, enhancing customer satisfaction and loyalty.

Big Data analytics play a pivotal role in optimizing supply chain management and distribution network operations. Organizations can streamline processes, reduce costs, and enhance customer satisfaction by leveraging real-time monitoring, predictive analytics, and simulation modeling. Case studies of companies like Procter & Gamble, UPS, Walmart, and Amazon demonstrate the transformative impact of Big Data on supply chain efficiency and effectiveness. As businesses continue to harness the power of Big Data analytics, they will gain a competitive edge in the dynamic and interconnected world of global supply chains.

3.3. Risk Management

Big Data analytics enables businesses to identify and assess risks within their business networks by analyzing vast amounts of data from various sources. Organizations can identify potential risks such as supply chain disruptions, market volatility, regulatory changes, and cybersecurity threats by analyzing transactional data, supply chain metrics, market trends, and external factors.

Once risks are identified, organizations can leverage Big Data analytics to develop proactive risk mitigation strategies. For example, predictive analytics models can forecast supply chain disruptions based on historical data and external factors, enabling organizations to implement contingency plans such as alternative sourcing, inventory diversification, and demand forecasting. Additionally, machine learning algorithms can analyze customer feedback, social media sentiment, and online reviews to identify potential reputational risks and take appropriate actions to address customer concerns and mitigate brand damage.

Big Data analytics supports the implementation of comprehensive risk management frameworks within organizations. By integrating risk analytics tools with enterprise risk management (ERM) frameworks, businesses can assess risks across various dimensions, prioritize mitigation efforts, and monitor risk exposure in real time. For example, financial institutions utilize Big Data analytics to monitor market, credit, and operational risks, enabling proactive risk management and compliance with regulatory requirements.

Big Data analytics revolutionizes customer relationship management by providing insights into customer interactions, preferences, and behaviors. By analyzing data from multiple touchpoints such as sales transactions, customer inquiries, website visits, and social media interactions, organizations gain a 360-degree view of their customers. This enables businesses to identify trends, anticipate needs, and personalize interactions to enhance the overall customer experience.

Big Data analytics enables personalized marketing efforts tailored to individual customer preferences and behaviors. By leveraging predictive analytics and machine learning algorithms, organizations can segment customers based on demographic characteristics, purchase history, and browsing behavior, allowing for targeted marketing campaigns and personalized product recommendations. For example, e-commerce platforms like Amazon use recommendation engines powered by Big Data analytics to suggest products based on customers' past purchases and browsing history, increasing customer engagement and driving sales.

Big Data analytics has a profound impact on enhancing customer satisfaction and loyalty by enabling organizations to deliver personalized experiences and address customer needs more effectively. By analyzing customer feedback, sentiment analysis, and service performance metrics, businesses can identify areas for improvement and take proactive measures to enhance customer satisfaction. For example, airlines use Big Data analytics to analyze customer feedback and flight performance data,

enabling them to identify pain points in the travel experience and implement service enhancements to improve customer satisfaction and loyalty.

Big Data analytics plays a crucial role in both risk management and customer relationship management within organizations. By leveraging Big Data analytics, businesses can identify and mitigate risks within their business networks, develop proactive risk management strategies, and enhance customer satisfaction and loyalty through personalized interactions and targeted marketing efforts. As organizations continue to harness the power of Big Data analytics, they will gain a competitive edge in managing risks effectively and building long-lasting customer relationships in an increasingly dynamic and competitive marketplace.

4. Conclusion

Big Data has significant potential to transform business network analysis, providing detailed insights and enabling optimization of complex systems. Despite the challenges, ongoing advancements in technology and methodologies promise to further enhance the capabilities and applications of Big Data in this domain. By embracing these innovations, businesses can achieve greater efficiency, resilience, and competitive advantage.

The integration of Big Data analytics into business network analysis represents a paradigm shift in how organizations understand, manage, and optimize complex systems. The vast volumes of data generated within business networks provide a treasure trove of insights, enabling organizations to uncover hidden patterns, identify inefficiencies, and drive strategic decision-making. Despite the challenges associated with data collection, processing, and interpretation, advancements in technology and methodologies continue to expand the capabilities and applications of Big Data in this domain.

Big Data has the potential to revolutionize business network analysis by providing granular insights into the structure, dynamics, and interactions within complex networks. By leveraging advanced analytics techniques such as machine learning, graph theory, and network visualization, organizations can unlock valuable insights from diverse datasets, including transactional data, sensor data, social media interactions, and public databases. These insights enable organizations to optimize processes, identify opportunities for collaboration, and mitigate risks within their business networks.

Despite the immense potential of Big Data, businesses face challenges in harnessing its full value. Data collection, integration, and quality assurance remain significant hurdles, requiring robust infrastructure, data governance frameworks, and compliance with privacy regulations. Moreover, the complexity and interconnectedness of modern business networks pose challenges in data analysis and interpretation, necessitating interdisciplinary collaboration and innovative methodologies.

However, these challenges are accompanied by opportunities for innovation and growth. Ongoing technological advancements, such as distributed computing, cloud computing, and edge computing, enable organizations to process and analyze Big Data at scale. Additionally, the proliferation of Internet of Things (IoT) devices and the increasing digitization of business processes generate new sources of data, expanding the scope and granularity of business network analysis.

We give some directions for future research as follows. The future of business network analysis is characterized by continued innovation and evolution. Emerging technologies such as artificial intelligence (AI), blockchain, and quantum computing hold promise for enhancing the capabilities of Big Data analytics in analyzing and optimizing business networks. AI-powered algorithms can automate data analysis tasks, uncovering insights at unprecedented speed and scale. Blockchain technology offers secure and transparent data sharing opportunities across business networks, enabling trustless

collaboration and streamlined transactions. Quantum computing, with its ability to perform complex calculations exponentially faster than classical computers, holds the potential to revolutionize optimization problems within business networks.

Furthermore, the democratization of data analytics tools and platforms enables businesses of all sizes to harness the power of Big Data, democratizing access to insights and leveling the playing field in competitive markets. By embracing these innovations and fostering a culture of data-driven decision-making, businesses can achieve greater efficiency, resilience, and competitive advantage in an increasingly interconnected and dynamic business landscape.

Big Data has the potential to transform business network analysis, providing detailed insights and enabling optimization of complex systems. Despite the challenges, ongoing advancements in technology and methodologies promise to further enhance the capabilities and applications of Big Data in this domain. By embracing these innovations, businesses can achieve greater efficiency, resilience, and competitive advantage, unlocking new opportunities for growth and innovation in the digital age. As organizations continue to harness the power of Big Data analytics, they will be better equipped to navigate the complexities of modern business networks and thrive in an increasingly interconnected and data-driven world..

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