Adoption of Big Data Analytics for Strategic Decision Making in a Technology Organization: A Qualitative Study

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Abstract

Big data analytics involves substantial data volumes and analysis of big datasets using statistical methods to uncover valuable insights. The problem addressed in this study was that organizational constraints create hurdles to the adoption of big data analytics for strategic decision-making, thereby decreasing the competitive edge and negatively impacting performance. Challenges exist across organizations, industry sectors, and countries in adopting big data analytics for strategic choices. The purpose of this qualitative exploratory study was to identify the organizational constraints that impact the adoption of big data analytics for strategic decision-making and to investigate how these impediments can be mitigated to achieve performance goals and gain a competitive advantage at a technology company. The theory of constraints framework was chosen to drive the research study. The research methodology that guided this study was a qualitative case study design. Snowball sampling was used to select 17 leaders at a technology company. Semi-structured interviews and focus groups were used to gather the data, followed by member checking. The instruments and participants in the study helped ensure triangulation and saturation. Thematic analysis was performed using manual coding and NVivo 14 software to generate themes. Results showed that various organizational constraints impede the adoption of big data analytics, including a lack of leadership support, organizational culture, data fragmentation created by internal groups and acquisitions, inadequate resource allocation, strategic prioritization, and regulatory and privacy challenges. Mitigation conditions included leadership commitment, data and tool consolidation, and strategic resource allocation. Competitive advantage can be achieved by optimizing product-market fit and leveraging insights from the customer journey. The study's primary contribution was to demonstrate that the constraints to big data analytics adoption identified by a product group at a technology company were fundamentally organizational rather than technical, with leadership

support and cultural transformation representing the critical path to achieving a competitive advantage. The research offered recommendations that organizations require leadership support, cultural transformation, and skilled resources to drive data-driven decisions and achieve their performance goals. The study suggested that future research should examine quantitative approaches across broader populations, different geographical locations, and integration with artificial intelligence technologies.

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Chapter 1: Introduction

Information technologies' increasing readiness and utilization in the past few decades have altered people's digital lives (Caputo et al., 2023). Technologies available for managing data and making organizational decisions must be enhanced to align with the current industry trends. This paradigm demands new managerial processes and methods to infer and comprehend the implications of increasing the use of new technologies in businesses. Big data analytics (BDA) entails substantial data volumes and data analysis on large data sets using statistical and machine learning (ML) methods to unearth new and valuable insights (Han et al., 2024). Businesses frequently use BDA to uncover helpful information from data for executing strategic choices, boosting operational performance, expanding revenue opportunities, and sustaining a competitive edge (Rodgers et al., 2024). Uncertainties in organizations and the data explosion have forced chief information officers (CIOs) to focus on big data (BD) adoption in the last 20 years (De Rijck, 2023). Data quality is vital for analysis and decision-making when using BDA.

Businesses must utilize the power of processes, technology, and people to enhance the quality of BD collection and usage (Caputo et al., 2023). Companies must consider relevant aspects, such as human approaches to BD and the consequences of BDA on decision-making processes. BD includes structured and unstructured data formats. While the collection, storage, and analysis of structured data are less complicated, 90% of the data in the current age is unstructured and involves audio, video, and text messages. The data storage requirements differ, with structured data needing relational databases and unstructured data needing NoSQL databases. Combining structured and unstructured data has many advantages, including superior prediction options and BDA quality. Data gathering, analysis of the data, and data utilization in

organizational decision-making have been increasing swiftly (Schuiling, 2020). Research indicated that companies had gained 4.1% productivity by leveraging BDA.

BD has been used in multiple sectors, including healthcare and banking. In healthcare, ongoing pressure exists to reduce costs and provide superior services (Britto, 2020). Insights from the data aid healthcare companies in proactively making the right decisions, enhancing service quality, and reducing costs. Research in the banking sector indicated that small and medium (SM) banks were pivotal in a country's economy (Abankwa, 2023). Banks produce enormous data sets every day by processing billions of financial transactions. Data creation and usage in banks necessitate the adoption of BDA for services and decision-making. Banks in the SM industries lag in integrating technological modernizations like BDA into their business processes. Without SM banks assessing readiness for BDA adoption, they were unlikely to attain a competitive edge, gain market share, and benefit the economy. BD was also used in organizations in different countries. In Malaysia, reports on BD revealed that organizations using third parties for analytical tasks may omit domain data when gathering important insights (Muhammad, 2022). The study concluded that frameworks were essential to manage data accuracy so organizations can benefit from data inflows and create insights using BDA. Scholars in another research work surveyed companies in Vietnam, China, and New Zealand to know the factors limiting leadership in using analytics on BD for strategic choices (J. Yu et al., 2022). Organizations understood the business value and saw a better competitive advantage with BDA, but the leaders within were reluctant to integrate the technology into business processes. The research concluded that the critical factors for using BDA to make decisions included data quality, knowledge and expectations of BDA within the organization, and technology readiness. Past research confirmed that BD helps businesses forecast, identify, and adapt to industry

disruption (Van Rijmenam et al., 2019). BDA provides organizational leaders with faster, more reliable insights when making decisions and helps drive strategy changes. Another research work highlighted that decision quality in organizations relies on data integrity, data processing methods, and the expertise of personnel in data acquisition and management (Manohar, 2021).

BDA helps create organizational benefits, including generating new prospects and retaining existing customers (Caputo et al., 2023). Organizations utilizing BDA have shown gains in business performance (De Rijck, 2023). BDA creates additional advantages for organizations beyond business intelligence, such as decision-making and business process optimization (Hirschlein & Dremel, 2021). BDA has garnered impetus in academia and industry, offering technological advancements that boost organizational revenue and productivity. BDA has been recognized as a fundamental force for data-driven innovation in the business sector. Hence, BDA is important in the creation of organizational value. One of the critical competencies needed to lead organizations and survive in competitive and challenging environments is effectively making strategic decisions (Akter et al., 2019). The foundation of decision-making stems from BDA and the decision-support processes. The desired results were not realized unless the decision-makers utilized the insights. Organizations can benefit from BDA with competitive advantages such as improving existing products, creating new products, identifying new customer segments, and supporting algorithm-based decision-making (Lukić, 2017). Other research works have recommended goals, including exploration of the effect of organizational culture on BDA adoption, the impacts of socio-technical systems, and the definition of the role of BDA in strategic choices in universities (Aseeri & Kang, 2023; Pattnaik & Shah, 2023). Understanding and mitigating the constraints help organizations gain a

competitive advantage and increase their performance, hence being relevant as an applied research topic.

Statement of the Problem

The problem addressed in this study was that existing constraints in organizations often create hurdles in the implementation of BDA for strategic decisions (Alexandre Terlizzi et al., 2024; Konanahalli et al., 2022), decreasing competitive edge and negatively affecting performance (Baker, 2022; M. U. Khan & Fatima, 2024; Manohar, 2021). Though BDA is a priority that helps create business value and a higher competitive advantage, companies have encountered impediments in transitioning to new technologies (Abankwa, 2023; J. Yu et al., 2022). The problem adversely affects companies, preventing them from extracting insights and generating value (J. Yu et al., 2022). A possible topic was how organizational constraints deter the embracing of BDA for strategic decisions (Aldossari et al., 2023). Researching to understand the constraints of a technology company on integrating BDA could lead to insights for improving the situation (Baker, 2022; Manohar, 2021).

The gigantic technological explosion, massive data generation, and organizational uncertainties have increased the need to adopt BD (Manohar, 2021). Decision-makers in organizations have faced challenges with data overload, as they had limited processing power (Van Rijmenam et al., 2019). Enhancing available technologies for data management and organizational decision-making is necessary (Caputo et al., 2023). Although purchasing new technologies is essential to embrace data growth, achieving success is not guaranteed, as the value results from the insights (De Rijck, 2023). While new capabilities frequently highlight business value, creating organizational value from BDA-specific investments is not fully known (Hirschlein & Dremel, 2021). Though generating value is a crucial benefit, companies have

grappled with successfully implementing BDA (Wiener et al., 2020). Challenges exist in the adoption and usage of BDA in organizations of different sizes (Schuiling, 2020), various sectors, including electric utilities (Ponnusamy et al., 2021), healthcare (Britto, 2020), banking (Abankwa, 2023), and across different countries (Muhammad, 2022; J. Yu et al., 2022).

Purpose of the Study

The purpose of this qualitative exploratory study was to find what organizational constraints impact the adoption of BDA for strategic decision-making and investigate how these impediments can be mitigated to reach performance goals and gain a competitive advantage at a technology company. Although BDA is a priority that helps create business value and a higher competitive advantage, organizations have encountered barriers to adoption (Abankwa, 2023; J. Yu et al., 2022). Researching to understand the constraints of a technology company on integrating BDA could lead to insights for improving the situation (Baker, 2022; Manohar, 2021). An exploratory case study design was used to collect and assess narrative data and explore how organizational constraints impeding BDA adoption can be identified and mitigated. Executives at the U.S. software publishing companies comprised the population for the research. The sampling frame (Stimpfel et al., 2025) consisted of executives chosen from Dun & Bradstreet with NAICS CODES: 5132 (Dun & Bradstreet, 2024). Participants were 21 or older and vice presidents (VPs), senior directors, directors, leaders, or managers in technology corporations. People in these roles were assumed to understand the importance of the BDA initiatives in the organization. Seventeen executives at a technology company were chosen using snowball sampling, and the research location was California, United States. Data collection occurred utilizing focus groups and individual semi-structured interviews (Chand, 2025; Lim, 2025). Consent from participants was obtained before data collection to ensure ethical

compliance (Antonsen et al., 2024). The instruments and participants were used to ensure saturation and perform triangulation. Ensuring data organization using categories, trustworthiness, and validity provided usefulness to the data analysis findings. Addressing the problem in this research aids in increasing organizational performance and gaining a competitive advantage.

Introduction to Theoretical Framework

Conceptual and theoretical frameworks establish focus and outline the principles and structure for research projects (Caffrey, 2023). Providing an academic structure necessary to progress from the gaps of using BDA for making strategic decisions to a fully conceptualized framework is vital to a comprehensive research study (Tegtmeyer, 2022). Adopting new technology has been guided by different theories, models, and frameworks, each offering a unique perspective. After performing an exhaustive literature review for the research topic, multiple suitable theoretical frameworks were identified for the study. The frameworks included the theory of constraints (TOC Institute, 2021) the "Technology-Organization-Environment framework" (Baker, 2022, p. 8; Tornatzky et al., 1990), dynamic capabilities theory, resource based view (Chaudhuri et al., 2024), "Unified Theory of Acceptance and Use of Technology" (Azam & Ahmad, 2024, p. 1460), "Diffusion of Innovation theory" (Wurster et al., 2024, p. 2) and information system success mode theory (Azam & Ahmad, 2024; Wolseley et al., 2024).

The theory of constraints (TOC) framework was chosen to drive the research study for the following reasons. The TOC framework was established by Eliyahu Moshe Goldratt in 1984 (TOC Institute, 2021). The TOC framework's core idea is to identify the constraints in an organization, influence the constraints to improve the situation, and gain advantages, such as increasing performance. Although the early focus of the TOC framework was to assist the

manufacturing sector, it rapidly gained appreciation in the 1990s in service and industrial organizations and is popular in the 2020 digital transformation era. To systematically know the constraints in an organization, TOC was applied to a group of management frameworks, including Boston Consulting Group's portfolio analysis model, the value chain model, and the stakeholder analysis model in an earlier study (Coman & Ronen, 1995). TOC is a methodology to improve processes and emphasizes the significance of identifying and utilizing organizational constraints to achieve financial goals. The TOC framework helps detect different organizational constraints, and some examples include culture, technology costs, and resources (R. J. Harris, 2018). Organizations have multiple challenges, including business policies, market conditions, and physical limitations. Though organizations create enormous amounts of data, they need time to gain an advantage from resources such as BD. A socio-technical framework was necessary to deal with the restrictions. Another research work detailed a need for a process like the "Business-Driven Data Supported process" (Rodgers et al., 2024, p. 705), inspired by TOC, to help leaders solve organizational problems by extracting insights from BD. TOC details the root cause of a problem as the source whose resolution leads to the mitigation or elimination of performance gaps in an organization. Identifying and managing constraints and providing continuous progress in organizations adopting BDA for strategic decisions was the goal of the TOC framework (R. J. Harris, 2018). As a result, the TOC framework is aligned with the dissertation's problem statement, purpose statement, and research questions.

Introduction to Research Methodology and Design

The research methodology and design that guided this study was a qualitative case study methodology and design. The problem, purpose, and research questions required collecting and assessing narrative data and exploring how organizational constraints impeding BDA adoption

can be identified and mitigated. Qualitative research is unique and can deliver value because various real-world issues can fall under its umbrella (Yin, 2016). It is not subject to limitations, such as conforming to sample sizes and lacking sufficient data. Qualitative methods in literature allow researchers to gather descriptive data encompassing observed behaviors and spoken or written words of subjects (Adeleke, 2020). Qualitative research helps develop theoretical insights for enhancing the understanding of organizational complexities (Bansal et al., 2018). For the above reasons, the qualitative studies were optimal and aligned with the problem statement, purpose, and research questions. Traditions and genres of qualitative methodology guide the selection of research design and methods (Lim, 2025). The need for alignment of the research approach with a problem, purpose, and research questions applies to the qualitative design. While different genres were available in the literature, case studies assisted in deciphering the relationship between different constructs and factors contributing to various outcomes (Bansal et al., 2018). Past research used case study designs in other industries on how BDA adoption helps organizations' decision-making (Alexandre Terlizzi et al., 2024). Case studies are contextual and comprehensive, help in deeper interaction with the research participants, and are suitable for the research problem (Lim, 2025).

While there was a lack of consensus in the research community on a standard approach for sample size definition in qualitative methodologies (Boutera et al., 2024; Patton, 1990), a recent study (Villamin et al., 2025) emphasized that 11 to 20 participants was most common. As participants in qualitative research provide rich information, sample sizes can be smaller (Boutera et al., 2024). Executives at the U.S. software publishing companies comprised the population for the research. The sampling frame (Stimpfel et al., 2025) consisted of executives chosen from Dun & Bradstreet with NAICS CODES: 5132 (Dun & Bradstreet, 2024).

Participants must be 21 or older and VPs, senior directors, directors, leaders, or managers in technology corporations. Subjects in these roles were assumed to understand the importance of the BDA initiatives in the organization. Seventeen (Villamin et al., 2025) executives at a technology company were chosen using snowball sampling, with the research location being the United States.

Data collection occurred using individual semi-structured interviews and focus groups to understand the phenomenon under study (Chand, 2025; Lim, 2025). Saturation, triangulation, and verification were achieved with multiple data sources. Content validity was increased by having doctoral-level researchers review the questions (Christalle et al., 2022). Field testing helped improve the reliability of the research instruments and maintain efficacy (Yin, 2016). Consent from participants was obtained before data collection to ensure ethical compliance (Antonsen et al., 2024). Data governance procedures and policies, such as data quality, strict access controls, anonymizing or encrypting data, audits, periodic privacy, and risk assessments, are necessary to safeguard participant data from unauthorized access or misuse. Identity and access management (IAM) and HashiCorp Vault are software solutions that can help protect research data and enforce access control (Z. Jiang et al., 2024). Analyzing data requires a meticulous process (Yakut Çayir & Saritaş, 2017) of organizing collected data, dividing into categories, theme generation, and publishing a report. Ensuring data organization, trustworthiness, and validity provided usefulness to the data analysis and findings.

Research Questions

RQ1

To what extent do the organizational constraints impact the adoption of BDA for making strategic decisions at a technology company?

RQ2

Under what conditions do the constraints impeding the adoption of BDA for making strategic decisions be mitigated to reach organizational performance goals at a technology company?

RQ3

Under what conditions does BDA adoption for strategic decision-making help a technology company gain a competitive advantage?

Significance of the Study

Organizations of different sizes and in multiple sectors, comprising telecom (M. U. Khan & Fatima, 2024), finance (Kasiraju, 2024), healthcare (Rodgers et al., 2024; Wolseley et al., 2024), insurance (Alexandre Terlizzi et al., 2024), and online software companies (Rodgers et al., 2024) can benefit from the use of BDA.

Businesses can utilize the power of BD to increase productivity and performance, leading to innovation (Tawil et al., 2024). Organizations can drive overall economic growth, as depicted in the study of SM enterprises in the United Kingdom, once they overcome the constraints that hinder the adoption of BD for decision-making. BDA was essential for businesses to gain a competitive edge and reach performance goals. Organizations with access to BDA capabilities significantly improved their performance, as shown in a study in Pakistan's telecom sector (M. U. Khan & Fatima, 2024). Financial institutions that provide digital banking services have shown ways to overcome the constraints in BDA adoption, prevent fraud, and offer enhanced customer experience (Kasiraju, 2024). In the insurance industry, a study emphasized architectural best practices such as auto-scaling alerts and overcoming barriers like accessing data sources in multiple clouds, leading to reduced fraud and increased revenue (Alexandre Terlizzi et al., 2024).

A research study in the healthcare industry had stressed the significance of socio-technical factors like government regulations, organizational readiness, system and information quality, and analytical skills in people as key to BDA adoption. The benefits of BDA adoption included better ways for patient care, reduced costs, and improved satisfaction (Wolseley et al., 2024).

Research has also shown the importance of understanding the business problem in organizations before generating large volumes of data (Rodgers et al., 2024). Understanding the gaps helps organizations use the correct data to obtain actionable insights.

Definitions of Key Terms

Autoscaling

Scaling is defined as the capability to expand a resource or an application to handle increased demand (Balla et al., 2020). Autoscaling is a highlighted feature of cloud computing, where resources are automatically adjusted to cater to increases and decreases in demand.

Big Data

BD encompasses structured and unstructured information characterized by volume, velocity, and variety (Baker, 2022; Manohar, 2021). BD is also described as large volumes of organized or unformatted data processed at high velocities in a sensor and information-laden world. BD requires analytical tools and technologies to transform data into valuable insights.

Big Data Analytics

BDA is a methodology to gain insights from raw data. BDA unearths historical patterns and new trends from the data to make future predictions (Baker, 2022; Manohar, 2021). BDA is a group of techniques, methods, and skills that help discover new business details and answer questions.

Business Intelligence

Business intelligence is a methodology, product, technology, or a combination of data, information, and knowledge for making decisions (Williams et al., 2024).

Data Governance

Data governance is a complete framework that includes the processes, policies, and structures required to effectively manage and use an organization's data assets (Z. Jiang et al., 2024).

Identity and Access Management

IAM involves the creation and management of identities for users and providing access to these users based on their roles in an organization (Alsirhani et al., 2022).

Machine Learning

ML, also called artificial intelligence (AI) or deep learning, comprises a set of statistical methods, algorithms, and models for managing large volumes of data (Han et al., 2024). ML methodologies are utilized to solve practical problems and make future predictions.

Multi-Cloud

Multicloud computing or multicloud systems use cloud computing resources from multiple cloud service providers such as Amazon, Microsoft, and Google (Hong et al., 2019). Multicloud refers to users or organizations utilizing the resources from multiple cloud providers for services and applications.

NoSQL Database

Data are stored in different locations, like relational databases for structured or ordered data and NoSQL databases for textual or document-based data (Caputo et al., 2023; W. Khan et

al., 2023). NoSQL databases are data stores that store and manage non-relational data. MongoDB is an example of a NoSQL database.

Summary

The problem addressed was that organizational limitations frequently impede the integration of BDA into strategic decision-making, resulting in decreased competitive advantage and negatively influencing performance targets. The purpose of this qualitative exploratory study was to find what organizational constraints impact the adoption of BDA for strategic decision-making and investigate how these impediments can be mitigated to reach performance goals and gain a competitive advantage at a technology company. Challenges exist across industry sectors and countries. Addressing the problem helps organizations gain a competitive advantage and increase performance. The research questions to be answered included the extent to which organizational constraints impact the adoption of BDA for making strategic decisions at a technology company, under what conditions these constraints can be mitigated to reach performance goals, and under what conditions adopting BDA can aid the company in gaining a competitive advantage. An exhaustive literature review ensued to identify a theoretical framework suitable for studying the research gap. The framework is called the TOC framework. The research methodology and design that guided this study were a qualitative case study methodology and design. The problem, purpose, and research questions require collecting and assessing narrative data and exploring how organizational constraints impeding BDA adoption can be identified and mitigated. Data collection occurred using individual semi-structured interviews and focus groups to understand the phenomenon under study (Chand, 2025; Lim, 2025). Saturation, triangulation, and verification were achieved with multiple data sources. Consent from participants was obtained before data collection to ensure ethical compliance

(Antonsen et al., 2024). Data governance procedures and policies, such as data quality, strict access controls, anonymizing or encrypting data, audits, periodic privacy, and risk assessments, are necessary to safeguard participant data from unauthorized access or misuse. Analyzing data requires a meticulous process (Yakut Çayir & Saritaş, 2017) of organizing collected data, dividing into categories, theme generation, and publishing a report. Ensuring data organization, trustworthiness, and validity provided usefulness to the data analysis and findings. Organizations of different sizes and in multiple industries comprising telecom (M. U. Khan & Fatima, 2024), finance (Kasiraju, 2024), healthcare (Rodgers et al., 2024; Wolseley et al., 2024), insurance (Alexandre Terlizzi et al., 2024) and online software companies (Rodgers et al., 2024) can benefit from the adoption of the use of BDA for strategic decision making. Understanding the gaps in BDA adoption helps organizations use the correct data to obtain actionable insights (Rodgers et al., 2024).

Chapter 2 details the topic of the current study from past research works and literature. The literature review is structured into different sub-sections. The literature analysis is organized into sub-sections, including BD overview, BD usage in organizations, BDA and strategic decision-making, and details on the theoretical framework used. The sources of the research work used to develop this section, like databases and search engines, along with search terms and combinations, are captured. The guiding theoretical framework is explained along with its origin and development over the years, details of the concepts, usage in other research works similarly, alternative frameworks considered, and why the chosen framework suits the current study and how it guided the problem, purpose statements, and research questions.

Chapter 2: Literature Review

The problem to be addressed in this study was that existing constraints in organizations often create hurdles in the implementation of BDA for strategic decisions (Alexandre Terlizzi et al., 2024; Konanahalli et al., 2022), decreasing competitive edge and negatively affecting performance (Baker, 2022; M. U. Khan & Fatima, 2024; Manohar, 2021). The purpose of this qualitative exploratory study was to find what organizational constraints impact the adoption of BDA for strategic decision-making and investigate how these impediments can be mitigated to reach performance goals and gain a competitive advantage at a technology company.

The literature review is organized into multiple sub-sections, including BD overview, the value of BD, BD Limitations, BD usage in organizations, different sectors and countries, BDA and strategic decision-making, and details on the theoretical framework used. The literature review supporting this research utilized scholarly and peer-reviewed articles, dissertations, and journals. The online resources comprised the National University (NU) library navigator search engine, Credo Reference, EBSCOHost, Google Scholar, IEEE, and ProQuest. The search aimed to gather historical information on categories including BD, BD adoption, BDA, organizational decision-making, information technology (IT), and frameworks such as the TOC and technology-organization-environment (TOE) framework connected to the problem under study. Online searches used keywords like BD, analytics, decision-making, adoption, organization, and IT to capture various works in BD and strategic decision-making in organizations.

Theoretical Framework

Theoretical and conceptual frameworks help to create focus and define the rules and structure of research work (Caffrey, 2023). While dissertations are analogous to constructing a house, theoretical frameworks are comparable to blueprints for a dissertation (Salawu et al.,

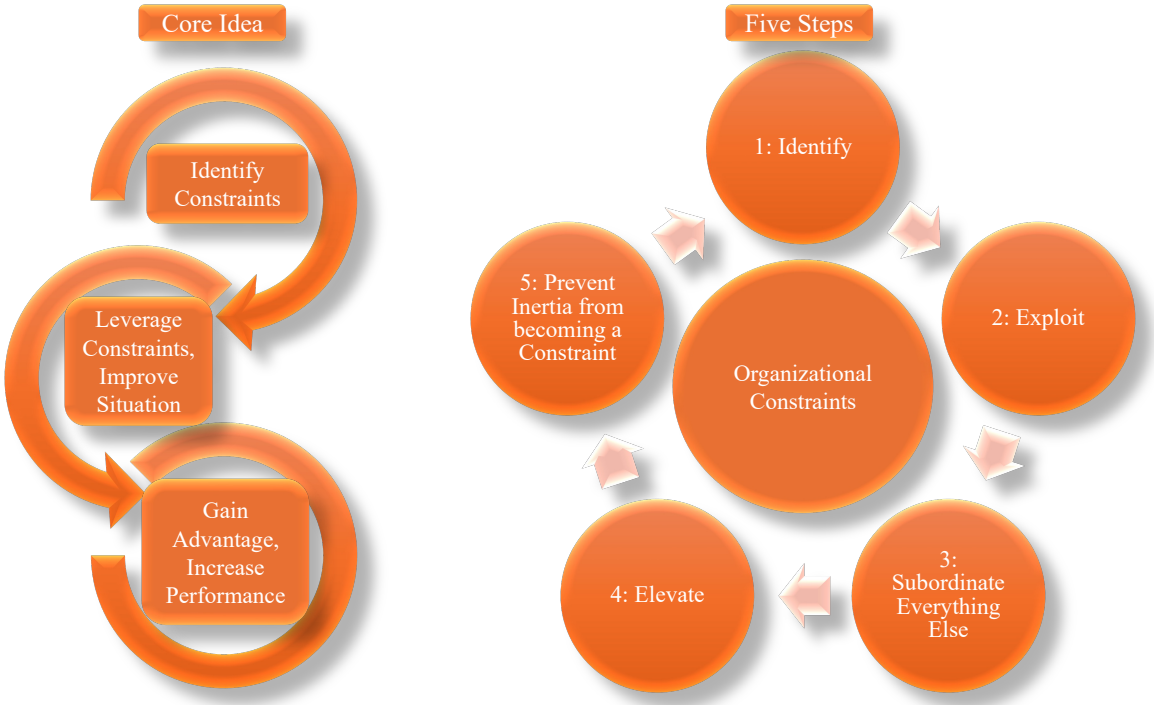
2023). The theoretical framework provides a structure to approach the dissertation methodologically, analytically, philosophically, and epistemologically (Oyewobi et al., 2024). Adopting new technology was guided by different theories, models, and frameworks, each offering a unique perspective. After performing an exhaustive literature review for the research topic, multiple suitable theoretical frameworks were identified for the study. The frameworks included the theory of constraints (TOC Institute, 2021) the "Technology-Organization-Environment framework" (Tornatzky et al., 1990), dynamic capabilities theory, resource based view (Chaudhuri et al., 2024), "Unified Theory of Acceptance and Use of Technology" (Azam & Ahmad, 2024), "Diffusion of Innovation theory" (Wurster et al., 2024) and information system success mode theory (Azam & Ahmad, 2024; Wolseley et al., 2024). The choice of theoretical framework for the dissertation should be driven by considering different theories and their applications to business problems in the literature.

The TOC theoretical framework introduced by Eliyahu Moshe Goldratt in 1984 was used to understand the research problem in focus. Dr. Goldratt was an author, business philosopher, and educationalist known for provoking other researchers to develop innovative ideas (TOC Institute, 2021). TOC is a methodology to improve performance. The core concept of TOC is that every organization has constraints. TOC defines constraint as a limitation in a system or organization in reaching high performance. Identifying and managing the constraint helps organizations increase their performance. Managing constraints involves eliminating the hurdles to adopting a process or technology. Reducing time to market or increasing profitability leads to performance increases (Hoyt, 2022; TOC Institute, 2021). TOC can be explained in five steps: identifying the constraint, eliminating or limiting the constraint, prioritizing the constraint relative to other non-constraints, providing more resources, and preventing inactivity from

becoming a constraint. The TOC framework's core idea and a five-step process to increase an organization's throughput are depicted in Figure 1. The TOC framework has been used in different sectors for decades since its inception.

Figure 1

Core Idea, Five-step Process to Increase Organizational Throughput



Note. The core idea of the TOC framework and the five-step process to grow the organizational output (TOC Institute, 2021).

While the early focus of the TOC framework was to support the manufacturing industry, it rapidly became applicable in other industries, including the information technology (IT) sector (R. J. Harris, 2018; Hoyt, 2022; TOC Institute, 2021). The TOC framework gained recognition in the '90s in industrial and service organizations and continues to be popular in the 2020 digital transformation era (Aljaž, 2024; Coman & Ronen, 1995). Historically, TOC was a subject of discussion in the manufacturing industry along with optimum production technology (Karakoç & Şik, 2021). TOC was used in the manufacturing sector for production scheduling and to reduce lead times in manufacturing products to gain a competitive advantage (Karakoç & Şik, 2021; Tersine & Hummingbird, 1995). One of the research projects applied TOC principles to IT management in an organization (Coman & Ronen, 1995). The research drew a process depicting how IT can be more efficient using the TOC management method. To methodically understand the constraints in an organization, TOC was applied to a combination of management frameworks comprising Boston Consulting Group's portfolio analysis model, the value chain model, and the stakeholder analysis model. A 2023 work in literature investigated the change in consumer buying behavior due to the global COVID-19 pandemic by integrating the TOC framework into buying cultures (Powless & Jarquin, 2023). The research attempted to identify solutions to the worldwide phenomenon by connecting TOC to consumer buying habits. More recently, TOC has shown performance improvements in services and supply chain logistics (da Silva Stefano et al., 2024; Khakifirooz et al., 2024). TOC was used with ML and AI methods to automate the management of tasks and resources (Khakifirooz et al., 2024) as well as improve sales and reduce inventories in supply chain logistics (da Silva Stefano et al., 2024).

After an extensive review of the literature for my research problem, I found that the TOC fits my dissertation. Understanding the business problem helps organizations apply a business-

driven data-supported (BDDS) process inspired by TOC to gather data, extract information, and produce actionable insights to solve the problem and gain a competitive advantage (Rodgers et al., 2024). Upcoming applications of TOC include BD and AI (Hoyt, 2022). TOC targets identifying and managing constraints, providing continuous progress, and adapting to organizational change (R. J. Harris, 2018). TOC has multiple applications, from project planning to managing common resources to parallel ongoing tasks and project management initiatives, such as project risk and cost. The TOC framework explains the importance of resource sharing for accomplishing concurrent IT projects in an organization. Though companies were sitting on enormous data sets, they needed more time to be ready to take advantage of the tactical resources. Taking on BD involved addressing business policy, technology, and resource constraints. BD was treated as a tactical resource like oil and gold. A socio-technical framework was essential to address the restrictions. The TOC framework helps identify IT personnel's constraints in adopting BD tools for analysis and recommends solutions to the problem. Change requires recognizing and documenting core issues. An organization has multiple conditions, including market, policy, and physical constraints.

Big Data Overview

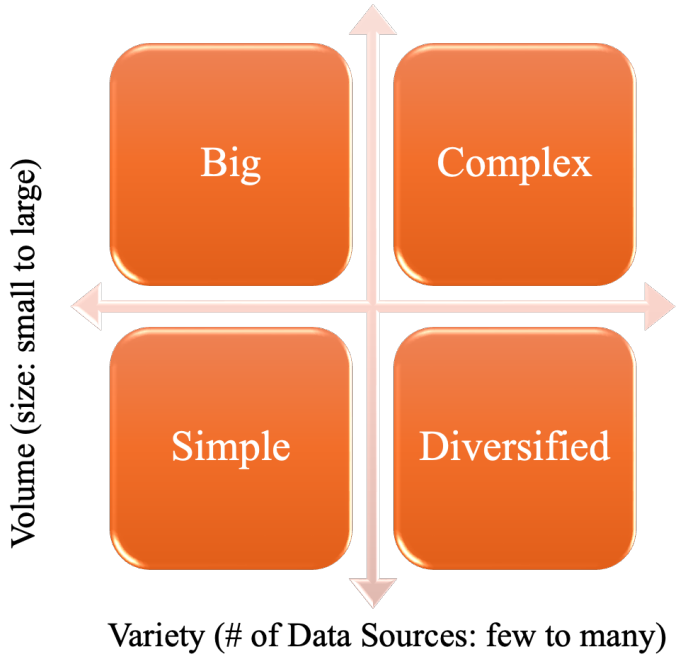
The origins of BD can be linked back to the 1970s, when the phrase was connected to managing and studying vast volumes of data (Raban & Gordon, 2020). Though the beginning of BD can be traced back to 1974, the word became prominent and sticky in 2008. Like many novel technologies, BD was defined many times, but researchers describe BD with characteristics of volume, variety, velocity, and veracity (V's) (M. A. Khan et al., 2014; Lokesh et al., 2022). An effort was made to formally define BD by identifying research works from industry and academia. The effort led to the definition of BD as the information asset with high volume,

veracity, and velocity that requires analytical and technological methods to translate into value (De Mauro et al., 2016). While attempts were being made to understand and define BD, there was a lack of consensus on what BD means and what it constitutes (Han et al., 2024). Hence, a universally agreed-upon definition was yet to be released. Although there was general agreement on the characteristics of BD comprising V's, researchers had their own understandings and descriptions of BD in the content of their respective works. Discrepancies exist between understanding the term BD theoretically and its practical implementation. BD could be called technology, datasets, and platforms in different research works. Therefore, a comprehensive understanding of BD was necessary.

BD's growth and complexity had increased the challenge of obtaining actionable insights from the data (Partners, 2017; Rodgers et al., 2024). A four-quadrant data complexity matrix shown in Figure 2 can depict BD characteristics, volume, and variety. As the volume of the data and variety increase, the complexity increases, and more challenges surface to identify relationships within the data (Rodgers et al., 2024). With growing data velocity, companies increasingly emphasize gathering real-time data, faster BD integration, and data processing.

Figure 2

Data Complexity Matrix with Volume and Variety



Note. As the data volume and variety characteristics increase, the data complexity increases (Rodgers et al., 2024).

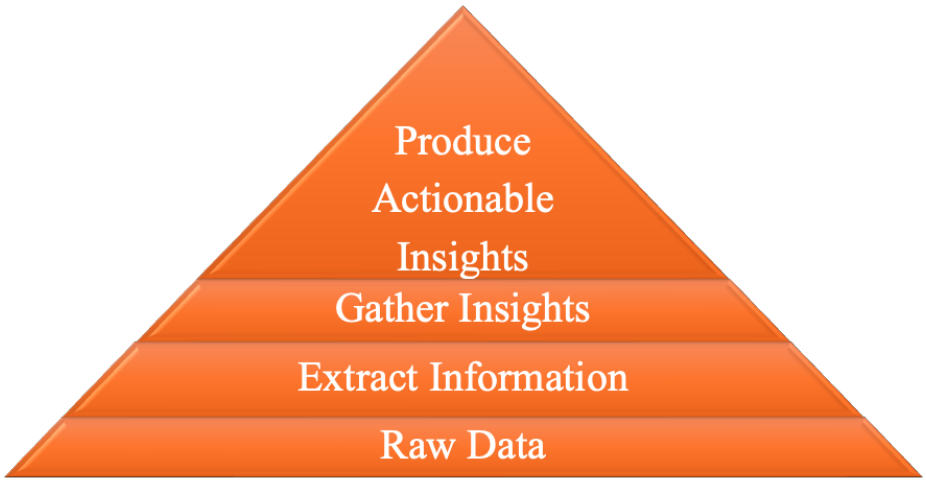
As the complexity increased, advanced algorithms were needed to analyze data with multiple dimensions to help organizational decision-making (Rodgers et al., 2024). Hence, AI methods and models were at the forefront of accurately interpreting complex data, learning from the data, and adapting to business problems. Generative AI technologies such as ChatGPT by OpenAI are gaining prominence, and they use deep learning methodologies for natural language processing (M. U. Khan & Fatima, 2024; Taecharungroj, 2023). These models depict the potential of learning from the data and producing innovative results. Further examples of generative AI include models for music and image generation for creating novel content (Gozalo-Brizuela & Garrido-Merchan, 2023; M. U. Khan & Fatima, 2024).

With increasing data complexity, challenges increased in extracting actionable insights from the data, and it had become essential to understand the data hierarchy (Rodgers et al., 2024). Data hierarchy can be understood through a data-driven, value-based pyramid with data at the bottom and information, insights, and actionable insights at the top (Ackoff, 1989; Rodgers et al., 2024). Data served as a foundation from which information was gleaned. Information was analyzed to extract understanding from which actionable insights at the top of the pyramid were produced. Roots of the data pyramid exist in T.S. Eliot's 1934 work, which articulated the variance between information, knowledge, and wisdom (Eliot, 2011; Rodgers et al., 2024). The seminal work of 1989 by Russell Ackoff offered a value-based hierarchy commonly called the data information knowledge wisdom framework for unearthing wisdom from data (Ackoff, 1989; Peters, 2024; Rodgers et al., 2024). In the rush for BD adoption and the relatively low cost of accumulating data supported by sophisticated data systems in their environments, companies gathered data with the assumption of generating value. Creating data volumes without knowing the outcomes businesses want and the needed value was a fallacy. While academic research preaches a data-driven, value-based hierarchy for data initiatives, practical literature emphasizes understanding the business problem (Court et al., 2015; Rodgers et al., 2024). A report from McKinsey Global Institute had shown how companies that embarked on the BD journeys have not created value, as they failed to ask the right business questions before implementing processes for data analysis. Organizations operate in complex environments and encounter various challenges in adopting data analytics with the growing availability of BD and the rise of AI technologies. As such, it was essential to have a guiding process for leaders in organizations to embark on BDA initiatives to create value by solving the correct business problems. While a data-driven value-based hierarchy started with collecting vast amounts of data, a BDDS process

began with the business problem and the key question to answer. The BDDS process started with the problem that impacted the business performance, and then answered the question of what caused the problem. Then, data was collected to extract information from which actionable insights were drawn. The BDDS process's methodology was known as the data to information extraction methodology (Rodgers et al., 2024, p. 710). The advantage of the BDDS process was that it accelerated the delivery of business value. The data-based value hierarchy is shown in Figure 3. Along with the details of BD complexity and data pyramid, it was vital to understand the growth of BD.

Figure 3

Data-Driven Value Based Hierarchy



Note. The figure depicts the Data Information Knowledge Wisdom hierarchy, which was used to understand how actionable insights can be drawn from raw data (Peters, 2024; Rodgers et al., 2024).

Big Data Growth

The enormous data generation in the era of rapidly evolving technologies has led to BD (Grander et al., 2021; W. He, 2025). In this era of technology evolution, BD was considered one of the breakthrough innovations (Elia et al., 2022). BD was described in different ways in literature, including as the next innovation (Han et al., 2024; Sivarajah et al., 2024), a paradigm of science (Dominik Balazka & Dario Rodighiero, 2020), a management revolution (Awan et al., 2021), and a cornerstone of productivity and competition (T. Liu et al., 2023). BD comprised structured and unstructured data, and the features made it unique relative to traditional data. BD has different features described as V's (Lokesh et al., 2022; Renugadevi et al., 2023). Volume refers to the large amount of data that is created and is measured in petabytes and exabytes (Dhulavvagol & Totad, 2023; Lokesh et al., 2022). The dataset was considered huge when it was not feasible to process the data using traditional methods or software. Massive data sets cause challenges for IT teams maintaining hardware and software in organizations (Badshah et al., 2024; Tosi et al., 2024). Past works indicated that 2.5 quintillion bytes (2500 petabytes or 2.5 exabytes) of data were generated daily (Pandey & Bist, 2024; Tawil et al., 2024), and 90% of the world's data was created between 2005 and 2015 (Tawil et al., 2024). Data in the digital era is compared to oil. Data is produced in different forms, including structured, unstructured, video, audio, and text, and hence the characteristic variety (Akter & Wamba, 2016; M. A. Khan et al., 2014; Lokesh et al., 2022; Sivarajah et al., 2017). The frequency and speed at which the data is generated in the era of new technologies refer to velocity (Akter & Wamba, 2016; M. A. Khan et al., 2014; Sivarajah et al., 2017). The amount of data, its different forms, and the rate at which the data were generated created uncertainty, and hence veracity became a key characteristic of BD (Akter & Wamba, 2016; Elragal & Klischewski, 2017; M. A. Khan et al., 2014).

Data had increased considerably and quickly with mobile applications, internet-connected devices, network sensors, social media, clickstreams, and satellites (Akter & Wamba, 2016; Elragal & Klischewski, 2017). These applications and devices generate enormous amounts of data with different structures and diversity. Data generation had also been catapulted by the quick evolution of the Internet of Things (IoT) and cloud computing. Despite rapid progress in BD, there are significant challenges that researchers must address, including standardization, technologies for storage, BD management, real-time performance, search, analysis of BD, development of BD applications, data security, and privacy (Mahmoudian et al., 2023). Hence, it is essential to understand the scope of BD.

Scope of Big Data

BD was perceived to have different areas of scope, including large datasets, ML techniques, and BD ecosystems (Han et al., 2024). The extensive data sources comprised databases, crowd-sourcing systems, and websites, which form the application targets of BD. BD as a technology can be categorized under several categories: infrastructure for computing, systems for storing data, BD mining, BD management, BD ML, and security and privacy (Han et al., 2024; Patgiri, 2019). Hadoop was the common computing infrastructure used for BD in multiple sectors, including healthcare, transportation, and environmental science (Han et al., 2024; Z. F. Khan & Alotaibi, 2020). From a distributed storage and retrieval perspective for BD, Apache Cassandra, MongoDB, Hadoop Distributed File System, and HBase were common choices. All these technologies provided scalability, could handle large volumes of data, and were fault-tolerant. From a BD management side, Hadoop, Hive, MapReduce, and Pig were utilized for processing and managing large volumes of data (Han et al., 2024; Pandey & Bist,

2024). While Hadoop was a common choice for BD solutions, Druid has performed better than Hadoop (Correia et al., 2019).

The ML category refers to BD as algorithms, models, and statistical methods for processing and managing large datasets related to ML, AI, data mining, and deep learning (Han et al., 2024). From a data mining and ML side, many ML models like artificial neural networks (ANN), support vector machine (SVM), random forest, bayesian methodology, and boosted regression tree were available for processing BD and gaining insights, gleaning patterns and trends from the data, and making predictions with analysis on the data. From a security and privacy angle, intrusion detection systems detected anomalies in the environment. ML models like deep learning methods and unsupervised online deep neural networks were used to identify attacks. Log parsers such as HDFS, Zookeeper, and Proxifier were used to secure data and adhere to privacy standards in distributed systems. These technologies provided authentication, access control, data encryption, and secured data from unauthorized use (Han et al., 2024).

The category of BD ecosystem encompasses applications like Hadoop and MapReduce, storage systems like Cassandra, MongoDB, and Druid (Correia et al., 2019), and tools like Flume and Sqoop for transferring data across storage systems with high efficacy (Han et al., 2024; Pandey & Bist, 2024; Saraswathi et al., 2022). Researchers applied the concept of BD to different areas to understand acceptance with popular frameworks like the technology acceptance model (TAM) and its variations (Al Rob et al., 2024). The research looked at the factors linked with using BDA by integrating TAM with organizational training and learning. With BD characteristics, categories, and growth, realizing the value of BD and BDA was crucial.

Value of Big Data

BDA refers to large volumes of data and analytics on massive data sets using statistical methods to extract new and valuable insights (Pandey & Bist, 2024; Saraswathi et al., 2022). BDA explores an enormous amount of data to find relationships among the data sets available and ultimately provides new opportunities and valuable insights to the organization (Azeem et al., 2022; Pandey & Bist, 2024; Saraswathi et al., 2022). Efficiencies of analyzing BD included knowledgeable business decisions, high profits through cost reduction, and happier customers by meeting their needs (Pandey & Bist, 2024; Saraswathi et al., 2022). BDA enables many sectors, including healthcare, banking, social media, transportation, government, education, insurance, manufacturing, retail, and agriculture. Past studies on BD focused on one of the dimensions, like characteristics, analytics, or visualization, or individually examined the application of BDA in different fields, such as transportation and agriculture (Rajaraman, 2016; Saraswathi et al., 2022). BDA is a set of tools and techniques utilized to overcome the challenges of volume, variety, and velocity at which data is generated (Lokesh et al., 2022; Saraswathi et al., 2022). Different BD tools and technologies were utilized in various sectors (Saraswathi et al., 2022). BD was measured by integrating different dimensions and their applications. Multiple types of analytics were used in the industry and academia.

BD technology comprised a set of tools, frameworks, and techniques for gathering, storing, processing, and analyzing large volumes of data, which could be unstructured, semi-structured, or structured (Kwasu et al., 2024; Rahul et al., 2023). Sources of vast data volumes included transactional systems, sensors, mobile phones, and social media activity. Traditional data systems could not handle the enormous data sets, and BD technology and systems were needed to process the data. The use of BD systems was vital as the volume of data grew daily,

along with variety and velocity (Batko & Ślęzak, 2022; Kwasu et al., 2024). BD technologies were used in ML models, predictive analysis, and analytical methods for making data-based decisions for business problems (Kwasu et al., 2024; Yaseen & Obaid, 2020). Understanding types of analytics is a helpful next step.

Types of Analytics

BDA can be organized into different types, including predictive, prescriptive, descriptive, and diagnostic analytics (Pandey & Bist, 2024; Rajaraman, 2016; Saraswathi et al., 2022). Organizations must drive their decision-making processes using the large amounts of available data. Descriptive analytics investigates historical raw data using statistical methods, processes it, and generates valuable insights (Gupta et al., 2014; Rajaraman, 2016; Saraswathi et al., 2022). Ways of representing descriptive data analytics included graphs, pie charts, maps, and scatter plots (Rajaraman, 2016; Saraswathi et al., 2022). Examples of descriptive analytics included calculating the profit of all supermarkets in a city daily and classifying population data by different characteristics like education, income, sex, and age group. Diagnostic analytics examined the data to find correlations between various dimensions (Gupta et al., 2014; Saraswathi et al., 2022). Examples of diagnostic analytics included analyzing the supermarket data of 100 shops to find the reasons behind the losses from, say, ten shops. Predictive analytics processes available data to generate details of what might happen. Predictive analysis alludes to what and when something might occur in the future (Gupta et al., 2014; Pandey & Bist, 2024; Rajaraman, 2016; Saraswathi et al., 2022). Time series analysis was created using statistical methods, ML algorithms, and neural networks, and was used in predictive analytics. In the supermarket example, the shopkeepers store the demanding products and forecast the demand for each product. Prescriptive analytics outlines the actions that must be taken to overcome existing

challenges (Saraswathi et al., 2022; Zargoush et al., 2025). Based on predictions, companies can create a prescription. An example from the healthcare industry included prescribing medications for a patient based on the predictions resulting from processing different combinations of medicines prescribed to other patients in the past. Experienced teams and organizations work with both predictive and prescriptive analytics. Another example of prescriptive analytics included the airline's seating pricing depending on the starting and destination locations (Rajaraman, 2016; Saraswathi et al., 2022). Other widely used techniques in BDA comprise AI, deep learning, ML, natural language processing, and data mining. An organization’s productivity improves with the use of technologies and tools by data scientists for BDA. Examples of tools included R, Excel, Rapid Miner, KNIME, Weka, and Pentaho. As much as it is essential to understand the value of BD, it is helpful to look at its limitations.

Big Data Limitations

Assumptions cannot be made about BD that having large volumes of data leads to accurate outcomes (Han et al., 2024). When BD was not used optimally or for the right applications, it wasted computing resources and increased costs. Not handling the data appropriately with access controls and encryption could lead to security and privacy issues. Small and medium-sized enterprises (SMEs) strive for data-driven innovation to transform business operations, gain sustained competitive advantage, adhere to regulations and government policies, and expand to new market segments (Tawil et al., 2024). Data-driven innovation at companies depends on the culture, availability of resources, including people and finances, and developing tools to process and analyze data. The availability of data and the culture must also factor in veracity, unbiasedness, and timeliness to draw accurate conclusions when analyzing the data. Some hurdles included protecting the data during gathering, processing, and storage to minimize risk

for SMEs. Other challenges included risk awareness of data, enhancing the skillsets of the employees in the organization to handle BD, aligning the investors and stakeholders, and understanding business risks and government regulations (Tawil et al., 2024).

Organizations adopting BDA encounter many challenges, including data quality and governance. Data governance and quality encompass accuracy, reliability, completeness, security, and privacy. Data quality was fundamental for effective BDA, as any inaccuracies in the data or lack of completeness led to erroneous decisions (Rauf et al., 2024; Rybicka, 2019; S. Shamim et al., 2020). It was essential to maintain data consistency across different sources to sustain the reliability of results driven by analytics (Rauf et al., 2024; Sivarajah et al., 2017).

Infrastructure costs for using new technologies were critical to adopting BD in organizations. For SMEs, the high costs of adopting BD technologies were a deterrent (Phung et al., 2021; Trieu, 2017). Companies need adaptable and scalable data storage solutions to manage and process large volumes of data (Boakye et al., 2022; Coşkun et al., 2022; Rauf et al., 2024). Organizations must significantly invest in hardware and software to store, process, and analyze large data sets in real time (Anaya & Qutaishat, 2022; Hadjielias et al., 2022; Rauf et al., 2024). Moreover, integrating legacy systems with BD technologies causes technical and logistical challenges for leaders as existing systems might not be compatible with newer BD architectures (Cottu et al., 2022; Lee et al., 2022; Rauf et al., 2024). Overcoming the cost hurdles required strategic planning and investments while ensuring the technology infrastructure was robust, flexible, scalable, and supported BD initiatives.

Security and privacy were crucial concerns with sensitive financial and personal data in BD initiatives (Nespeca et al., 2020; Rauf et al., 2024). It was necessary to understand the ethical concerns, such as allowing transparency and collecting explicit consent when using data to

maintain public trust and adherence to regulatory requirements (Niknejad et al., 2021; Rauf et al., 2024). To address the limitations, efficient governance frameworks with transparent practices for managing data, ethical use, and security were essential (Ospanova & Kukharenko, 2021; Ostapenko, Y. P., 2021; Rauf et al., 2024).

Privacy and Security

The characteristics of BD and the technologies involved made security and privacy key issues when handling BD (Moreno et al., 2019). Security and privacy issues hamper the adoption and use of BDA in organizations. Environmental factors impacting BD adoption included privacy, security, and ethical concerns in data collection, regulatory environments, and market turbulence (Sun et al., 2018). Technology changes and societal expectations have increased BD's legal and ethical issues. BD presents different privacy issues in health data, consumer data, government, and intelligence. Security and privacy issues also impact the integration of the data-driven decision-making process. The most common ethical issues for businesses included the problems with intrusion and violation of privacy, data consent from providers, and the level of transparency companies used in collecting data (Flyverbom et al., 2019). BDA often included personally identifiable information, and this data, in combination with other data sources, can create ethical and legal issues linked to the private information of individuals (Manohar, 2021).

The explosion of data in the digital era and BDA has influenced data-driven decision-making in different industries and, more prominently, in healthcare (Asthana et al., 2024; Z. Jiang et al., 2024; Lysaght et al., 2019). The availability of data from diverse sources, including healthcare records, social media, and wearables, opened doors for new areas of research and innovation (Brown & Anderson, 2023; Z. Jiang et al., 2024). Multimodal behavioral research (MMBR) was one area that gained prominence, utilizing BDA to study human health and

behavior (Alvarez-Romero et al., 2023; Z. Jiang et al., 2024). MMBR encompassed collecting, integrating, and analyzing data from various sources, including body sensors, self-reported information, and video recordings (Z. Jiang et al., 2024; Mu et al., 2020). Management and analysis of human-centric data to study health and behaviors pose many challenges (Z. Jiang et al., 2024; Mangaroska et al., 2021). The diversity of data formats, the need to harmonize the data, and the ethical aspects of privacy and security force the need for data governance processes (S. Choudhury et al., 2014; Z. Jiang et al., 2024). Data governance methodologies address data management's strategic and operational aspects to achieve research goals while conforming to privacy, security, and regulatory compliance (Z. Jiang et al., 2024). Data governance processes also help alleviate risks related to unauthorized access, data breaches, and misuse (Azzi et al., 2025; Z. Jiang et al., 2024). Data breaches and misuse can cause catastrophic issues for institutions managing data, patients, and research participants.

Although data governance in behavioral research was crucial, and frameworks such as the maturity model from Data Governance Institute were available, there was a general lack of guidelines, and the frameworks did not fully address the research area (S. Choudhury et al., 2014; Z. Jiang et al., 2024). The deficiency in the frameworks arises from behavioral research involving heterogeneous data categories, enormous datasets, and ethical issues surrounding the handling of sensitive personal data (G. Jiang et al., 2023; Z. Jiang et al., 2024). Hence, there was a need for a comprehensive data governance framework for multimodal behavioral research to address the privacy and security concerns.

Big Data Usage in Organizations

BD was linked to collecting and storing vast amounts of data for future analysis (Rodgers et al., 2024). BD implementations were successful when companies answered critical business

questions, gathered insights from market trends, and adjusted to a competitive landscape. Successful BD deployments in organizations encourage other firms to create BD campaigns to realize benefits (Amalina et al., 2020; Dash et al., 2019; Rodgers et al., 2024). With multiple companies embracing BD, market revenues from the software and services sector could increase by 145% to $103 billion by 2027 from 2018 (Rodgers et al., 2024). Companies must have a strategy to use BD and insights from the data effectively and not rush into BD adoption and integration. Organizations embarking on BD initiatives without understanding the outcomes they would like to achieve collect and analyze data, leading to costs and chaos (Rodgers et al., 2024; G. Smith, 2020). A survey conducted in 2017 by New Vantage Partners to study fortune 1000 companies found that only 27.9% of the participating firms had success in transforming their businesses for the future. Approximately 48% of the firms have not started any projects to utilize the power of BD.

BDA was seen as a source of creating business value in organizations. While capabilities frequently describe business value, building that value from BDA-related organizational investments has yet to be fully known. Process models were in vogue, involving two stages, with the first stage including a BDA conversion process that details the steps between BDA investments and resources (Hirschlein & Dremel, 2021). The second stage comprised the BDA synergy process that explains the steps from BDA capability to realizing business value. The amount of data collection, analysis, and usage in decision-making in organizations has been rising rapidly (Schuiling, 2020). Studies have shown that organizations have seen productivity increase by 4.1% using BDA. While some large organizations can adopt BDA, SMEs frequently cannot do so because of a lack of resources to overcome the hurdles, leading to a competitive disadvantage. There was a gap in the literature concerning feasible and desirable approaches for

SME adoption of BDA. BDA provides new value paths for organizations, such as decision-making and business process optimization beyond traditional business intelligence (Hirschlein & Dremel, 2021). BDA has gained momentum in practical uses and academia as it provides technological advancements in companies for revenue growth and increases productivity. For practical usage in the industry, BDA was a vital factor for driving data-driven transformation. Hence, BDA was central to creating organizational value. BD helps organizations predict, detect, and respond to disruption in the industry (Van Rijmenam et al., 2019). While value creation was a significant advantage, organizations struggled to implement BDA successfully (Wiener et al., 2020).

For organizations embarking on data-driven initiatives and deployment of tools, it was essential to understand how to gain the advantages of BD to make informed decisions and drive increased performance. A comprehensive strategy aligns the data initiatives with business goals (Akter et al., 2016; Rodgers et al., 2024). Efficient data governance was needed to produce quality data, creating a platform for dependable insights (Rodgers et al., 2024; Vasanth et al., 2024). Apart from the strategy, the right choice of architecture and technology stack was essential to deploy the needed data tools and technologies (Rodgers et al., 2024; M. A. Salman et al., 2025). The chosen tools should align with the business goals and assist in the complete data life cycle from data collection to processing, storage, analysis, and visualization. Furthermore, the adaptability and scalability of the tools were essential. Evaluating the advantages of data-driven initiatives was a necessary topic for organizations, as it was vital to understand how utilizing BD drives business performance. Organizations executing data projects must measure metrics and key performance indicators (KPIs) to assess the outcomes of the initiatives (J. G. Harris & Davenport, 2017; Rodgers et al., 2024). A comparison of the same metrics before and

after the implementation of BD projects in organizations helps determine if the work produced tangible benefits. Benefits can encompass gains beyond financial performance, including customer satisfaction, efficient processes, and better decision-making (Rodgers et al., 2024; Stobierski, 2019). Integrating information quality, system quality, and user satisfaction helps assess the advantages of data-driven initiatives. Organizations must include qualitative and quantitative measures to evaluate data-driven initiatives that align with business goals.

Processing data to produce actionable insights was vital for organizations that utilized data to make informed decisions. Data processing involved cleansing and transforming to ensure consistency and quality (Nesca, M. et al., 2022; Rodgers et al., 2024). The next step was aggregating and analyzing the data using ML models and visualization methods. ML models help uncover relationships and patterns among the data (P. Choudhury et al., 2021; Rodgers et al., 2024). Visualization techniques help present complex data in an understandable view to decision-makers in the organization. In summary, processing helps organizations transform raw data into insights and drive business strategies (Adewusi et al., 2024; Rodgers et al., 2024). Many valuable applications of BDA exist for organizations to increase operational performance.

Managing employee performance encompasses evaluating and improving the performance of employees in the organization (Kwasu et al., 2024; Nowicka et al., 2024). Performance management involves setting challenging goals aligned with the company's objectives and providing periodic employee feedback through appraisals. Companies used BD to enrich the performance measurement processes (Kwasu et al., 2024; Sajid et al., 2020). Data-driven assessments helped objectively measure employee performance and provide fair and accurate evaluations. Surveys were conducted using BD tools like Survey Monkey and Qualtrics to obtain employee feedback on job satisfaction, engagement, and aspects of employee performance

(Cvetkoska et al., 2023; Kwasu et al., 2024; Tanasescu et al., 2024). Organizations used Bamboo HR and Workday to track employee and team goals and measure performance using the customer satisfaction scores, project efficiency, tasks completed, and progress made toward achieving the objectives (Gravili et al., 2023; Kwasu et al., 2024; Yang & Tang, 2023). The data can be used to identify high performers who can be rewarded and low performers who can be provided feedback to improve. BD applications like Microsoft Teams and Slack are collaborative tools that human resource (HR) managers can use to measure the performance of teams in a company (Cvetkoska et al., 2023; Kwasu et al., 2024; Tanasescu et al., 2024). HR leaders can measure communication patterns and benefit from the insights produced by the tools on employee contribution, teamwork, and productivity. The use of BD applications like Lattice and Leapsome has facilitated obtaining 360-degree feedback for an employee from various sources, including peers, subordinates, management chain, and customers (Cvetkoska et al., 2023; Kwasu et al., 2024; Sardi et al., 2023). Real-Time feedback helped HR managers assess the performance of employees towards the company's objectives and not wait for yearly reviews. BDA tools like Microsoft Power BI and Google Analytics provided visualization through dashboards that captured the KPIs that help HR managers observe the progress of employees, teams, and groups toward the goals in real-time (Cvetkoska et al., 2023; Kwasu et al., 2024; Tanasescu et al., 2024). Challenges in managing employee performance using BD tools and applications included privacy issues if the data was not safeguarded with access control, collected, and analyzed without prior consent from the employee (Kwasu et al., 2024; Nowicka et al., 2024; Yang & Tang, 2023). Security issues with cyber-attacks, where employee data can be compromised, were another challenge. Using historical data for modeling can also create bias in the outcomes and

could lead to reporting inaccurate employee performance, leading to incorrect decisions and harming the organization.

Employee compensation was integral to hiring talent with the required skills in an organization. Aspirants were motivated by their compensation (Cvetkoska et al., 2023; Kwasu et al., 2024; Yang & Tang, 2023). Employee performance was a key aspect of compensation in organizations. Historically, Performance systems used qualitative instead of quantitative metrics, resulting in compensation recommendations that were at odds with the performance (Kwasu et al., 2024; Maley et al., 2021). HR managers also use BDA tools in organizations to overcome the gaps. The insights from the BDA tools drive decisions on the performance of employees, compensation structure, promotions, and training needs. BD tools also aid sentiment analysis using natural language processing (NLP) to extract insights from textual data. Sentiment analysis on the data gathered from surveys, feedback forms, emails, and internal communications helps understand employees' morale and engagement levels (Cvetkoska et al., 2023; Kwasu et al., 2024; Yang & Tang, 2023). BDA tools also help forecast employee attrition. HR managers can use BDA tools to obtain insights that aid in developing strategies for retaining high-performing employees and proactively addressing dissatisfaction (Kwasu et al., 2024; Sardi et al., 2023). Efficiently managing employees was essential for the best performance and, ultimately, profitability in organizations (Kwasu et al., 2024). HR leaders must deal with many challenges, such as safety and security, and gain insights when handling employee data. BDA helps HR departments in their practices, such as hiring, compensation, developing employees, and managing employee performance. BD technologies shape organizational compensation models (Cvetkoska et al., 2023; Kwasu et al., 2024).

BDA became an essential tool during the recruitment process, which involved identifying job requirements, advertising for open positions, gathering applications, shortlisting candidates, interviewing, and finalizing the right candidate for the job (Heliana & Wahyuni, 2024; Kwasu et al., 2024). BDA helps predict candidates' performance potential by using educational credentials and past employment experiences. BDA techniques help shortlist candidates who can contribute positively to the organization's goals, leading to higher operational performance. The process also eliminated the recruiting error of choosing the wrong candidate for the job, which was expensive and derailed operational excellence. Using historical hiring data, BDA also helps drive targeted recruitment processes and saves time and costs. Data from the past, including the performance of hires and retention percentage, can be utilized to choose the right candidates for the current open positions using predictive analytics (Hang & Tat, 2023; Kwasu et al., 2024). Recruitment teams in the organizations used BDA tools to triangulate the information about a candidate from social media (Gravili et al., 2023; Kwasu et al., 2024), professional networks like LinkedIn, and public records, which were not readily available in the resume of the prospective candidate (Gravili et al., 2023; Kwasu et al., 2024; Nowicka et al., 2024). BDA made the recruitment process objective and eliminated any bias of the hiring team (Gravili et al., 2023; Kwasu et al., 2024). The process helped choose the candidate with a culture and values that align with the organization. BDA made real-time screening possible with automation using questionnaires and chatbots (Gravili et al., 2023; Kwasu et al., 2024; Nowicka et al., 2024). BDA analytics usage in recruiting had challenges (Gravili et al., 2023; Hang & Tat, 2023; Kwasu et al., 2024). Challenges included the limited availability of quality data to be used by the model, which can bias the outcomes, and the complexity of processing data from multiple sources (Heliana & Wahyuni, 2024; Kwasu et al., 2024; Nowicka et al., 2024). Other gaps included the

lack of a human touch to assess the candidate's personal traits and soft skills and the limitations of technologies in those areas (Kwasu et al., 2024; Nowicka et al., 2024).

Employee development involves enhancing the skills and knowledge that help the employees' overall performance and career growth (Arulsamy et al., 2023; Kwasu et al., 2024). BDA also plays a key role in developing employees in an organization (Heliana & Wahyuni, 2024; Kwasu et al., 2024; Nowicka et al., 2024). Companies used BDA to customize and personalize training programs for the employees (Kwasu et al., 2024; Núñez-Cacho Utrilla et al., 2023) by factoring in the weaknesses, strengths, and career aspirations of the participants (Gravili et al., 2023; Kwasu et al., 2024; Manroop et al., 2024). Personalizing training programs accounts for the employee's prior education and training, existing skills, preferences for learning, and career goals (Kwasu et al., 2024; Núñez-Cacho Utrilla et al., 2023). BDA tools help organizations find the skill gaps in the employee's performance data (Kwasu et al., 2024; Zhao, 2024). Tools such as Axonify, Adaptive, Docebo, and Ed Cast helped assess the effectiveness of the training in real-time by identifying areas where employees were finding difficulty and taking more time to digest the information and adjust the training (Cui et al., 2022; Kwasu et al., 2024). Companies can track the KPIs before and after training and assess the impact of the training programs on employees (Kwasu et al., 2024; Manroop et al., 2024). The employee training outcomes can be measured by completing projects, gaining customer satisfaction, and increasing sales, which drives the organization (Alsalamah & Callinan, 2021; Kwasu et al., 2024). Some challenges in using BD tools in employee development included a lack of quality performance data of employees (Gravili et al., 2023; Kwasu et al., 2024) and resources needed to incorporate customized training (Heliana & Wahyuni, 2024; Kwasu et al., 2024; Nowicka et al., 2024).

Organizational Culture

The cultural barriers to BD adoption were essential and challenging for organizations to overcome (S. Shamim et al., 2019). Hence, companies must work on embracing a decision-making culture based on data to gain the full advantage of BD opportunities. Organizations must develop a BD decision-making culture, acquire required technologies, and focus on leadership managing BD and BD-related talents. Businesses must have a dedicated process to generate data and make decisions. Organizations pretend to be data-driven but make decisions in traditional ways, and this culture hurts the effectiveness of an organization's decisions (S. Shamim et al., 2019). Companies lack clarity in the role of decision-makers and leaders in all steps of BDA and how that ultimately impacts data-driven decision efficiency and quality. A thriving cultural change can be realized in organizations by documenting, implementing, and communicating the vision of BD, ensuring top leadership is aligned with the vision, and managing the drivers that sway the organizational culture. Developing a clear vision of how BD aligns with the overall organization's strategy drives faster acceptance of BD within the organization. Organizations need to change the decision-making culture among leaders to drive the skillful use of data analytics for better decision-making (Manohar, 2021).

Data-driven culture in organizations was a significant catalyst for growth (Chaudhuri et al., 2024). The data-based culture in organizations had an advanced view because it involved AI integration of business analytics (BA) tools. Data culture in the organization influences product strategy and process performance, which ultimately drives up product innovation and business value and increases overall company performance. Companies need data science technologies to analyze the collected data and overcome hurdles to product innovation (Chaudhuri et al., 2024; Natividade Joergensen & Zaggl, 2024). Data were collected internally and externally to

understand the business problems (Chaudhuri et al., 2024; Huy & Phuc, 2023). A data-driven culture is a set of practices and behaviors among employees who believe data and information are necessary for organizational success (Chaudhuri et al., 2024; Hussinki et al., 2025). The practices and behaviors align with the best business analytical tools (Anton et al., 2023; Chaudhuri et al., 2024). The beliefs, practices, and behaviors that drive a data-driven culture were also pertinent to the organizational decision-making norms. BA can be treated as technology or expertise for analyzing large volumes of data in an organization and acknowledges the need for IT and data science (Aseeri & Kang, 2022; Chaudhuri et al., 2024). Statistical analysis of the enormous amount of data was necessary to accelerate product innovation, meet customer needs, and increase organizational performance (Chaudhuri et al., 2024; Delen & Zolbanin, 2018). A data-driven culture is vital for product innovation in businesses in the current era of digitization. Technology titans like Facebook, Apple, Alibaba, and Google were gaining a competitive advantage and increasing business value by creating a data-driven culture in their respective organizations (Chaudhuri et al., 2024; Upadhyay & Kumar, 2020). With this culture, organizations can manage and analyze large volumes of data to drive innovation and adapt to changes in the industry. Although the concept of data-driven culture had long been a trend, the advent of BD has increased the attention of researchers (Chaudhuri et al., 2024; Thanabalan et al., 2025). Organizations must practice this culture to extract maximum gains from analytical tools and increase business value. Data-driven culture stems from organizational values, standards, beliefs, and behavioral patterns (M. U. Khan & Fatima, 2024). Systematic data collection, storage, processing, and analysis result from the culture instilled in organizations (Aseeri & Kang, 2022; M. U. Khan & Fatima, 2024; Mikalef et al., 2020). Businesses need a lot of effort to acquire and process data to gather insights and make decisions, and they require the

involvement of employees at all levels. Organizations where employees at all levels, from top-level executives to managers and individual employees, make decisions based on the insights obtained from data exhibit a data-driven culture.

Employee skills and organizational culture create challenges in adopting BDA and require resources to be trained in data science and analytics, and to develop a data-oriented decision-making mindset. Companies encounter a shortage of personnel with data science and data analysis skills who can efficiently handle BD technologies (Pan & Zhang, 2021; Rauf et al., 2024). Attracting talent who can process and analyze vast data volumes and produce actionable insights was a big challenge for organizations (Papi et al., 2022; Rauf et al., 2024). Creating a data-driven culture was another hurdle in organizations and required managing change from a traditional decision-making method to one that valued and used insights from the data (Hadjielias et al., 2022; Morozov, 2020; Rauf et al., 2024). Change management initiatives incorporating training at all organizational levels and leadership support were crucial to steer employees into embracing a data-oriented culture (Cottu et al., 2022; Mc Donnell et al., 2020; Rauf et al., 2024). Effective adoption of BDA in an organization results from developing an environment where data integration occurs in business practices and decision-making processes (Lutfi et al., 2022; Rauf et al., 2024).

In the evolving data landscape, to stay competitive, organizations must guarantee sustained performance improvements from data-driven projects (Clancy et al., 2023; Rodgers et al., 2024). A data-driven culture was crucial in organizations to maintain performance over long periods (Abbas et al., 2025; Rodgers et al., 2024). The culture shift involved training the company employees, practicing data-driven decision-making at all levels, and using data in all continuous improvement initiatives in the organization. Adding a feedback loop into the data-driven process

was essential in monitoring and optimizing the process (Alshar et al., 2025; Rodgers et al., 2024). Also crucial for organizations was continuous learning, adhering to industry best practices, and adapting to new technologies and changing business needs to have long-term success and consistently meet business goals (J. G. Harris & Davenport, 2017; Rodgers et al., 2024). Sustaining performance improvements with data-driven initiatives helps organizations in efficient decision-making, effective operations, and in continuously identifying new opportunities.

Organizational Readiness

In the ever-changing environment with uncertainty and ambiguity, BDA can help companies understand the competition and support them in strategic decisions (Van Rijmenam et al., 2019). Organizational readiness includes the intent, attitudes, and beliefs of the organization's employees, and a company's readiness was an essential factor in adopting BDA (Sun et al., 2018). After adopting BDA, enterprises need managerial and cultural changes. Many organizational factors, including management support, human resources, technology resources, technology readiness, decision-making culture, change efficiency, business strategy orientation, IT structure, organizational structure, business resources, and firm size, influence the adoption of BD in companies (Sun et al., 2018). Leadership support, the data environment in organizations, and the perceived cost to implement the technologies were organizational factors that drove the adoption of BDA. The hurdles to embracing BD for organizational performance included new management practices and a change in organizational culture (Manohar, 2021).

Organizations were increasingly adopting BDA to extract valuable information from BD for making strategic decisions, increasing operational efficiencies, driving new revenue streams, and gaining a sustained advantage over competition (Sivarajah et al., 2017). With the enormous

amount of data, businesses in all sectors were looking at ways to use the data to stay competitive (Z. Liu et al., 2025). SMEs can utilize the power of technologies like BD and AI to innovate and increase efficiencies and performance (Tawil et al., 2024). BD technologies and tools allow researchers to process and analyze large volumes of data to extract insights and improve performance (Han et al., 2024). Benefits galore in multiple industries and sectors, including healthcare, finance, automotive, insurance, telecommunications, college libraries, traffic management, service research, and electrical smart grids.

Big Data Usage in Different Sectors and Countries

BDA comprised technologies, applications, and processes that help companies understand their industry sector business and make data-supported decisions (Niu et al., 2021; Wolseley et al., 2024). IT experts continuously innovate new technologies and applications to support BD, which helps the healthcare industry create value (Galetsi, P. et al., 2019; Wolseley et al., 2024). The ascent of information systems has led to the availability of enormous amounts of data in the healthcare industry. Analyzing the data has immense prospects for gaining knowledge. Analytics of the vast data sets in healthcare provided benefits such as personalizing medicine for patients. In addition, BDA provided advantages like detecting outbreaks of diseases, monitoring the quality of healthcare, understanding disease mechanisms, enhancing treatment development, developing effective devices and drugs, and offering rapid services (S. Khan et al., 2022; Wolseley et al., 2024), and addressing worldwide health challenges, which included preventing diseases, surveillance of public health, and efficient medical aid. Adopting BD in the healthcare sector provided various advantages, including data-driven decision-making, operational effectiveness, and improved patient health (Al Teneiji et al., 2024). It was essential to understand the factors that impacted the adoption of BD in the healthcare industry. BDA provides businesses

with a competitive advantage (Al Teneiji et al., 2024; Z. Liu et al., 2025) and allows policies and procedures in the organization to be dynamic, leading to better performance. Analyzing BD leads to insights and drives superior decision-making in an ever-changing business environment (Al Teneiji et al., 2024; Bag et al., 2021). Accelerating the adoption of BDA requires using AI technologies, predictive analytics, and BD technologies together (Al Teneiji et al., 2024; Bragazzi et al., 2020; Duan et al., 2019). Worldwide, there has been an increase in the adoption of BD since 2019, with 59.5% of companies adopting BD to drive innovation in their organizations (Al Teneiji et al., 2024; Taylor, 2023). Integration of BDA empowers healthcare companies to make data-driven decisions, leading to better patient healthcare and improved overall patient experience in health facilities. Adoption of BD in the healthcare sector was complex and involved multiple facets. BD experts utilized data analysis tools to gain insights and made faster decisions to improve performance and drive successful results for firms. A substantial hurdle in healthcare data was the integration of hardware, procedures, and advanced computational tools in a clinical setting (Al Teneiji et al., 2024; Dash et al., 2019). Overcoming the hurdle involved the collaboration of subject matter experts from different areas, including mathematics, statistics, biology, IT, and data science. Adopting BDA in the healthcare sector creates significant prospects for decision-makers, patients, employees, and employers (Al Teneiji et al., 2024; Bag et al., 2023). BDA in healthcare eliminates the need for hand-written reports, thus reducing the costs of office supplies and physical labor. Healthcare administrators had all the information available online with BDA, which reduced the costs of traveling to various locations to get the data (Al Teneiji et al., 2024; Habimana et al., 2020).

The costs of healthcare have risen in the last few decades, putting pressure on the healthcare sector to provide superior services at reduced costs (Britto, 2020). In addition, the

extensive use of new technologies like smartphones, sensors, wearable devices, IoT devices, and healthcare systems has created enormous amounts of data that traditional systems cannot analyze and use. As IT systems continuously evolve, the healthcare sector must reform its business operations to stay competitive. The large size of data created at a considerable rate daily in healthcare organizations creates challenges to storing and analyzing the data to find valuable information for better planning, forecasting, and decision-making. It was essential that data from various sources was monitored and processed to find insights. Insights help healthcare organizations spot emerging patterns, proactively make correct decisions, improve the quality of healthcare services, and reduce costs. Aligning an organization's resources, technologies, and people was identified as a problem area. In addition, user resistance was impeding the effectiveness of healthcare analytics due to limited knowledge of cloud-based analytics. Cloud computing also introduces security and privacy concerns. Future studies were needed in other industries, as BDA with cloud computing has massive potential and broad applicability. BDA adoption in the healthcare sector was found to be dependent on four categories: people, technology, organization, and environment. The category of people included an individual's analytical skills, whereas technology comprised the quality of the system’s processing data and the quality of the data. From an organizational perspective, leadership support, resource allocation for the initiative, employee training, data-driven decision-making, and data governance were required. Government regulations fall under the classification of environment (Wolseley et al., 2024).

The innovations in BD disrupt the processes and create a learning curve that requires time for adoption. Regulatory, legal, and ethical concerns exist regarding data-related initiatives in the healthcare sector, which explains delayed implementation in the healthcare industry (Javan Jafari

Bojnordi et al., 2025; Wolseley et al., 2024) compared to banking, retail, and marketing (Wolseley et al., 2024). Regulatory and legal goals should balance the promotion of new technologies and the protection of public interests. While there was an understanding of the importance of BDA in the healthcare sector, full benefits were not realized because of different challenges. The gaps included a lack of IT infrastructure, high costs, data complexity, data quality, and privacy and security issues (Muhunzi et al., 2024; Wolseley et al., 2024). Failing to set a clear vision and strategy for implementing BDA in healthcare organizations also causes challenges and delays (Wolseley et al., 2024). The barriers to BDA adoption in the healthcare industry were not fully understood. While research suggested the evolution of architectural methods and analytical techniques for healthcare applications to use BDA (Galetsi, Panagiota et al., 2020; Sakr & Elgammal, 2016), the impact of socio-technical factors was poorly understood. Hence, healthcare organizations that wish to update their outdated systems with newer tools that support BDA must consider socio-technical factors (Sakr & Elgammal, 2016; Wolseley et al., 2024).

Technology modernization was a massive investment in the insurance industry and accounted for seven percent of worldwide investments, amounting to US$200 billion in 2021 (Alexandre Terlizzi et al., 2024). Modernization included moving from legacy monolith technologies to componentization to support BDA using real-time data processing. Embracing BDA was increasing in every industry sector (Alexandre Terlizzi et al., 2024; Mazzei & Noble, 2017), and Statista forecasted that the BD market will reach US$103 billion in worldwide revenue by 2027 (Alexandre Terlizzi et al., 2024; Statista, 2022). BDA was an important area of study in academia and industry (Alexandre Terlizzi et al., 2024; Niu et al., 2021) and involved acquiring, managing, processing, and analyzing large quantities of real-time data to generate

actionable insights (Alexandre Terlizzi et al., 2024; Aseeri & Kang, 2022). Utilizing BDA has increased the insurance sector in the last few years (Alexandre Terlizzi et al., 2024) as these systems store and manage data on customer profiles, claims, and fraud history (Alexandre Terlizzi et al., 2024; Ellili et al., 2023). Adopting BDA helps organizations make data-driven decisions, driving business value (Alexandre Terlizzi et al., 2024; Gökalp et al., 2022). While BDA technology has rapidly risen, many organizations have failed to integrate the technology into making decisions (Alexandre Terlizzi et al., 2024; Reggio & Astesiano, 2020; Tabesh et al., 2019). Statistically, only 20% of BD analytic platforms deliver intended organizational results (Alexandre Terlizzi et al., 2024), suggesting hurdles in embracing and utilizing BDA. While BDA provided benefits in managerial strategy and competitive advantage, companies encountered barriers to adoption. Challenges were in the areas of technology and management. From a technology side, data complexity, legacy infrastructure needing investments, missing guidelines for BD usage, and missing skills among employees, including managers. From a management perspective, BD has a misaligned vision and goals, a lack of a data-driven culture, resistance to embracing BD, and privacy concerns. To overcome the hurdles, companies can adhere to some best practices (Alexandre Terlizzi et al., 2024). The practices have two categories, technical and managerial, similar to the barriers. Technical best practices included utilizing specialized tools and technology, integrating legacy systems with BD tools, adopting technical guidelines, and collaborating with academic institutions. From a managerial side, learning initiatives with both internal and external sessions, commitment to a longer-term budget to support BD adoption, complying with privacy regulations, defining a BD strategy, advocating and hiring for the position of chief data officer, and aligning the organization on BD goals. To gain efficiency and profitability, insurance companies were adopting BDA in underwriting,

marketing, claims, and reporting (Alexandre Terlizzi et al., 2024; Venkatesh, 2019). BDA supports actuaries in insurance companies in accurately assessing risk and determining pricing by analyzing the customer's lifestyle and behavioral data. Accurately predicting customer premiums was vital in the insurance industry, as premiums need to be set before the costs for the company from the claims that occur later.

While research has shown that small and midsize banks play an important role in a nation's economy, these banks lag in adopting technological innovations like BDA (Abankwa, 2023). Banks process billions of financial transactions every day, producing large data sets. Data generation and usage in the banking sector necessitate adopting BDA for services and decision-making. Integrating BDA in banks has provided a competitive advantage to those ready to implement BDA capabilities. The drivers and enablers for BDA adoption in SME companies were limited. Hence, a need exists to research the readiness of SME banks to adopt BDA. Without measuring the readiness for BDA adoption, SME banks fail to gain a competitive advantage and market share, and positively impact the economy. The differences between small and medium-sized banks and the BDA adoption level across different enterprise enablers, including leadership, data, technology, targets, and analysts, were unclear. A research study was done to find if there was a statistically significant difference between small and midsize banks and their BDA adoption level for different enablers.

Integrating BDA into financial management was of immense interest to academic researchers and industry practitioners. In the ever-changing business environment, BD was transforming the enterprise financial management sector and decision-making (Rauf et al., 2024; Ren, 2022). BD was revolutionizing the financial management industry with improved operational efficiencies and the ability to make strategic decisions (Fong et al., 2021; Rauf et al.,

2024). Organizations with a data-driven approach can modernize financial processes quickly, adapt to market variations, and have a sustained competitive advantage in the industry (Phung et al., 2021; Rauf et al., 2024). BD has a radical and profound impact on the financial management sector. Many areas included complex processing of financial information, altering the depth and breadth of financial management, improving efficacy, and enhancing the ability to control risk. Exploiting the benefits of BD results in accurate financial forecasts and reduces the risk probability (Rauf et al., 2024). However, incorporating BD into the financial sector was difficult (Q. He et al., 2019; Rauf et al., 2024).

The adoption of BD in financial management was fraught with many hurdles. The challenges included legacy financial concepts used by finance managers, resistance to innovation, low sharing of information internally, limited understanding of financial risks, and insufficient control capabilities of financial IT personnel (Dhar et al., 2019; Rauf et al., 2024). Moreover, BD delivers essential information vital for organizations to reduce costs, increase revenue, and create new business opportunities, models, and markets (Cottu et al., 2022; Rauf et al., 2024). Fully utilizing BD can considerably increase the quality and effectiveness of decision-making. BD has the potential to transform financial management practices by delivering in-depth insights into managing risk, financial performance, and strategic planning. Various frameworks were in vogue for implementing BD in the financial sector, which showed the importance of data governance, quality, and analytics capabilities (Rauf et al., 2024; M. M. I. Shamim & Khan, 2022). There were also challenges in adopting BD, which included security, privacy, and the need for skilled individuals.

BD characteristics that include volume, velocity, variety, and veracity were highly relevant for financial management (Araz et al., 2020; Rauf et al., 2024). In the financial industry, massive

volumes of data were generated quickly, with diverse information from different sources. The data included transactional and customer information from internal sources, social media activity, and market trends from external sources. This data could be structured or unstructured (Koot et al., 2021; Rauf et al., 2024). BD complexity in the financial sector requires resilient systems to process real-time data and create essential insights. Veracity is linked to the reliability and quality of the data, which is vital for accuracy in financial decisions (Catyanadika et al., 2024; Rauf et al., 2024). The historical progress of BD in finance has transformed financial reporting from traditional ways to advanced analytics (Mikalef et al., 2019a; Rauf et al., 2024). The onset of new technologies like cloud computing and ML has revolutionized traditional practices. Cloud computing helps with scalable storage and processing and enables real-time analytics (Rauf et al., 2024; Ren, 2022). On the other hand, ML algorithms facilitate predictive analytics, which allows for accuracy in financial forecasting and risk (Rauf et al., 2024; Rybicka, 2019).

BD significantly improves financial data management by enhancing data integration, cleansing data, and real-time analytics capabilities. Integrating disparate sources to create a unified data environment was necessary for accurate financial analysis. Data cleansing was a vital step that increased the quality and reliability of financial data by eliminating any errors and inaccuracies (Rauf et al., 2024). Real-time analytics applications helped in faster processing of data and creating insights that were important for decision-making (Dhar et al., 2019; Fong et al., 2021; Rauf et al., 2024). Advanced reporting applications and visualization tools aided in presenting complex data in a way that was comprehensible and actionable for finance leaders (Ciola, 2020; Rauf et al., 2024) and allowed for faster identification of anomalies (Rauf et al., 2024; Zhou & Li, 2019). The onset of BD has increased the scope of financial management with

process optimization, scenario analysis, and application of predictive analytics. Predictive analytics support accurate forecasts of future financial results (Rauf et al., 2024). Scenario analysis evaluates future events and their effect on an organization's financial performance (Fatieieva, 2020; Rauf et al., 2024). Process optimization supports organizations' inefficient allocation of resources and reduction in costs (Q. He et al., 2019; Rauf et al., 2024). These advances increase the reliability and correctness of financial forecasts and allow companies to respond efficiently to market uncertainties (Koltai & Tamás, 2022; Rauf et al., 2024). BD also plays a vital role in financial operations by automating repetitive tasks, structuring financial statements, and improving fraud detection and prevention.

BDA can help the telecom sector in many ways. Telecom companies generate vast amounts of unstructured and structured data from mobile cellular networks (Kumar et al., 2023). Analyzing unstructured data generated by telecom companies using conventional data analytics methods was expensive and complex. BDA can improve management operations using machine logs and real-time data analysis. Using predictive analytics and generating timely warnings, BDA can allay quality worries and performance variances. Companies in the telecom sector generate vast amounts of data when their customers connect to the telecom network and services with multiple devices like laptops, phones, and tablets (M. U. Khan & Fatima, 2024). BDA makes processing and analyzing massive volumes of customer-generated data easier by replacing older statistical methods with newer ways. Academics consider BDA the next big management revolution to drive higher business performance with financial and non-financial improvements. Organizations saw gains in business performance and a competitive edge when using BDA (Awan et al., 2021; M. U. Khan & Fatima, 2024). Some advantages companies gained with BDA

include mitigating risks, reducing expenses, and enhancing visibility into the supply chain processes.

In the automotive industry, the features of BDA were strategic and aided organizations in decision-making, thereby reducing the impact of supply chain disruptions (Bronzo et al., 2024). BDA enables organizations to detect and predict disruptions proactively, leading to reduced reaction time and stability. Reaction time was faster with quicker data availability, analytics, and decision-making steps. Organizations with longer digital readiness journeys enjoy lower reaction time and superior resilience using BDA capabilities. Embracing rapidly evolving digital technologies in organizations results in faster responsiveness to supply chain events and greater operational efficiency (Bronzo et al., 2024). BD involves large volumes of structured and unstructured data generated from different sources at high velocities and continuously modified (Bronzo et al., 2024; W. Y. C. Wang & Y. Wang, 2020). The volume, velocity, and variety characteristics cause enormous organizational challenges and necessitate building BDA capabilities. The capabilities of BDA allow organizations to process, analyze, gain insights, and make faster decisions (Bronzo et al., 2024; Ladeira et al., 2021). These capabilities were relevant and allowed companies to be preemptive in their operations when dealing with the uncertainties of supply chain infrastructure. A disruption in the supply chain workflow was an unanticipated event that interrupted or stalled the normal flow of operations. Examples of unanticipated events included delays, demand fluctuations, industrial accidents, environmental calamities, and quality issues. Reaction time is the time taken to identify, register, analyze, and make decisions to address the problem (Bronzo et al., 2024; Schwöbel et al., 2024). BDA capabilities in an organization allow for shorter reaction times and increased resiliency to supply chain issues. Resiliency to supply chain mishaps in an organization entails preparing, anticipating, and

responding to these events (Bronzo et al., 2024; Ergun et al., 2023). Companies must adapt to planned and unplanned disruptions in supply chain processes to be operationally efficient.

Technological advances were transforming university libraries (N. Islam et al., 2023; Shahzad & Khan, 2024). The onset of BD provided contextual and personalized library services to users. BD's complexity due to its volume, variety, and velocity requires sophisticated technology tools to process, store, analyze, visualize, and gain insights (Panda, 2021; Shahzad & Khan, 2024). BDA provided insights into trends, patterns, and user behaviors. Librarians can capitalize on the advantages of BD to efficiently market library products, make data-driven decisions, and deliver personalized user services (Azam & Ahmad, 2024; Shahzad & Khan, 2024). BD was critical in maintaining information resources for longer durations and creating digital libraries (Bhat, 2018; Shahzad & Khan, 2024). Organizational performance encourages librarians to adopt BD (A. Y. M. A. Islam et al., 2021; Shahzad & Khan, 2024). The use of BD in libraries delivers several advantages, including personalized user services, effective marketing of library resources, and faster information retrieval for users (Oladokun et al., 2023; Shahzad & Khan, 2024). Creating innovative services motivates library administrators to adopt BD (Shahzad & Khan, 2024; Zotoo et al., 2021). BD tools in libraries allow the delivery of value-added services like integrating data from digital books, print books, journals, and documents. BD applications facilitate the effective delivery of user-specific services by processing raw user, research, and citation data (M. S. Salman et al., 2020; Shahzad & Khan, 2024). BD also enables the integration of different university resources and helps librarians identify the most desired information resources (Hooper, 2023; Shahzad & Khan, 2024). BD management policies were essential for adopting BD in libraries (Anna & Mannan, 2020; Shahzad & Khan, 2024). IT tools, applications, and infrastructure need upgrades to get the benefits of BD. Sufficient financial

resources and funding were required to adopt and sustain BD usage in organizations (Bhat, 2018; Shahzad & Khan, 2024). BD management systems must be created through collaboration and strategy to maintain innovative services in the age of digital transformation and the connected world (Shahzad & Khan, 2024; Tzanova, 2020). The influencing factors in the adoption of BD in libraries included acquisition, preservation, and management (N. Islam et al., 2023; Shahzad & Khan, 2024), facilitating conditions (Azam & Ahmad, 2024; Shahzad & Khan, 2024), enabling services, and professional development. The challenges comprised technical skills (M. S. U. Islam & Roknuzzaman, 2021; Shahzad & Khan, 2024), infrastructure readiness (Dunmade & Hamzat, 2022; Shahzad & Khan, 2024), managing data, including considerations of privacy and security (Hamad et al., 2023; Shahzad & Khan, 2024), and legal issues (Shahzad & Khan, 2024; Zakria et al., 2024).

Big Data Usage in Different Countries

Past research has evaluated companies' readiness for BD adoption in different countries worldwide. One research examined Malaysian companies' readiness to adopt BD (Muhammad, 2022). While the growth of BD was motivating businesses to adopt BDA, there was limited empirical evidence and research literature indicating business value. The research noted an affinity for BDA solutions with effective organizational decision-making, leading to a growth mindset. The work outlined different parts of BD to realize the value of adopting BD in organizations. The research utilized the TOE framework to describe the enterprise's adoption of innovative technologies and resource-based views for upskilling the workforce. The study assessed the relationship between data quality management and data usage experience, which form the intangible assets that drive a firm to have more outstanding IT capabilities. High-Quality enterprise data was a forcing function in forming an organizational culture that

motivated the use of internal and external data for strategic and operational decisions. Expanding IT capabilities in managing and utilizing data creates network effects in adopting data-related IT capabilities. The technological context considers the organization's internal and external technologies that drive improvements in the company's productivity. The organizational factors included the resources available to help accept innovative technologies. In Malaysia, while there were many reports on BD, companies used third parties to perform analysis, which could ignore domain information to develop valuable insights. Moreover, there were limited executions in organizations on BD to show maturity. The study concluded that there was a need for a framework to govern the accuracy of data so that organizations can take advantage of data inflow and create insights using BDA (Muhammad, 2022). Another study was conducted as a survey among leaders in companies from Vietnam, China, and New Zealand to understand the factors impacting leaders' use of BDA for making decisions (J. Yu et al., 2022). Organizations saw the business value and improved competitive advantage and listed BDA as their top priority, but the leadership was reluctant to embrace the technology. The research found that the critical factors across countries connecting BDA to decision-making were data quality, organizational and leadership knowledge of BDA, technology readiness, and organizational expectations.

Strategic Decision-Making Using Big Data Analytics

Organizations were under extreme pressure to expand globally and stay competitive (Aldossari et al., 2023). Hence, companies need to use new data analysis techniques like BDA to extract insights from the data they collect to make strategic decisions. Gaining insights into their companies helps leaders measure performance and progress in decision-making (Lutfi et al., 2022; Maroufkhani et al., 2023). Organizations were transforming their businesses by treating BDA as a strategic asset for decision-making and improving processes and results. The

availability of data, tools, and technologies for analysis helps organizations gather information, make better decisions, and reduce risk (Aldossari et al., 2023; Sedkaoui et al., 2021). BDA helps businesses develop new business models, novel products and services, and enhance existing products. Companies used data-driven decision-making to prioritize product features, price strategies, and customer segmentation. Compared to traditional business intelligence tools, BDA paves the way for more significant insights, leading to competitive advantage through superior decision-making, innovation, and efficiencies (Aldossari et al., 2023; Mikalef & Krogstie, 2020). In addition, companies utilize BDA for analyzing data from different sources to reduce costs, decrease time, develop new products, optimize existing offerings, and make informed decisions (Al-Dmour et al., 2023; Aldossari et al., 2023; Kushwaha et al., 2021; Ranjan & Foropon, 2021; Shahbaz et al., 2021). It was more challenging for SMEs to adopt BDA because of their resource constraints than for larger enterprises (Aldossari et al., 2023).

Data overload creates challenges for decision-makers in organizations as they have limited processing power (Van Rijmenam et al., 2019). With efficient processing, BDA provides reliable information to an organization's decision-makers. The dimensions of BD enable organizations to make superior, tactical, operational, and strategic decisions from dependable data. BDAs should have an essential role in decision-making in organizations as they provide crucial insights and help drive strategy changes. Previous work showed that data integration for making decisions in organizations remains challenging, and it needs to be apparent that the targeted advantages were realized using available data (Manohar, 2021). Rational integration of analytical tools was a critical success factor in decision-making using data. The quality of decisions in organizations dramatically depends on the quality of input data, data processing

techniques, and individuals' data collection and processing skills. One of the vital capabilities needed to lead organizations in today's digital era is making efficient strategic decisions.

Companies have data that increases the efficiency of making strategic decisions (M. U. Khan & Fatima, 2024; S. Shamim et al., 2020). Organizations were using that data to make superior operational and strategic choices. BD could be structured or unstructured and has different characteristics, including volume, veracity, variety, and velocity (Hassan et al., 2022; M. U. Khan & Fatima, 2024). However, data alone cannot help; a complete system for the data analytics process was needed (Ashaari et al., 2021; M. U. Khan & Fatima, 2024). The availability of databases and BDA tools has created the possibility of acquiring, processing, and managing enormous data volumes and complexity. BDA comprises analytical tools and processes for handling complex data to obtain insights for taking action and enhancing company performance. The evolution of new technologies and growing international competition forced companies to embark on BDA innovations to increase their competitive advantage. BDA has prospects to be a key resource for business models, which are essential for strategy implementation in organizations. The capacity of organizations to generate value was measured in terms of the business models they supported. The effectiveness of companies depends on their approach to using BD in their business models. To maintain efficient business models, companies have to employ and use data analytics on BD to gain insights.

Past works in literature that researched understanding the relation between BDA capabilities and company performance emphasized the value of data-driven decision-making (M. U. Khan & Fatima, 2024). There was a correlation between business performance and IT competencies. The positive relationship between information management capabilities and business success was related to the performance of business processes and decision-making.

Using BDA capabilities was a moderating factor in aligning organizational strategies impacting firm performance. BD practices and organizational business performance were also linked to employee BD skills and the processes used. Competitive performance gains were achieved from the organizational culture that strategically utilized resources and practiced data-driven decision-making.

Competitive Advantage

Organizations must depend on internal resources and adopt externally available capabilities like AI and automation to sustain competitive advantage (Halim et al., 2024; Raj et al., 2020). With continuous changes in the marketplace and uncertain business environments, competitive advantage helps organizations stay ahead of their rivals and increase efficiency and performance (Azeem et al., 2021; Halim et al., 2024). Strategic foresight includes having skills like strategic decision-making, knowledge of integrating new technologies, and evaluating the environment in which the company operates (Halim et al., 2024; Murphy et al., 2021; Sarabi et al., 2023). Strategic foresight emphasizes acquiring these skills in the organization that can drive success and future growth (Haarhaus & Liening, 2020; Halim et al., 2024; Sarabi et al., 2023). Companies must be strategic to stay competitive in ever-changing markets (Ahmed et al., 2021; Halim et al., 2024). Organizations must rely on sustained competitive advantage to achieve results with changing customer needs and business practices. Adopting sustainable development in businesses requires modern infrastructure, technologies, and innovation. With companies creating massive amounts of data in the BD age, there was a dire need for BDA capabilities to gain insights from the data (Akter et al., 2016; Halim et al., 2024; Mikalef et al., 2019b). Gaining insights from the data aids companies in understanding customer interests and usage patterns of products and services, leading to a competitive advantage (Ghasemaghaei & Calic, 2020; Halim

et al., 2024; Mikalef et al., 2019b). BDA capabilities help firms reduce uncertainty, gain sustainable performance, and stay competitive (Halim et al., 2024; Z. Liu et al., 2025).

An organization's competitive advantage stems from providing higher value by delivering the same benefits at a lower cost or outpacing the competition so much that it justifies a higher price (Halim et al., 2024; M. E. Porter, 1996). Successful companies consistently outclass their competitors and stay competitive in the marketplace. Apart from essential performance differences, businesses enjoy perpetual advantage from their striking brands (Halim et al., 2024; Koshksaray et al., 2023) and substantial brand equity (Banmairuroy et al., 2022; Gujar et al., 2025; Halim et al., 2024). Organizations tirelessly pursue dominant technologies and product innovations and gain sustained competitive advantage (Halim et al., 2024; Zhang et al., 2023). If the factors were complex to copy, valuable, and uncommon, a competitive advantage is long-lasting, making it arduous for competition to reach parity (Halim et al., 2024; Henry et al., 2024).

The BDA and decision support processes became the foundation of decision-making in highly competitive business environments (Akter et al., 2019). Organizations can gain from competitive advantages like identifying new customer segments, improving existing products and services, creating new products, and supporting algorithm-based decision-making with BDA (Lukić, 2017). Making correct and timely decisions is essential for survival in today’s competitive and complicated business environments (Akter et al., 2019). Adopting BD technologies drives better operational and strategic activities in organizations and thus becomes an essential factor in competitiveness (Lukić, 2017). Since BD technologies provide faster, proactive, and superior decisions, they positively impact an organization's strategic activities (Lukić, 2017). Past works have noted that integrating BDA into decision-making remains a

challenge, as required outcomes cannot be achieved unless the decision-makers act on the insights and derived information from the data (Akter et al., 2019).

Technology in Decision-Making

While BD has evolved rapidly and is a growing adoption target, governments and most organizations must actively use data analytics (Manohar, 2021). A prior survey reported that over half the companies reported that BDA did not deliver the expected value. While BDA promises benefits, organizations across all sectors lag in using data analytics to make strategic decisions. The bias and error levels involved in the process were primary concerns when using BDA for strategic decision-making. Strategic decisions addressed ambiguous and complicated issues; hence, gathering reliable data and analysis was vital for decision-making. The correct evidence, data, and accurate analysis result in the right strategy. The BDA drives better decisions, but contingent characteristics impact the decision-making quality. The potential of the decision-makers to understand the data and work closely with others in the data processing chain improves the quality of decisions. While ML algorithms and AI were discussed in BDA, researchers were highly doubtful about these technologies' influence on decision-making and erasing errors in delivering better strategic decisions. The technology factors of BD consist of relative advantage, cost of adoption, complexity, observability, and compatibility (Sun et al., 2018). The BDA capabilities and adaptable infrastructure influence significant data-driven decision-making quality. Technological characteristics such as compatibility, complexity, and IT assets drive BD adoption. The quality of decisions was also related to the strategies used for collecting and analyzing data and the data itself (Moreno et al., 2019). The absence of BD and analytical skills and privacy worries were the primary barriers for many companies when going

after BD initiatives (Manohar, 2021). The quality and the way of using data were vital to organizations.

Adopting BDA in organizations leads to higher performance (M. U. Khan & Fatima, 2024). Data integration capabilities and data-driven decision-making (DDDM) improve telecommunication companies' efficiencies. Data-driven decisions necessitate integrating technology, management, and human factors to improve knowledge. While BDA resources aid companies in making strategic and practical decisions leading to better performance, additional aspects must be considered. BDA cannot lead to data-driven decision-making; it needs integration to acquire and process data. DDDM in companies entails using data to make decisions in product and service innovations (M. U. Khan & Fatima, 2024). Decision-making using data involves a methodical process of collecting, assessing, processing, analyzing data, and compiling findings to make company decisions. DDDM helps organizations understand data, create solutions for complex problems, and eliminate stubborn and non-compliant actions by critical decision-makers (Awan et al., 2021; M. U. Khan & Fatima, 2024).

The resources organizations need for BDA capabilities to facilitate decision-making using data for increased company performance were tangible technological skills (Awan et al., 2021; M. U. Khan & Fatima, 2024). Technological environments enhance the processing of information, which was vital for managing and processing data from multiple sources, leading to superior DDDM (M. U. Khan & Fatima, 2024; W. Yu et al., 2021). Organizations with technological environments were agile and have superior BDA capabilities (Awan et al., 2021; M. U. Khan & Fatima, 2024). One of the essential technology enablers of organizational responsiveness was to make superior information available at the correct location and time. Hence, technical skills in BD make organizations successful because of the increased ability to

make data-driven conclusions. While technically skilled resources were a tangible asset for BDA capabilities, business proficiency was an intangible asset (Awan et al., 2021; M. U. Khan & Fatima, 2024). To effectively use BDA for DDDM, organizations must aggressively and efficiently utilize tangible and intangible assets. Companies should have processes integrating different functions for using BDA for DDDM and a strategy to coordinate tangible and intangible assets. Organizations must supplement BDA capabilities with quality data patterns to forecast effective outcomes. Data patterns, which were part of the data integration capabilities in a business, drive performance, increase sales, profitability, and return on investments.

BD drastically improves strategic planning by delivering essential insights into developing products, market analysis, customer segments, and competitive intelligence. Using BD for market analysis allows organizations to learn customer behaviors and market trends correctly, which aids in data-driven strategic decision-making (M. D. Bari & Ara, 2024; M. H. Bari et al., 2024; Fong et al., 2021; Rahaman & BARI, 2024; Rauf et al., 2024). Competitive intelligence originated from BDA helps companies narrow competitive advantages and develop performance standards (L. Li et al., 2022; Rauf et al., 2024). Customer segmentation was improved with larger data sets, resulting in unique customer groups and their preferences (Park & Song, 2020; Rauf et al., 2024). BD also plays a vital role in product development and pricing strategy by analyzing customer feedback and market demand, allowing companies to innovate products and adjust prices in real-time (Phung et al., 2021; Rauf et al., 2024). Another area in which BD has a significant impact is in optimizing investment decisions. BDA can improve portfolio management and asset allocation by delivering clear insights into market dynamics and investment opportunities (Rauf et al., 2024; Ren, 2022; S. Shamim et al., 2020; Sivarajah et al., 2017). Sophisticated analytical tools permited accurate valuation and due diligence processes,

leading to investment decisions that were accurate and comprehensive (Rauf et al., 2024; Trieu, 2017). BD further allows investors to improve their portfolios for superior performance with a more specific analysis of risk and return tradeoffs (Eachempati & Srivastava, 2022; Rauf et al., 2024). Integrating BD into investment decision-making supported more strategic and knowledgeable financial management (Cottu et al., 2022; Rauf et al., 2024). BDA aids financial management performance through continuous progress, financial simulations, and tracking of KPIs. Real-time tracking KPIs using BDA provided a dynamic view of an organization's performance and helped in agile practices and faster changes (Fong et al., 2021; Koltai & Tamás, 2022; Rauf et al., 2024). Organizations can proactively deal with financial contingencies using BD in financial modeling and simulations that allow scenario analysis and predictive insights (L. Li et al., 2022; Park & Song, 2020; Rauf et al., 2024). BD supports continuous improvement initiatives in organizations by identifying inefficiencies and improvement areas, thereby driving operational excellence and strategic success (Peng & Bao, 2023; Phung et al., 2021; Rauf et al., 2024). Organizations adopting BDA for managing financial performance can deliver accurate forecasts, improved allocation of resources, and sustained competitive advantage (Rauf et al., 2024; Ren, 2022).

Summary

The literature review was structured into different sub-sections and captures details of the current study from a historical perspective. The chapter starts with a description of the study's problem and purpose statements. The problem to be addressed was that organizational limitations frequently impede the integration of BDA into strategic decision-making, resulting in decreased competitive advantage and negatively influencing performance targets. This qualitative exploratory study aimed to find what organizational constraints impact the adoption

of BDA for strategic decision-making and investigate how these impediments can be mitigated to reach performance goals and gain a competitive advantage at a technology company. The following section contains details on the guiding theoretical framework, along with its origin and development over the years, details of the concepts, usage in other research works similarly, alternative frameworks considered, and why the chosen framework suits the current study and how it guided the problem, purpose statements, and research questions. The theoretical framework section was followed by details on BD, starting with an overview of BD, BD growth, the scope of BD, the value of BD, types of analytics used in businesses, and BD limitations, including privacy and security, and the need for data governance. BD usage in organizations, organizational culture that supports the adoption of BDA, and organizational readiness for BDA were captured in the following sections. Following that, BD usage in different sectors and countries was discussed. The final section describes strategic decision-making using BDA, competitive advantage with the use of BDA, and technology used in decision-making.

Chapter 3 starts with restating the problem and purpose statement. The nature of the study, which includes research methodology and design, is discussed. Research methodology and design's relevance to the problem, purpose, and research questions is elaborated. The following section details the population and sample used for the study. The next section describes the materials and instruments used to collect data. The following section details the study procedures followed by information on data analysis. Assumptions, limitations, delimitations, and ethical assurances are captured in the final sections.

Chapter 3: Research Method

The problem to be addressed in this study was that existing constraints in organizations often create hurdles in the implementation of BDA for strategic decisions (Alexandre Terlizzi et al., 2024; Konanahalli et al., 2022), decreasing competitive edge and negatively affecting performance (Baker, 2022; M. U. Khan & Fatima, 2024; Manohar, 2021). This qualitative exploratory study aimed to find what organizational constraints impact the adoption of BDA for strategic decision-making and investigate how these impediments can be mitigated to reach performance goals and gain a competitive advantage at a technology company.

The research methodology and design that guided this study were a qualitative case study methodology and design. The problem, purpose, and research questions require collecting and assessing narrative data and exploring how organizational constraints impeding BDA adoption can be identified and mitigated. Qualitative research is unique and can deliver value because various real-world issues can fall under its umbrella (Yin, 2016). The TOC framework was chosen to drive the research study as it aligns with the problem, purpose, and research questions (TOC Institute, 2021). The TOC framework's core idea is to identify the constraints in an organization, influence the constraints to improve the situation, and gain advantages such as increasing performance.

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followed by a summary. Conducting a qualitative study examining the organizational constraints on adopting BDA could provide an understanding of remedying the situation (Baker, 2022; Manohar, 2021).

Research Methodology and Design (Nature of the Study)

The research methodology and design used to guide this study were a qualitative case study methodology and design. Qualitative research is distinctive, and almost everything happening in the real world can be a topic of qualitative research (Yin, 2016). The diversity of issues that can fall under the umbrella of qualitative research makes it unique. Qualitative research is a craft that involves challenging original research with goals including adhering to evidence, transparency, and being methodical. The interest in qualitative research arises from scholars wanting to understand how people survive in real-world situations. Qualitative research delivers value as it is not limited by the constraints seen in other research techniques, like meeting required research conditions, conforming to sample sizes, and lacking sufficient data or required variables. Five features made qualitative research remarkable (Yin, 2016, p. 9). First, the research allows people's lives and their roles in the real world to be studied. Second, qualitative studies prioritize representing participants' views and perspectives. Third, qualitative research unambiguously incorporates contextual conditions. Fourth, qualitative studies aim to explain social behaviors and thoughts using new and existing concepts. Fifth, qualitative research recognizes the importance of accumulating, integrating, and presenting data from various verified sources as part of the study.

Qualitative research is not subject to limitations, such as conforming to sample sizes and lacking sufficient data (Yin, 2016). Qualitative methodologies rely on human perception and understanding (Stake, R. E., 1995). These methodologies help study the essence and meaning of

individual experiences (Willig, 2017). Qualitative methods facilitate gathering rich information from the discussion with the participants (Stake, R. E., 1995; Willig, 2017). Qualitative methods in literature allow researchers to gather descriptive data encompassing observed behaviors and spoken or written words of subjects (Adeleke, 2020). Qualitative research helps develop theoretical insights for enhancing the understanding of organizational complexities (Bansal et al., 2018). While different genres were in vogue, variance-based case studies helped understand the relationships between different constructs and factors contributing to different outcomes. Traditions and genres of qualitative methodology guided the selection of research design and methods (Lim, 2025). The need for alignment of the research approach with a problem, purpose, and research questions also applies to the qualitative design. Case studies are contextual and comprehensive, helping in deeper interaction with the research participants, and are suitable for the research problem (Lim, 2025). Case studies are preferred when answering how and why questions. Qualitative research was apt for collecting and analyzing narrative data and exploring how various factors impeding the adoption of BDA can be identified and mitigated to meet performance goals. For the above reasons, the qualitative studies were optimal and aligned with the problem statement, purpose, and research questions.

Case studies entail analyzing individuals, organizations, decision processes, procedures, or systems using a complete approach to collect data in multiple ways (Lim, 2025; Thomas, 2021). Case studies explore a case in a bounded environment with a clear segregation between the boundary and the context (Stake, R. E., 1995; Yin, 2018). The boundary was a technology organization, and the context involved executives at that company who understood the BDA initiatives. Case studies were employed across multiple disciplines, including sociology and organizational and management studies (Stake, R. E., 1995, 2005; Yin, 2018). The goal was to

generate deeper insights and understanding to apprise the community, policy development, professional practice, and social action. A case study is both an object and a methodology and triangulates three aspects. Case study research refers to a mode of inquiry or genre, research method, or method of investigation, and unit of inquiry or cases. Case studies have different terms in the literature. Yin (2018) classifies case studies as exploratory and descriptive. Stake (2005, 1995) described case studies as instrumental or intrinsic and suggested the main difference in case study design was whether it was a single or multiple case study. The primary consideration in case study methodology was to ensure that the researcher's chosen methods were aligned with their epistemological and ontological beliefs. Case study researchers work on real-life cases to collect accurate information. Case studies involve deeper interaction with the research participants, providing a detailed picture of the study. Research in case studies is exhaustive and involves multiple data collection methods from numerous sources. Triangulation is needed for an in-depth understanding and for providing evidence on the data obtained. The choice of the data collection methods must be aligned with the research questions and the data needed to answer the questions. The researcher's interpretation, conclusion, recommendation, and reflection help a reader to understand the case study thoroughly. The above details on case studies make them a suitable choice for the research problem of understanding what organizational constraints often hinder the adoption of BDA in strategic decision-making across an organization (Baker, 2022; Manohar, 2021).

Past research used case study designs in other industries on how BDA adoption helps organizations' decision-making (Alexandre Terlizzi et al., 2024). The study highlighted that although there was increased adoption of BDA in many industries, organizations have failed to capture the benefits and efficiently use BDA for making decisions. The researchers conducted a

case study on a Brazilian insurance carrier, using interviews with ten managers and executives, and documented the analysis. The research reached saturation with the ten interviews and added the review of internal documents like policies, business cases, technical documents, and project presentations. Another research work analyzed the crucial role of business intelligence and BDA in influencing organizational decision-making using a case study approach (Caputo et al., 2023). Case study methodology has been used as the research method, allowing multiple data sources to explain a phenomenon and develop and test theories. A standard methodology is to use case studies in qualitative analysis. Case studies are very applicable in situations where the phenomenon's why and how are the study's goals. Hence, a case study approach with qualitative analysis was appropriate for investigating and finding new insights. Another research work analyzed BD adoption and human resource analytics in nine Finnish companies to find the obstacles that hinder the adoption of data for making decisions in organizations (Dahlbom et al., 2020). The work utilized a qualitative case study approach. The three works showed that qualitative research with a case study approach was appropriate for the research problem of understanding what organizational constraints often hinder the adoption of BDA in decision-making.

Other qualitative research methods included phenomenology, ethnography, grounded theory (GT), and narrative design (ND) (Ali et al., 2024). Phenomenological research involves studying a small number of subjects for extended periods to develop meaningful patterns and relationships. In the process, the researcher anchors their own experiences to understand the participants' experiences (Abraham & P., 2025). Rather than studying the unique nature of individual experiences, phenomenologists assume something familiar in human experience and try to understand this essence or commonality (Van Manen, 1990, 2016). Phenomenology is not

a theory that explains the world; instead, the main aim is to enable more significant contact within the world (Senger et al., 2025; Van Manen, 1990, 2016). Phenomenological studies are more interpretive than descriptive, where the researcher interprets the meaning of a lived experience. The researchers analyze the data by looking for essential statements linked to the phenomena under study and then derive themes and meanings. Following the analysis, the researchers create a combination of textual and structural descriptions of participants' experiences to communicate the overall essence of the phenomenon. As a final step, the researcher incorporates member checking, where participants review the described findings and interpretations. Limitations or critiques of phenomenological studies include a deeper understanding of the philosophical assumptions, which the researcher should identify and explain. Furthermore, bracketing personal experiences is not easy, so researchers should incorporate their understanding into the study and the overall analysis. Quality and rigor continue to evolve and were focus areas of critique of phenomenological research.

Ethnographic design mainly studies organizational culture (Ali et al., 2024; Sørstrøm et al., 2025). Ethnographic designs are studies that obtain a deeper understanding of the participants or a group under study and how the group's culture influences their activities (Lim, 2025). The ethnographic design creates challenges as the methodology necessitates researchers to have a deeper understanding of cultural anthropology and familiarity with the social-cultural system (Creswell & Poth, 2018). Ethnography necessitated spending a lot of time immersed as part of a group or community to understand the culture, and, hence, was not suitable for dissertations that have deadlines and timelines. Researchers might become deeply involved with the group and, as such, might not finish the study or get compromised by the study. With the possibility of biases, triangulation of observations and data sources became critical for ethnographic designs.

GT was more appropriately used in studies where little was known about the phenomenon under research (Lim, 2025). Critiques of GT included the researcher's ability to set aside theoretical ideas to develop substantial analytical concepts (Rogo, 2024). Researchers also face difficulty determining the saturation of categories and the readiness of a sufficiently detailed theory. Interpretation became highly subjective, and it was necessary for researchers involved in social justice GT studies to be specific about prior ideas and experiences. Hidden challenges in GT design made it less desirable for dissertation-type research. Developing the theory forced the researcher to repeatedly test the evolving theory to determine its existence. GT methods are rigorous, time-consuming, and unsuitable for dissertations.

ND allows the participants' voices to be heard, which were otherwise never heard in the studies (Ali et al., 2024; Creswell & Poth, 2018). ND provided a way to understand the real-life experiences told as tales by those who lived those experiences. In the ND, the goal is to understand a chain of experiences and the linkage of events within the experiences. Narrative research does not provide certainty or conclusions; the methodology offers meaning and understanding (Creswell & Poth, 2018). ND research is time-consuming because of the need to spend numerous hours with subjects to collect data.

While other designs like observations (Ali et al., 2024; Daněk & Urgošíková, 2024), field research (Ali et al., 2024; Türkyilmaz & Üçok, 2024), action research (Ali et al., 2024; Lim, 2025), Delphi (Ali et al., 2024; Hasson et al., 2025), generic qualitative inquiry (Ali et al., 2024; Lim, 2025), content analysis (Ali et al., 2024; Hennessy et al., 2023), and photovoice (Ali et al., 2024; Asigbee et al., 2025) are available in literature, case study was deemed appropriate for the current research problem.

Choosing between a quantitative and qualitative method for a research study begins with how the problem statement can be explained (Ali et al., 2024). If the problem statement can be addressed numerically, the quantitative research method is appropriate for attempts to test or confirm something (Ali et al., 2024; Hands, 2022; Mohajan, 2020). On the other hand, if the problem is explained through text, phrases, and sentences, a qualitative research method is more suitable where the goal is to understand something (Ali et al., 2024; Mohajan, 2020; Rogo, 2024). A qualitative problem involves multiple aspects or features, and the factors influencing them are unknown (Ali et al., 2024; Lim, 2025). The problem is explained through numerous phrases and their influencing factors (Ali et al., 2024; Taherdoost, 2022). Quantitative studies are appropriate when understanding the relationship between the independent and dependent variables and are explained using statistics and numbers (Ali et al., 2024; Ghanad, 2023; Mohajan, 2020). Qualitative studies are subjective and present what is learned from experts in the area of study (Ali et al., 2024; Lim, 2025). Hence, the qualitative method was more suitable for the research problem under study than the quantitative method.

For many years, research scholars have used a mixture of quantitative and qualitative data, called mixed methods research, in their studies (Pregoner, 2024). In the mixed methods approach, researchers used quantitative and qualitative techniques for gathering data, analysis, and inference for a broader and deeper understanding of the problem and possible solutions. A mixed methods design is time-consuming and is not employed in the current research.

Population and Sample

For the research work, which utilized a case study, open-ended questions in semi-structured interviews and focus groups were used with participants at a technology organization in the San Francisco Bay Area in the United States of America (USA). While there is a lack of

consensus in the research community on a standard approach for sample size definition in qualitative methodologies (Boutera et al., 2024; Patton, 1990), a recent study (Villamin et al., 2025) emphasized that 11 to 20 participants was most common.

Reaching saturation in qualitative studies requires a minimum sample size of five (Yin, 2018). A review of multiple qualitative studies using different types of saturation methods indicated that a sample size of five to 24 measurements is sufficient for qualitative studies (Hennink & Kaiser, 2022). As participants in qualitative research provide rich information, sample sizes can be smaller (Boutera et al., 2024). Attaining saturation involves obtaining data from multiple sources (Fusch Ph D & Ness, 2015). Saturation is reached when no new insights or themes emerge from the data (Bouncken et al., 2025; Fusch Ph D & Ness, 2015; Naeem et al., 2024).

Executives at the USA software publishing companies comprised the population for the research. The sampling frame (Stimpfel et al., 2025) consisted of executives chosen from Dun & Bradstreet with NAICS CODES: 5132 (Dun & Bradstreet, 2024). Participants must be 21 or older and VPs, senior directors, directors, managers, or leaders in technology corporations. Subjects in these roles understood the importance of the BDA initiatives in the organization and were chosen as participants for the study. The population was appropriate as the study involved understanding the constraints of technology organizations when adopting BDA for strategic decision-making. Seventeen executives at a technology company were selected using snowball sampling (Sebele-Mpofu, 2021), and the research location was California, USA. The participants were chosen from a product development function in the organization. The researcher focused on selecting a sample representative of a population to uncover details of the larger group (Faulkner & Faulkner, 2019). For qualitative studies, where the focus is not on generalizability but on

reproducing and understanding real life, non-probabilistic sampling, like snowball sampling, was practical. Considering participants' flexibility for qualitative studies helps researchers increase their chances of access, recruitment, and getting replies from the subjects. Participants were recruited with the help of a VP in the product development group. Email lists of VPs, senior directors, directors, leaders, and managers in the group were obtained with the help of a contact at the technology company, and individuals were emailed with a request to participate in the study.

Instrumentation

The instruments included semi-structured individual interviews and focus groups with participants. The National University's Academic Success Center professor reviewed the questions to increase the content's validity (Christalle et al., 2022). The interview questions aligned with the research questions were field tested with subjects who knew BDA. Two executive leaders from companies outside the target population were used for the field testing. Field testing helped preserve efficacy and enhance the reliability of the research instruments (May et al., 2024; Yin, 2016). Choosing data collection methods must align with the research questions and the data needed to answer the questions. It is usual for researchers to use multiple interview methods for their projects (Chand, 2025; Lim, 2025). The data represent the views on organizational constraints limiting BDA adoption for strategic decisions. Qualitative studies require data-gathering methods like focus groups and interviews to collect descriptive data to describe a phenomenon (Chand, 2025). The data sources have detailed information from subjects' responses to research questions. Focus groups provide multiple views, some guided by responses from other group members. Focus groups should have subjects with comparable experience and knowledge (Akyıldız & Ahmed, 2021). Multiple data sources allow for

saturation, triangulation, and verification, resulting in a depth and breadth of understanding of the phenomenon. A combination of participant data sets using semi-structured individual interviews and focus groups was deliberately collected to obtain a complete view of the phenomenon under study. Getting different opinions eliminates biases and guarantees that the questions addressed the purpose of the study (Noble & Smith, 2025). The instruments for data collection, including interview questions and focus group questions, are available in Appendix A and Appendix B, respectively. The materials in the study included the National University's Institutional Review Board (IRB) form, recruitment letter, and interview consent form. The recruitment letter and consent form are captured in Appendix C and Appendix D. The protocol information sheet and the interview questions were shared with the participants after receiving approval on the research study from the NU's IRB.

Triangulation

The data sources used in triangulation included data gathered from semi-structured interviews and focus groups, followed by member checking. Triangulation in case studies helps gain a more profound knowledge of the phenomenon, adds rigor, depth, and breadth, and provides supportive proof of the data collected. Triangulation can also be achieved using different participants' and researchers' observations, utilizing multiple analysts to review the findings, and employing various theoretical perspectives. Qualitative studies are inductive and comprehensive and triangulate data from different sources to validate the results (Billups, 2024). Multiple data sources allow for saturation and verification, resulting in an understanding of the phenomenon. A solo approach is insufficient in social research, and triangulation reinforces its authenticity (Lim, 2025). Data gathered from focus groups enhances the data collected through the semi-structured interviews. Utilizing member checking of the interview transcripts improves

accuracy, credibility, and trustworthiness, reducing unintentional researcher bias (Stahl & King, 2020). Researchers are vital in their observations and discussions with subjects (Yin, 2016). Researcher observations are a secondary research instrument, while the interview questions remain primary (Monday, 2020).

Study Procedures

Site permission from the technology organization and IRB approval were obtained before collecting participant data (Christian et al., 2022). Snowball sampling was used to select 17 executives at the technology company (Sebele-Mpofu, 2021). Email lists of VPs, senior directors, directors, managers, and leaders in the product development group were obtained with the help of a contact at the technology company, and individuals were emailed with a request to participate in the study. Data collection occurred using individual semi-structured interviews and focus groups to understand the phenomenon under study (Chand, 2025; Lim, 2025). Saturation, triangulation, and verification were achieved with multiple data sources. Content validity was increased by having subject matter experts review the questions (Christalle et al., 2022). Field testing helped improve the reliability of the research instruments and maintain efficacy (Yin, 2016). Consent from participants was obtained before data collection to ensure ethical compliance (Antonsen et al., 2024). Data governance procedures and policies, such as data quality, strict access controls, anonymizing or encrypting data, audits, periodic privacy and risk assessments, were necessary to safeguard participant data from unauthorized access or misuse. Identity and Access Management (IAM) and HashiCorp Vault are software solutions that can help protect research data and enforce access control (Z. Jiang et al., 2024).

The records of this study were kept private, and reasonable measures were taken to protect the security of all participants' personal information. In any report made public, the study

will not include any information that identifies the participants. The data from the participants will be securely stored in a password-protected folder for three years. After three years, the electronic and paper data will be destroyed. Analyzing data requires a meticulous process (Yakut Çayir & Saritaş, 2017) of organizing collected data, dividing it into categories, generating themes, and publishing a report. Ensuring data organization, trustworthiness, and validity provided usefulness to the data analysis and findings.

Data Analysis

Case studies necessitate extensive research with data collection from multiple sources (Stake, R. E., 1995; Yin, 2018). Multiple sources used in the research study included semi-structured one-on-one interviews, focus groups, and participant data review. Analyzing data for a qualitative research study is complex and exhaustive and necessitates an intensive and meticulous process (Yakut Çayir & Saritaş, 2017). Computer software provided enormous benefits in organizing the collected data, dividing it into categories, generating themes, and publishing a report. The analysis step in qualitative research started with preparing and organizing data. Encoding of the data occurred in the next stage, and themes were generated with a combination of codes. Finally, the data was interpreted, discussed, and presented visually as tables. Computer-aided data analysis in qualitative studies helps researchers efficiently process, formulate, and decipher textual and audio-visual data. Computer software allowed researchers to make the complete study specific, accurate, fast, and comprehensive. NVivo has been widely discussed within the education sector and literature, and has shown increased usage in research studies for qualitative thematic analysis. Multiple research studies in the past utilized NVivo software solutions for qualitative research (Dixon-Woods et al., 2020; Knight et al., 2022; Taifi, 2022). While traditional manual pen-and-paper methodologies for creating codes, categories, and

themes are in practice, they need multiple researchers and an immense amount of time to analyze, validate, triangulate, and draw conclusions (Lim, 2025). Manual code generation and computer software were used to analyze qualitative data (Dierckx de Casterlé et al., 2021). Software alone cannot create segments and attach codes to the segments.

Coding and Thematic Development

The manual stage involved the preparation of the codes, which included exhaustive reading of the transcripts, creating a narrative report with an abstract of the storyline, and iterative forward and backward review within and across transcripts (Dierckx de Casterlé et al., 2021). The automated stage involved using the qualitative software NVivo 14 for the coding step. The actual coding steps comprised drawing up a list of concepts, linking fragments from the transcripts to appropriate codes, analyzing concepts, extracting the essential storyline or structure, and describing the results.

Trustworthiness

Trustworthiness in qualitative research increases the study's value (Riazi, A. M., 2025). Trustworthiness and the transparency with which the study was conducted provided integrity and usefulness to the results. The factors constituting trustworthiness included credibility, confirmability, dependability, and transferability. Establishing credibility involves prolonged engagement with participants to achieve saturation and member checking. Dependability is data stability over time, with procedures that include keeping an audit trail of the procedure logs. The level to which the findings from the study were consistent and can be repeated reinforces confirmability. One of the techniques for achieving confirmability is triangulation, apart from member checking (Riazi, A. M., 2025). Transferability is the extent to which the results apply to

people in other contexts. Authenticity is the level to which the researchers comprehensively show a variety of realities and credibly show subjects' lives (Lim, 2025).

Assumptions

Assumptions in research works are presented as statements and are considered accurate (Yin, 2018). The assumptions of the study included those of the researcher and participants. The researcher's conclusions are subjective and are swayed by assumptions (Goundar, 2025). Some of the assumptions in qualitative studies that investigate a phenomenon include trustworthiness, accuracy, unbiased responses, and the ability of the members of the study to complete without quitting mid-way. The researcher assumes that the participants willingly participated, understood the problem being studied, answered the questions, and were confident that their responses would be kept confidential (Goundar, 2025; Yin, 2018).

Limitations

With qualitative studies, the sample size is small, sometimes limited to one specific organization with fewer participants. Generalization of the results to a broader population of all technology companies cannot be reached. Every research study has limitations, and the researcher has identified gaps or weaknesses (Rogo, 2024). Limitations include uncontrollable events that may delay the study if some of the participants withdraw from the study. Defining the accurate sample size and sampling method was complex and could create gaps in attaining saturation and produce valuable insights. The recruitment process included a broader reach to 20 participants to mitigate the limitation of participants dropping out or delaying study participation (Brenchley, 2024).

Delimitations

Delimitations of a study indicate the variables or factors that govern the boundaries of research (Yin, 2018). In scholarly work, the problem, purpose, and research questions drive the focus of what the researcher completed (Rogo, 2024). Hence, the research work was confined to the problem to make the scope of the study pragmatic. The research identified the constraints organizations encounter while embracing BDA for strategic decision-making. The TOC framework was selected for research as it aligns with the problem, purpose, and research questions (TOC Institute, 2021). The TOC framework's primary idea is to decipher the constraints in an organization and manage them to improve the situation and increase performance. TOC provided details on the leading cause of a problem, and the resolution results in mitigating or eliminating performance gaps in an organization. Identifying and managing constraints and providing continuous progress in organizations is the goal of the TOC framework (R. J. Harris, 2018). The research work was done to obtain answers to the research questions from 17 participants in the product development function at a specific technology organization. The sampling technique was also part of the study's delimitation. Since delimitations affect the generalization of the results and external validity of the study, participants who understood BDA in the organization were chosen to eliminate oversimplification or overextension of the scope of work.

Ethical Assurances

Before beginning the study and collecting data, the researcher obtained approval from NU's IRB and authorization from the research site. Ethical considerations were vital, necessitating consent from participants before data collection (Antonsen et al., 2024). An informed consent document was distributed to the participants for review, and acceptance was

taken at the start of the interview. The informed consent document detailed the data collection, rights, responsibilities, risks, and benefits of the voluntary participation of the subjects. Ethical aspects were more pronounced in healthcare research, necessitating the registration of the studies with data protection agencies. Data governance is crucial in research studies and involves data quality, ethical handling of data, and protecting participants (Z. Jiang et al., 2024). Governance processes and policies, such as strict access controls, anonymizing or encrypting data, audits, regular privacy, and risk assessments, were needed to protect subject data from misuse or unauthorized access. Software like Azure Active Directory, Amazon Web Services (AWS) Identity and Access Management (IAM), or HashiCorp Vault provides solutions for enforcing access control and protecting research data (Z. Jiang et al., 2024). Participants in the study were given aliases to anonymize their actual names, which helps with privacy and identity. All the data collected as part of interviews and focus groups was stored in a computer in a folder that was password-protected. Participants could decline to answer questions during data collection through the interviews and focus groups. The researcher had a collaborative institutional training initiative (CITI) certification, which was valid for the duration of the study. The researcher works at a different technology company than the research site, and there was potential for bias because of the researcher's understanding of the technical subject of the study. A mitigation was that the researcher did not have direct authority over the participants or influence them. It must be noted that the participants were asked open-ended questions.

Summary

This section details the research methodology and study design. The problem being addressed was that prevailing constraints in an organization often hinder the adoption of BDA in strategic decision-making (Konanahalli et al., 2022), reducing competitive advantage and

impacting performance goals negatively (Baker, 2022; M. U. Khan & Fatima, 2024; Manohar, 2021). The study used the TOC framework to address the research questions. An exploratory case study approach was used as the methodology. Snowball sampling was used to select 17 executive managers at a technology company. Informed consent was obtained from the participants. Semi-structured interviews and focus groups were used to gather the data. Subject matter experts reviewed the questions to increase the content's validity (Christalle et al., 2022). The interview questions were field tested with executive leaders who knew BDA from a different company outside the target population. The instruments and participants were used to ensure saturation. The data sources used in triangulation included data collected from semi-structured interviews and focus groups, followed by member checking. The materials in the study included the NU's IRB form, recruitment letter, and interview consent form. The protocol information sheet and the interview questions were shared with the target organization and participants after receiving approval on the research study from the NU's IRB. The data were managed and protected by enforcing access controls and secure storage mechanisms.

Analyzing data for a qualitative study is exhaustive, involves textual and audio-visual data, and necessitates a meticulous process of organizing data. Data were organized and analyzed using a balance of manual steps and software, as software alone cannot create the codes, categories, and themes. Automated processes included the NVivo 14 software. Data analysis involved the organization, coding, and theme generation. Thematic analysis drives the study's dependability, validity, and replicability. Validity methods comprised triangulation, researcher's reflexivity, and member checking. Trustworthiness involves multiple aspects, including credibility, confirmability, dependability, and transferability, that provide integrity and usefulness to the results.

Chapter 4 describes the results and evaluates the findings from the data collected and analyzed from the participants at the technology company. Data was obtained in the form of participant responses to the questions. Data was organized into themes and categories for analysis.

Chapter 4: Findings

The problem to be addressed in this study was that existing constraints in organizations often create hurdles in the implementation of BDA for strategic decisions (Alexandre Terlizzi et al., 2024; Konanahalli et al., 2022), decreasing competitive edge and negatively affecting performance (Baker, 2022; M. U. Khan & Fatima, 2024; Manohar, 2021). The purpose of this qualitative exploratory study was to find what organizational constraints impact the adoption of BDA for strategic decision-making and investigate how these impediments can be mitigated to reach performance goals and gain a competitive advantage at a technology company. The research methodology and design that guided this study were a qualitative case study methodology and design. The problem, purpose, and research questions require collecting and assessing narrative data and exploring how organizational constraints impeding BDA adoption can be identified and mitigated. Qualitative research is unique and can deliver value because various real-world issues can fall under its umbrella (Yin, 2016). Conducting a qualitative study examining the organizational constraints on adopting BDA could provide an understanding of remedying the situation (Baker, 2022; Manohar, 2021).

The findings from the qualitative study are discussed in this chapter. Trustworthiness of the data, which includes credibility, transferability, dependability, and confirmability, was discussed. The following section details the results from the study for each research question and does not include any conclusions or speculations on the results. The next section provides an interpretation of the results in light of the theoretical framework presented in chapter two. The extent to which the findings were consistent with the existing research and theory is highlighted, and the research questions organized the discussion. The next section that follows details the summary.

Trustworthiness of the Data

Trustworthiness is a prejudiced reality in qualitative research where writers and readers find a common ground in their processes (Stahl & King, 2020). Analogous to validity in quantitative research, qualitative researchers strive for the goal of trustworthiness so that the readers interpreting the study have confidence in the work of the qualitative researcher. Trustworthiness in qualitative research expands the study's value (Riazi, A. M., 2025). Trustworthiness and the transparency with which the study was conducted provided integrity and usefulness to the results. The factors constituting trustworthiness include credibility, transferability, dependability, and confirmability (Lincoln & Guba, 1985; Riazi, A. M., 2025).

Credibility involves understanding how the research findings can be held together and share a relationship (Stahl & King, 2020). One way of achieving credibility is by using different methods of triangulation (Lincoln & Guba, 1985; Riazi, A. M., 2025; Stahl & King, 2020). Triangulation is a process of using multiple data sources to identify like patterns and recognize similar outcomes. Another way to achieve credibility is through a process of member checking, which involves the participants validating the researcher's interpretations of the conversations (Stahl & King, 2020). Different participants in the study performed member checking, which is an efficient method in qualitative research and increases the trust in the findings. Establishing credibility involves engagement with participants to achieve saturation and member checking. The current study utilized individual semistructured interviews, a focus group for triangulation, followed by member checking.

Transferability is the extent to which the results apply to people in other contexts (Lim, 2025; Riazi, A. M., 2025). While transferability is akin to generalizability in quantitative research, there is an appreciation of uniqueness and specific contexts of qualitative research

(Lim, 2025; Lincoln & Guba, 1985). Transferability entails providing detailed descriptions of a study so that it can help future researchers in their contexts and group settings. The detailed descriptions should include the study's context, characteristics of the participants, and interactions that occurred during the interviews. Transferability is a difficult concept in qualitative research as the aim of replication is tricky (Lincoln & Guba, 1985; Riazi, A. M., 2025; Stahl & King, 2020). However, researchers using qualitative designs provide patterns and descriptions that can be applied in other contexts. The importance of a study is enhanced when future researchers can extend the study to a different situation. As much as it is logical and significant to create new knowledge from a qualitative study, it is valuable and practical to gain understanding from a qualitative research and draw analogies to generalizability and external validity (Lincoln & Guba, 1985; Stahl & King, 2020). Transferability is possible when thick descriptions portray rich information from the study's setting, which can be applied in a future researcher's context.

Dependability refers to trust in trustworthiness (Lincoln & Guba, 1985; Stahl & King, 2020). In qualitative research, as both scholars, those who produce the research and consume the research create their trust as different events are uncovered, there are solid research activities that generate trust and provide trustworthiness in their execution. Dependability is data stability and constancy of the research discoveries over time, with procedures comprising keeping an audit trail of the procedure logs and triangulation (Lim, 2025; Riazi, A. M., 2025). While qualitative research often investigates evolving and dynamic problems, the procedures make the study dependable (Lim, 2025). Dependability is an essential characteristic of trustworthiness as it ensures the results from the research study were not unpredictable or arbitrary but an outcome of a planned research procedure. Dependability helps scholars consider the reality of qualitative

research and changing situations to guarantee these situations do not negatively impact the research results. Notable strategies include triangulation and audit inquiries to achieve dependability in qualitative studies. In the current study, combining individual semistructured interviews and focus groups helps achieve triangulation.

The fourth characteristic or attribute of trustworthiness is confirmability. Confirmability entails the level of alignment sustained in the study and reaching objectiveness as much as possible (Lincoln & Guba, 1985; Riazi, A. M., 2025; Stahl & King, 2020). Instead of building reality in results, qualitative researchers who look for objectivity depend on procedures like precision and the involvement of other researchers. To keep the environments pristine, involving fewer researchers was preferred, especially in studies related to education (Stahl & King, 2020). As a result, the confirmability feature is small and limited or restricted in qualitative research. The level to which the findings from the study are consistent and can be repeated reinforces confirmability. Confirmability evaluates whether the results, interpretations, and conclusions are aligned with the data and theories and not subjective and influenced by the researcher's personal bias or motivations (Lim, 2025; Lincoln & Guba, 1985). Confirmability stresses the significance of ensuring the findings were based on participants' responses, shaped by data collected and analyzed, and not on the researcher's views. Replicability of the study in similar contexts and consistency is possible by ensuring the findings were aligned with participants' viewpoints and experiences, and the theory or paradigm, if any. Techniques for achieving confirmability are triangulation, reflexivity, and audit trail (Lim, 2025; Riazi, A. M., 2025), apart from member checking and peer debriefing (Lim, 2025).

Audit Trail

The complete data collection process for the current research involved creating questionnaires for individual semistructured interviews and the focus group to obtain insightful and meaningful information from the study participants. The questions were reviewed with a National University's Academic Success Center professor and further field-tested by two technologists. Data were collected from semistructured individual interviews and a focus group using Webex recordings. The participants were asked for their consent before each of the interviews. To make it easy for participants and create an environment for free flow of information, participants were informed they could skip any questions. The participants were also told that with respect to privacy, the transcripts summarized into a document did not contain any information about the participants' names or company names. The transcript texts of each participant from the interviews and the focus group were manually transcribed into a Microsoft Word document to analyze the data collected. The participants' names and company names were recorded as pseudonyms as part of the manual transcription. The documents were sent to respective participants for member checking to ensure data confirmability, credibility, accuracy, and trustworthiness (Lim, 2025). After participants verified the transcript summary documents, they were read multiple times to understand the responses, and were imported into NVivo for coding and analysis. NVivo is broadly used in research studies for qualitative thematic analysis. Numerous research studies in the past utilized NVivo software solutions for qualitative research (Dixon-Woods et al., 2020; Knight et al., 2022; Taifi, 2022). Manual code generation and computer software were used to analyze qualitative data collected (Dierckx de Casterlé et al., 2021). The manual stage involved the preparation of the codes, which included exhaustive reading of the transcripts, creating a narrative report with an iterative forward and backward

review within and across transcripts (Dierckx de Casterlé et al., 2021). A six-step thematic analysis (Barry et al., 2024) was performed to create codes, categories, and themes from the transcribed participant responses. The six steps included: (a) getting familiarized with the data through extensive reading; (b) generating codes manually from the transcribed documents; (c) grouping codes into categories and searching for themes; (d) reviewing the themes; (e) analyzing the codes and categories to define and name themes. (f) final analysis to produce a report.

Reflexivity

Reflexivity involves the researcher's reflection on the complete research process and documentation of the assessments, biases, and methodical decisions (Lim, 2025; Riazi, A. M., 2025). The researcher works at a different technology company than the research site, and there was potential for bias because of the researcher's understanding of the technical subject of the study. A mitigation was that the researcher did not have direct authority over the participants or influence them. It must be noted that the participants were asked open-ended questions. For the current study, both triangulation and member checking were utilized.

Saturation

Data saturation is a concept in research studies where no new information or themes emerge and no additional coding is possible, indicating that the data has been fully explored (Fusch Ph D & Ness, 2015; Naeem et al., 2024). Reaching saturation requires a minimum sample size of five in qualitative studies (Yin, 2018). A review of multiple qualitative works using different types of saturation methods indicated a sample size of five to 24 was sufficient (Hennink & Kaiser, 2022). As participants in qualitative research provide detailed information, sample sizes can be smaller (Boutera et al., 2024). Attaining saturation involves obtaining data from multiple sources (Fusch Ph D & Ness, 2015). Saturation was reached when no new insights

or themes emerged from the data (Bouncken et al., 2025; Fusch Ph D & Ness, 2015; Naeem et al., 2024). The data were collected from 17 participants through individual semistructured interviews and a focus group in the current study. No new codes arose after the 10th participant in individual interviews, and two additional participants were interviewed. The researcher followed through with a five-member focus group with participants at a level lower in the organization hierarchy. The focus group with participants at a lower level in the organizational ladder meaningfully supplemented the interview corpus. The study attained data saturation with no new codes emerging after the 10th participant, and the focus group confirmed code stability.

Results

The study was conducted to explore what organizational constraints impede the adoption of BDA for strategic decision making in a technology organization, and when the constraints were overcome, how does that help the company gain a competitive advantage and reach performance goals. The findings of the study are summarized below and ordered by research question. The alignment of the findings to the theoretical framework, TOC, has been highlighted. The results obtained from this exploratory case study were based on the interview and focus group participant responses. A total of 17 participants were interviewed, of which 12 were individual interviews using a semistructured method, and five were interviewed using a focus group. All participants were part of a product group at a technology company with titles including vice president, senior director, director, leader, and manager. Interviews were conducted using Webex and ranged between 45 and 60 minutes, and the focus group took about 60 minutes. The participants were given pseudonyms. The interview participants were named from P1 to P12, and the focus group participants were named PA to PE. With the participants and the company names coded as pseudonyms, there was no reidentification risk, and it protected

the privacy of the participants and the company. Table 1 provides the demographics of interview participants, including name, title, role, and years of service, and Table 2 provides the demographics of focus group participants.

The data were collected from 17 participants through individual semistructured interviews and a focus group in the current study. No new codes arose after interviewing 10 subjects individually, and two additional participants were interviewed. The researcher followed through with a five-member focus group with participants at a level lower in the organization hierarchy. The focus group with participants at a lower level in the organizational ladder meaningfully supplemented the interview corpus. The study attained data saturation with no new codes emerging after the 10th participant, and the focus group confirmed code stability.

Table 1

Demographics of Interview Participants

Participant name	Title	Role	Years of service
P1	Leader	Product Management - Product 1	5 to 8
P2	Vice President	Product Management - Product 2	5 to 8
P3	Director	Product Management - Product 3	1 to 4
P4	Director	Product Management - Product 4	1 to 4
P5	Director	Product Management - Product 5	< 1
P6	Director	Product Management - Product 6	1 to 4
P7	Director	Product Management - Product 7	> 12
P8	Sr. Director	Product Management - Product 3	1 to 4
P9	Leader	Product Management - Product 8	1 to 4
P10	Leader	Product Management - Product 8	1 to 4
P11	Leader	Product Management - Product 4	1 to 4
P12	Director	Product Management - Product 3	1 to 4

Note. Table 1 provides demographic information of the interview participants, including name, title, role, and years of service.

Table 2

Demographics of Focus Group Participants

Participant name	Title	Role	Years of service
PA	Manager	Product Management - Product 5	1 to 4
PB	Manager	Product Management - Product 7	1 to 4
PC	Manager	Product Management - Product 4	1 to 4
PD	Manager	Product Management - Product 9	< 1
PE	Manager	Product Management - Product 7	1 to 4

Note. Table 2 provides demographic information of the focus group participants, including name, title, role, and years of service.

The questions for individual interviews and the focus group were created to obtain insightful and meaningful information from the study participants. The questions were reviewed with a National University's Academic Success Center professor and further field-tested by two technologists. The transcript texts from the interviews and focus groups were manually transcribed into a Microsoft Word document to analyze the data collected through Webex interviews. As part of the manual transcription, any participant's identifying information was changed to pseudonyms. The transcript documents were sent for member checking. Post completion of member checking, the documents were imported into NVivo for coding. A six-step thematic analysis (Barry et al., 2024) was performed to generate codes, categories, and themes from the transcribed participant responses. A total of 82 codes, eight categories, and four themes were generated from the data. The following section describes the connection of themes to each research question and explains the results.

Results for RQ1

To what extent do the organizational constraints impact the adoption of BDA for making strategic decisions at a technology company?

The findings had revealed constraints in various areas, including leadership support, organizational culture and skills, data silos, tools, technology and infrastructure, regulatory and privacy, resources and budget, and strategic prioritization. Four themes emerged from the codes and categories for research question one, including leadership support and organizational transformation, data silos and technology fragmentation, regulatory and privacy policies, and resources and strategic prioritization.

The impact of each of the constraints is shown in Table 3. Leadership support and organizational transformation had the highest impact, with 15 out of 17 participants mentioning that area. Data silos and fragmentation affected 12 out of 17 of the participants. Regulatory and privacy aspects had the lowest impact, with 7 out of 17 participants mentioning that area. Resource allocation and prioritization impacted 11 out of 17 of the participants. The counts shown here are descriptive aids, and the meaning is grounded in qualitative patterns.

Table 3

Impact of Constraints Matrix

Theme	Participants' responses
Leadership Support and Organizational Transformation	15/17
Data Silos and Technology Fragmentation	12/17
Regulatory and Privacy Concerns	7/17
Resource Allocation and Prioritization	11/17

Note. Table 3 provides the number of participants mentioning the specific area as a constraint.

Theme 1: Leadership Support and Organizational Transformation. In the theme of leadership support and organizational transformation, 15 of the 17 participants, including P1, P2, P3, P4, P5, P6, P7, P8, P9, P11, P12, PA, PB, PC, PE, highlighted constraints in the areas of leadership support, organizational culture, teams, data literacy, and skills. Table 4 provides the transparency from codes to categories to Theme 1.

Table 4

Theme 1: Leadership Support and Organizational Transformation

Theme	Categories	Codes
Leadership Support and Organizational Transformation	CAT_Organization	Leadership Support Organizational Culture
	CAT_Market and Strategy	Make strategic decisions Product Planning and Strategy
	CAT_Challenges	Challenges and Constraints Overcome Constraints
	CAT_View of BDA	BDA Awareness, Training, Governance

Note. Table 4 provides the details of theme one, along with categories and codes.

Participants P1, P6, P8, P9, and P12 discussed leadership support as a factor. Participant P6 mentioned, “When the executive management supports decisions being made that are data-driven. The first requirement and condition was that executive management establishes how the organization will work.” Participant P8 asserted, “Without our leaders' support, it is challenging to get adoption of BDA.” Participant P9 confirmed,

> It also comes down to the organization's strategic aims. Suppose an organization is aware and its executives are fully aligned that better decisions can be made using data. In that case, that organization is setting itself up for success, using past events or evidence to inform future decisions.

Participants P1, P2, P3, P4, P5, P6, P7, P8, P9, P11, P12, PA, PB, PC, PE discussed organizational culture, teams, and skills as a factor. Participant P3 stated, “having the organizational culture of making sure that, in some capacity, the data captured is usable.” Participant P7 emphasized, “It's not just within product or engineering organizations or those building the data lake and analytics. But this must be in the culture of the whole company.” Participant P9 confirmed, “You may be collecting all the data, and your data analysts may be understanding what's going on, but if you're executives and your product management leaders are not looking at the data while making decisions (culture of data-driven decision-making).”

Participants talked about organizational teams and skills as a factor. Focus group participant PE stated, “How accessible are these metrics to every team within the company? How many teams do I need to hop to before I can access the specific data I'm interested in?” Participant P4 asserted, “You have multiple stakeholders to try to keep appeased, and not all of them will always be aligned.” Focus group participant PC emphasized, “Challenges getting data moved between silos, or between different tools and different realms.” Participant P1 noted,

"Sales and marketing team members are so skilled in Excel, and are invested in manual processes, and it is difficult to change. Basic data literacy for customer-facing associates is helpful."

Theme 2: Data Silos and Technology Fragmentation. In the theme of data silos and technology fragmentation, 12 of the 17 participants, including P1, P2, P4, P6, P7, P8, P9, P12, PA, PB, PC, and PD, highlighted constraints in the areas of data silos, tools, data quality, technology, and infrastructure. Table 5 provides the transparency from codes to categories to Theme 2.

Table 5

Theme 2: Data Silos and Technology Fragmentation

Theme	Categories	Codes
Data Silos and Technology Fragmentation	CAT_Market and Strategy	Make strategic decisions Product Planning and Strategy
	CAT_Challenges	Challenges and Constraints Overcome Constraints
	CAT_Data Access, Acquisition, Ownership, and Analysis	Access to Data and Tools Data Silos and Availability Data Analysis, Insights from Data

Note. Table 5 provides the details of theme two, along with categories and codes.

Participants P2, P4, P6, P7, P8, P9, PA, PB, and PD mentioned data silos and consolidation issues stemming from different product groups and product portfolio expansion with acquisitions as a constraint. Participant P2 stated, “Multiple teams have their own data lakes, engineering, product-centric, customer success and support, and sales. Data fragmentation makes it challenging to drive cross-domain correlation.” Participant P6 mentioned, “With mergers and acquisitions, you end up having different tools and bringing that together can be a complex process.” Focus group participant PB said, “In Tableau, we have one sub-data set, and then they use a different tool called Looker. We ran into discrepancies in the data.” Participants P1, P4, P7, P9, P12, and PC mentioned data acquisition gaps from legacy products versus cloud products, and subjects P1, P12, PB, and PD discussed data quality. Participant P4 asserted, "Yeah, I highlighted that the legacy products have a harder time generating quality telemetry for us to get that information." Participant P12 stated, “Metrics not documented, unreadable variable names used by engineers.” Participant PB from the focus group confirmed, “We don't understand the terminology, or they're not feeding us all the possible data we need, which skews our interpretation and makes us come to the wrong conclusions.”

Theme 3: Regulatory and Privacy Policies. In the theme of regulatory and privacy policies, 7 of the 17 participants, including P2, P4, P5, P8, P9, P10, and P11, highlighted regulatory and privacy constraints. Table 6 provides the transparency from codes to categories to theme 3.

Table 6

Theme 3: Regulatory and Privacy Policies

Theme	Categories	Codes
Regulatory and Privacy Policies	CAT_Regulation and Privacy Compliance	Privacy and Confidentiality Data Regulations
	CAT_Market and Strategy	Make strategic decisions Product Planning and Strategy
	CAT_Challenges	Challenges and Constraints Overcome Constraints

Note. Table 6 provides the details of theme three, along with categories and codes.

Regulatory and privacy constraints were described as another set of gaps. This area included geographic and regulatory compliance restrictions and customer privacy concerns. Participants P2, P4, P8, P9, P10 highlighted compliance gaps and participants P5, P9, P10, and P11 mentioned customer privacy concerns. Participant P4 noted, “Privacy is the most significant constraint right now. European customers can't share data like we do in the US.” P8 confirmed, “European agencies don't want telemetry returning to US-based companies. Geopolitical element restricts visibility.” Participant P5 asserted, “Next layer of GDPR will be difficult, moving from an organizational to an individual basis.” Participant P9 emphasized, “Data collection turned off by default to guard customer privacy.”

Theme 4: Resource Allocation and Prioritization. In the theme of resource allocation and prioritization, 11 of the 17 participants, including P1, P3, P7, P8, P9, P10, P11, P12, PA, PB, and PC, highlighted constraints in the areas of engineering resource allocation and tooling and technology costs. Table 7 provides the transparency from codes to categories to Theme 4.

Table 7

Theme 4: Resource Allocation and Prioritization

Theme	Categories	Codes
Resource Allocation and Prioritization	CAT_Organization	Organizational Investment, Future Investment Organizational Priorities Organizational Resources
	CAT_Market and Strategy	Market Needs Make strategic decisions
	CAT_Challenges	Challenges and Constraints Overcome Constraints

Note. Table 7 provides the details of theme four, along with categories and codes.

Two significant gaps regarding resource allocation and prioritization were highlighted: engineering resource allocation and tooling and technology costs. Both interview and focus group participants, P3, P7, P9, and PC, noted resource allocation as a constraint. Participant P3 said, “If I can either do a big data assessment or build a feature for a $2 million deal, every executive will vote for the deal over big data.” Focus group participant PC confirmed, “Getting the capability to monitor a particular data item is engineering work in itself that's always in contention with other development work.” In the prioritization-related constraint, participants highlighted prioritizing short-term versus long-term needs. Subjects P3 and P10 considered short-term versus long-term priorities as a constraint. For the short-term versus long-term priorities constraint, subject P3 mentioned, “It's the money now versus a theoretical money in the future, problem.” Participant P10 confirmed, “Different groups have ad hoc priorities, and they're set at various levels.”

Tooling and technology costs were stated as a constraint by interview subjects P1, P8, P11, P12, and focus group participants PA and PB. P12 said, “Grafana is expensive in the range

of $250,000-500,000, and it is hard to justify when we offer features free to customers." P11 asserted, "Resources and budgets have an impact. I have not invested in new tools, and am using existing ones." Participant PA emphasized, "Tools require a license, and we have a limited number. We discovered that not everyone who wants access to specific tools can do so." Participant P8 confirmed, "Without leadership support, budget for tooling, a vision for what we want that experience to look like, the outcome cannot be met."

Results for RQ2

Under what conditions do the constraints impeding the adoption of BDA for making strategic decisions be mitigated to reach organizational performance goals at a technology company?

The findings revealed different conditions under which constraints impeding BDA adoption for strategic decisions can be mitigated to reach performance goals. The conditions included leadership support and organizational transformation, standardization of technologies, modernization of analytics capabilities, resource allocation, and strategic investments. Three themes emerged from the codes and categories for research question two, including leadership support and organizational transformation, data silos and technology fragmentation, and resource allocation and strategic prioritization.

Theme 1: Leadership Support and Organizational Transformation. In the theme of leadership support and organizational transformation, participants, including P1, P6, P7, P9, and P12, highlighted leadership support and data-driven organization as conditions. Table 8 provides the transparency from codes to categories to Theme 1.

Table 8

Theme 1: Leadership Support and Organizational Transformation

Theme	Categories	Codes
Leadership Support and Organizational Transformation	CAT_Organization	Leadership Support Organizational Outcomes and Results
	CAT_Market and Strategy	Make strategic decisions Product Planning and Strategy
	CAT_Challenges	Overcome Constraints
	CAT_Data Access, Acquisition, Ownership, and Analysis	Data Driven Organization

Note. Table 8 provides the details of theme one, along with categories and codes.

Multiple participants, P1, P6, P7, P9, and P12, mentioned that leadership support was needed. Participant P1 stated, “If you get a director-level person very interested in product adoption, those constraints go away because they'll push for it.” Participant P6 emphasized, “A data-driven organization is successful under the following conditions: when the executive management supports decisions being made that are data-driven.” Participant P7 confirmed, "Some top-down support, leaders entertaining data-driven decisions as a key means, as opposed to going with the tribal knowledge kind of decision-making methodology."

Theme 2: Data Silos and Technology Fragmentation. In the theme of data silos and technology fragmentation, participants, including P1, P2, P3, P6, P9, and PC, highlighted overcoming data silos and standardization of tools and technologies as conditions. Table 9 provides the transparency from codes to categories to Theme 2.

Table 9

Theme 2: Data Silos and Technology Fragmentation

Theme	Categories	Codes
Data Silos and Technology Fragmentation	CAT_Market and Strategy	Make strategic decisions Product Planning and Strategy
	CAT_Challenges	Overcome Constraints
	CAT_Data Access, Acquisition, Ownership, and Analysis	Access to Data and Tools Data Silos and Availability Data Analysis, Insights from Data
	CAT_Organization	Organizational Outcomes and Results

Note. Table 9 provides the details of theme two, along with categories and codes.

Different participants described data, tools, and overcoming technology fragmentation as conditions. Participant P1 mentioned, “From my perspective, the business data needs to be fundamentally linked to the product and person-level data.” Participant P2 asserted, “Design for the right metric, centrally stored in a common data lake and managed by a single analytics team, will yield a better outcome for the company.” Participant P6 emphasized, “Getting all the data, understanding if it's the correct data we need, and interpreting it.” Participant P3 confirmed, “I think it comes down to the flexibility of the big data tools.”

Theme 4: Resource Allocation and Prioritization. In the theme of resource allocation and prioritization, participants, including P1, P2, P3, P7, P12, and PC, highlighted resource allocation, strategic investments, and prioritization as conditions. Table 10 provides the transparency from codes to categories to Theme 4.

Table 10

Theme 4: Resource Allocation and Prioritization

Theme	Categories	Codes
Resource Allocation and Prioritization	CAT_Organization	Organizational Investment, Future Investment Organizational Priorities Organizational Resources Organizational Outcomes and Results
	CAT_Market and Strategy	Market Needs Make strategic decisions
	CAT_Challenges	Overcome Constraints
	CAT_Product Usage and Dissemination	Product Adoption

Note. Table 10 provides the details of theme four, along with categories and codes.

Participants P1, P2, P3, P7, P12, and PC described resource allocation and strategic investments as conditions. Participant P1 stated, “It is always helpful for executive teams to know whether the product is being adopted. Whether to further invest in product adoption, driving it, or making sure that it exists is up to the goals of those executives.” Participant P2 asserted, “Utilize the product usage behavior from BDA for future investments and the investment envelope to define the product roadmap for capturing future revenue. You can take resources and prioritize for that.” P3 emphasized, “It's a matter of finding the engineering resources.” P7 confirmed, “Unfortunately, even though the intent might be there with the team, it won't move forward unless you have those resources and budget.”

Results for RQ3

Under what conditions does BDA adoption for strategic decision-making help a technology company gain a competitive advantage?

The findings showed different conditions under which BDA adoption for making strategic decisions can help a technology company gain a competitive advantage. The conditions included leadership support and organizational transformation, and overcoming data silos and technology fragmentation. Two themes emerged from the codes and categories for research question three, including leadership support and organizational transformation, and data silos and technology fragmentation.

Theme 1: Leadership Support and Organizational Transformation. Participants, including P2, P5, P9, and PA, highlighted leadership support and organizational transformation as conditions in theme 1. Table 11 provides the transparency from codes to categories to Theme 1.

Table 11

Theme 1: Leadership Support and Organizational Transformation

Theme	Categories	Codes
Leadership Support and Organizational Transformation	CAT_Organization	Organizational Culture Organization's Product Portfolio
	CAT_Market and Strategy	Market Needs Make Strategic Decisions Competitive Advantage
	CAT_Product Usage and Dissemination	Product Adoption
	CAT_Sales and Customers	Customers Product Usage Customer Satisfaction
	CAT_Data Access, Acquisition, Ownership, and Analysis	Data Driven Organization

Note. Table 11 provides the details of theme one, along with categories and codes.

Multiple participants, P2, P5, P9, PA, mentioned that a data-driven organizational culture is needed. Participant P2 noted “customer quotes and their usage patterns to show that 9 out of 10 customers use the products and their features. Use the product adoption behavior from BDA for future investments.” Participant P5 asserted, “Using the data we have within the product, we can hone what we're building and target that more, and therefore create more innovative stuff that we know our customers need because we see it in our data sets.” Participant P9 emphasized,

> If you have twenty features in your product and you see customers interacting with seven of them and not thirteen of them, you should understand that those seven features are most valuable to your customers. Let's use data to see how you can make all twenty features valuable. That's how you gain a competitive advantage over your adversaries.

Participant PA confirmed, “Advanced segmentation capabilities let us create product-market fit that competitors can't replicate with their broad, generic approaches. Predictive market analysis allows us to enter new market segments 6-12 months before competitors even recognize the opportunity exists.”

Theme 2: Data Silos and Technology Fragmentation. In the theme of data silos and technology fragmentation, participants, including P3, P10, and PC, highlighted overcoming data silos and standardization of tools and technologies as conditions. Table 12 provides the transparency from codes to categories to Theme 2.

Table 12

Theme 2: Data Silos and Technology Fragmentation

Theme	Categories	Codes
Data Silos and Technology Fragmentation	CAT_Market and Strategy	Market Needs Make Strategic Decisions Competitive Advantage
	CAT_Sales and Customers	Customers Product Usage Customer Satisfaction
	CAT_Data Access, Acquisition, Ownership, and Analysis	Data Silos and Availability Big Data Usage Data Analysis, Insights from Data

Note. Table 12 provides the details of theme two, along with categories and codes.

Different participants, P3, P10, and PC, described that BD usage helps gain a competitive advantage. Participant P3 mentioned,

We were able to provide the same outcome to customers at a same or lower price point while being much more operationally efficient, and the only way we sort of came to that conclusion was by looking at the total cost, the total operations overhead, all of the data that we had on how users are using their instances.

Participant 10 emphasized “understanding that customer journey and understanding the customer better, as well as what is most used in the install base, and then seeing how you can apply that to new customers.” Participant PC confirmed,

There can be challenges getting data moved between silos, I guess you could call it or between different tools and different realms… getting that holistic picture for our customers across their environments is something that we have potential than some of our more single point product competitors.

The results described the themes that evolved for each research question based on analyzing participant responses by generating codes and categories. The following section provides an interpretation of the results.

Evaluation of the Findings

The design of this research was an exploratory case study that involved understanding the constraints that create hurdles in the organization to adopt BDA for strategic decision-making and how these impediments can be alleviated to reach performance goals and gain a competitive advantage. The findings addressed the problem that existing constraints in organizations often create barriers in the implementation of BDA for strategic decisions (Alexandre Terlizzi et al., 2024; Konanahalli et al., 2022), decreasing competitive edge and negatively affecting performance (Baker, 2022; M. U. Khan & Fatima, 2024; Manohar, 2021). The results from the study conducted using individual semi-structured interviews and a focus group provided themes and linked Eliyahu Moshe Goldratt's TOC framework (TOC Institute, 2021). Connected to TOC, the participants in the study from a technology organization identified constraints that impede the adoption of BDA for strategic decision-making. The participant responses had indicated that alleviating the constraints helps the organization gain a competitive advantage and reach performance goals associated with the TOC framework (Hoyt, 2022; Rodgers et al., 2024; TOC Institute, 2021). The themes evolved were the following:

1. Theme 1: Leadership Support and Organizational Transformation
2. Theme 2: Data Silos and Technology Fragmentation
3. Theme 3: Regulatory and Privacy Policies
4. Theme 4: Resource Allocation and Prioritization

The themes for each research question, along with their alignment to existing research and theory, are discussed in the following section.

RQ1

To what extent do the organizational constraints impact the adoption of BDA for making strategic decisions at a technology company?

The findings unveiled constraints in various areas, including technology and infrastructure, resources and budget, cultural and skills, regulatory and privacy, and leadership and strategic regions. Four themes emerged from the codes and categories for research question one, including leadership support and organizational transformation, data silos and technology fragmentation, regulatory and privacy policies, and resources and prioritization. From the data silos and technology fragmentation area, the current work aligned with past research that tools and technology were a factor in BDA adoption (Aldossari et al., 2023; Alexandre Terlizzi et al., 2024; Alharthi et al., 2017; Konanahalli et al., 2022). In previous research, technology readiness was seen as a factor for using BDA in decision-making in other countries (J. Yu et al., 2022). The current research has not found a gap in the monitoring and observability of BD systems compared to a previous study (Alexandre Terlizzi et al., 2024). A unique finding in this research was that there is a linkage of data silos to an organization's acquisitions. Regulations and privacy compliance were also considered factors in past research (Alexandre Terlizzi et al., 2024; Krotov & Johnson, 2023; Manohar, 2021). Organizational transformation, resources, and strategic prioritization were aligned with the themes of organizational culture, business strategy, and cost factors identified in past research (Baker, 2022). Past research noted leadership support in SMEs as a strong influential factor for BDA adoption (Aldossari et al., 2023).

RQ2

Under what conditions do the constraints impeding the adoption of BDA for making strategic decisions be mitigated to reach organizational performance goals at a technology company?

The findings disclosed different conditions under which constraints impeding BDA adoption for strategic decisions can be mitigated to reach performance goals. The conditions included leadership support and organizational transformation, standardization of technologies, modernization of analytics capabilities, resource allocation, and strategic investments. Three themes emerged from the codes and categories for research question two, including leadership support and organizational transformation, data silos and technology fragmentation, and resource allocation and strategic prioritization. The findings align with the theoretical framework, and past research has shown performance improvements in services and supply chain logistics (da Silva Stefano et al., 2024; Khakifirooz et al., 2024). Past work in the telecom industry has also shown that a firm's performance can be improved by adopting BDA (M. U. Khan & Fatima, 2024).

RQ3

Under what conditions does BDA adoption for strategic decision-making help a technology company gain a competitive advantage?

The findings showed different conditions under which BDA adoption for making strategic decisions can help a technology company gain a competitive advantage. The conditions included leadership support and organizational transformation, and data silos and technology fragmentation. Two themes emerged from the codes and categories for research question three, including leadership support and organizational transformation, and data silos and technology fragmentation. The findings aligned with previous research in that understanding the business

problem helps organizations apply a data-supported process inspired by TOC to gather data, extract information, and produce actionable insights to solve the problem and gain a competitive advantage (Rodgers et al., 2024). Past research also indicated that adopting data analytics has shown gains in competitive advantages in organizations, such as data-driven predictions (Manohar, 2021). In a past study, organizational culture and technology changes in SMEs in Thailand were key factors for BDA adoption, leading to sustained growth and competitiveness in the industry (Chummee, 2025).

Summary

This section details the findings from a qualitative study. The problem being addressed was that prevailing constraints in an organization often hinder the adoption of BDA in strategic decision-making (Konanahalli et al., 2022), reducing competitive advantage and impacting performance goals negatively (Baker, 2022; M. U. Khan & Fatima, 2024; Manohar, 2021). The extent to which the findings were consistent with the existing research and theory was highlighted, and research questions organized the discussion. Trustworthiness of the data, which includes credibility, transferability, dependability, and confirmability, is discussed.

The detailed results from the study for each research question are presented. For research question one, the findings revealed constraints in various areas, including technology and infrastructure, resources and budget, cultural and skills, regulatory and privacy, and leadership and strategic regions. Four themes emerged from the analysis, including leadership support and organizational transformation, data silos and technology fragmentation, regulatory and privacy policies, and resources and prioritization. Organizational culture and skills were seen as having the highest impact, followed by data silos and technology fragmentation. For research question two, the findings revealed the conditions under which constraints impeding BDA adoption for

strategic decisions can be mitigated to reach performance goals. The conditions included leadership support and organizational transformation, standardization of technologies, modernization of analytics capabilities, resource allocation, and strategic investments. Three themes emerged from the codes and categories for research question two, including leadership support and organizational transformation, data silos and technology fragmentation, and resource allocation and prioritization. For research question three, the conditions and the themes that emerged from the codes and categories included leadership support and organizational transformation, and data silos and technology fragmentation. The findings align with the theoretical framework and past research. A unique finding observed in this research was that there is a linkage between data silos and an organization's acquisitions.

Chapter 5 describes the implications, recommendations, and conclusions drawn from evaluating the findings from the analysis of data collected from the participants at the technology company. Data were obtained in the form of participant responses to the questions.

Chapter 5: Implications, Recommendations, and Conclusions

The problem addressed in this study was that existing constraints in organizations often create hurdles in the implementation of BDA for strategic decisions (Alexandre Terlizzi et al., 2024; Konanahalli et al., 2022), decreasing competitive edge and negatively affecting performance (Baker, 2022; M. U. Khan & Fatima, 2024; Manohar, 2021). The purpose of this qualitative exploratory study was to find what organizational constraints impact the adoption of BDA for strategic decision-making and investigate how these impediments can be mitigated to reach performance goals and gain a competitive advantage at a technology company. The research methodology and design that guided this study were a qualitative case study methodology and design. The problem, purpose, and research questions require collecting and assessing narrative data and exploring how organizational constraints impeding BDA adoption can be identified and mitigated. Qualitative research is unique and can deliver value because various real-world issues can fall under its umbrella (Yin, 2016).

A summary of the study results and limitations is described here. For research question one, the findings have shown constraints in various areas. Four themes emerged from the analysis, including leadership support and organizational transformation, data silos and technology fragmentation, regulatory and privacy policies, and resources and prioritization. Organizational culture and skills were seen as having the highest impact, followed by data silos and technology fragmentation. For research question two, the findings have shown conditions under which constraints impeding BDA adoption for strategic decisions can be mitigated to reach performance goals. Three themes emerged from the codes and categories for research question two, including leadership support and organizational transformation, data silos and technology fragmentation, and resource allocation and prioritization. For research question three,

the conditions and the themes that emerged from the codes and categories included leadership support and organizational transformation, and data silos and technology fragmentation. A unique finding observed in this research was that there is a linkage between data silos and the organization's acquisitions.

Every research study has limitations, and the researcher has identified gaps or weaknesses (Rogo, 2024). Defining the accurate sample size and sampling method was complex and could create gaps in producing valuable insights. The recruitment process included a broader reach to 20 participants to mitigate the limitation of participants dropping out or delaying study participation (Brenchley, 2024). In the current qualitative study, the sample size was 17 participants in the product group at a technology company. Generalization of the results to a broader population of all technology companies cannot be reached. The current study ensured that data saturation was attained. Saturation was reached when no new insights or themes emerged from the data (Bouncken et al., 2025; Fusch Ph D & Ness, 2015; Naeem et al., 2024). No new information arose after the 10th participant in individual interviews, and two additional participants were interviewed. The researcher followed through with a five-member focus group with participants at a level lower in the organization hierarchy. The focus group with participants at a lower level in the organizational ladder meaningfully supplemented the interview corpus. The study attained data saturation with no new codes emerging after the 10th participant, and the focus group confirmed code stability. The researcher works at a different technology company than the research site, and there was potential for bias because of the researcher's understanding of the technical subject of the study. A mitigation was that the researcher did not have direct authority over the participants or influence them. It must be noted that the participants were

asked open-ended questions. For the current study, both triangulation and member checking were utilized, and an audit trail was documented.

Here is a brief overview of the chapter. The Implications of the qualitative study are presented. The discussion is organized around each research question and supported by findings from the study. The relevance of the results to the study's problem and purpose, and their contribution to the existing framework and literature, is discussed. Any divergence of the results from existing research is highlighted. The next section details the recommendations for practice, followed by recommendations for future research. The final section summarizes the conclusions.

Implications

Implementing and using BDA in the organization's decision-making processes has positive effects, including gaining a competitive advantage and better performance results. The research explored the hurdles organizations face when embracing BDA in their strategic decisions, and when they overcome the constraints, what benefits they see in performance improvements and gaining a competitive advantage.

The constraints identified in the study, including leadership support, organizational transformation, data and technology fragmentation, resource and strategic prioritization, and regulatory and privacy challenges, directly align with the TOC framework's (Hoyt, 2022; Rodgers et al., 2024; TOC Institute, 2021) fundamental premise that constraints limit organizational performance. When these constraints are overcome, companies gain a competitive advantage and improve their performance. For example, TOC's first step is to identify the constraints, and 15 of the 17 participants noted that leadership support and organizational issues were the primary hurdles.

The study's findings closely align with the research questions, providing insight into the constraints organizations face when integrating BDA into their decision-making processes and the benefits they gain from improving performance and sustaining a competitive advantage by overcoming these constraints. The study's results demonstrate the extent to which they address the problem, purpose, and contribute to existing literature. The following section outlines the study's implications by research question and provides a comprehensive analysis of the findings, highlighting their relevance to practice.

RQ1

To what extent do the organizational constraints impact the adoption of BDA for making strategic decisions at a technology company? Findings from the study that address the research question are detailed below.

Leadership Support and Organizational Culture Significantly Impact the Adoption of BDA. The research disclosed that leadership commitment and organizational culture are essential for BDA success. Lack of leadership support and a data-driven organizational culture result in significant impediments. The evidence exists and was supported by participants' replies to the interview questions. Participant P8 asserted, "Without our leaders' support, it is challenging to get adoption of BDA." Participant P9 confirmed,

It also comes down to the organization's strategic aims. Suppose an organization is aware and its executives are fully aligned that better decisions can be made using data. In that case, that organization is setting itself up for success, using past events or evidence to inform future decisions.

Participant P7 emphasized, "It's not just within product or engineering organizations or those building the data lake and analytics. But this must be in the culture of the whole company."

Data silos and technology integration challenges severely impact decision-making. The research revealed that data silos and technology fragmentation create hurdles and severely impact decision-making. The study establishes that data silos are caused by organizational structure, where different business units in the company keep the data isolated, causing fragmentation and limiting comprehensive data analysis. Data and technology silos were exacerbated by the organization's acquisitions, which is a unique finding in this research. Supportive proof is available from participants' responses. Participant P2 stated, "Multiple teams have their own data lakes, engineering, product-centric, customer success and support, and sales. Data fragmentation makes it challenging to drive cross-domain correlation." Participant P6 asserted, "With mergers and acquisitions, you end up having different tools and bringing that together can be a complex process." Participant PB confirmed, "Our group is ready to embrace big data analytics. The challenge is always, especially in a big organization that grows through acquisitions like ours, there's a lot of complexity in that."

Resource and Budget Constraints Create Fundamental Hurdles. The study shows that resource and budget constraints create limitations in a technology company that builds products. Multiple participants voiced that there were competing priorities between BDA investments and building product features that customers need. Supporting evidence was available with participant P1 mentioning, "If there are budget constraints, you can't buy any of the data warehouses you need. If you can't hire a data engineer, you can't automate." Participant P3 emphasized, "If I can either do a big data assessment or build a feature for a $2 million deal, every executive will vote for the deal over big data." Participant P7 confirmed, "Like any other organization, we are constrained by the resources and the budget availability."

These findings from the current study extend prior research by Aldossari et al. (2023) on BDA adoption, demonstrating that even SME companies face similar leadership challenges, which suggests that this constraint transcends organizational size. Leadership support in SMEs was seen as a strong and influential factor for BDA adoption in the earlier research (Aldossari et al., 2023). From the data silos and technology fragmentation area, the current research aligns with past works that tools and technology are a factor in BDA adoption (Aldossari et al., 2023; Alexandre Terlizzi et al., 2024; Alharthi et al., 2017; Konanahalli et al., 2022). In previous research, technology readiness was seen as a factor for using BDA in decision-making in other countries (J. Yu et al., 2022). A past study had found a technology gap in the monitoring and observability of BD systems, which the current research did not address (Alexandre Terlizzi et al., 2024). Resources, strategic prioritization, and cost factors are aligned with this implication identified in past research (Baker, 2022). Contrary to previous research (Alexandre Terlizzi et al., 2024), which primarily focuses on technical barriers, this study reveals that organizational and cultural factors are significant constraints, in addition to technical capabilities.

RQ2

Under what conditions do the constraints impeding the adoption of BDA for making strategic decisions be mitigated to reach organizational performance goals at a technology company? Findings from the study that address the research question are detailed below.

Executive Leadership Commitment Is Vital for Systematic Change. The study reveals that leadership commitment needs to percolate within the organization to mitigate constraints that impact BDA adoption successfully, establishing a culture of data-driven decision-making. As the technology organization makes data-based strategic decisions, it helps reach or exceed performance goals. The support for the implication is evident from the responses

of the participants. Participant P7 emphasized, “Some top-down support must exist for earlier constraints, like resourcing and budget.” Participant P12 said, “I think top down. If they track metrics regularly, the entire organization will eventually start working towards ensuring enough data to give them the metrics.” P7 confirmed, “From sales reps to product people to engineers who develop this capability, everybody must have the same motive of wanting to be data-driven. It must be embedded into the culture of the whole company.”

Consolidation and Standardization of Data and Tools Are Prerequisites for Scalability. The research demonstrated that consolidation of data that exists in silos and standardization of tools used to process and analyze data, and overcoming fragmentation in an organization, have a profound positive impact and enable organization-wide BDA adoption. Supporting evidence is available from the responses of the participants. Participant PC stated, “Standardization and consolidation. We have several of these efforts happening around the business, and I'm encouraged by them. So, data standardization and consolidation, which make it easier and more accessible for any group, are massive benefits to me.” Participant P2 confirmed, “Another problem is the ability to put data in a common data lake and use the same set of tools to analyze the data.”

The participant responses have indicated that overcoming the constraints helps the organization reach performance goals associated with the TOC framework (Hoyt, 2022; Rodgers et al., 2024; TOC Institute, 2021). The findings align with the theoretical framework, and past research has shown performance improvements in services and supply chain logistics (da Silva Stefano et al., 2024; Khakifirooz et al., 2024). Prior research in the telecom industry has also shown that a firm’s performance can be improved by adopting BDA (M. U. Khan & Fatima, 2024).

Participants highlighted leadership support and a data-driven organization as conditions. Participant P6 noted, "A data-driven organization is successful under the following conditions: when the executive management supports decisions being made that are data-driven." Participants highlighted overcoming data silos and standardizing tools and technologies as key conditions. Participant P2 asserted, "Design for the right metric, centrally stored in a common data lake and managed by a single analytics team, will yield a better outcome for the company." Participants also highlighted resource allocation, strategic investments, and prioritization as conditions. Participant P2 said, "Utilize the product usage behavior from BDA for future investments and the investment envelope to define the product roadmap for capturing future revenue. You can take resources and prioritize for that." The findings align with previous research on the telecom sector, which suggested that data integration capability and data-driven decision-making lead to improved organizational performance (M. U. Khan & Fatima, 2024). Contrary to past research (M. U. Khan & Fatima, 2024), this study highlights organizational culture as a factor.

RQ3

Under what conditions does BDA adoption for strategic decision-making help a technology company gain a competitive advantage? Findings from the study that address the research question are detailed below.

Competitive Differentiation Can Be Reached by Optimizing Product Market Fit. The findings from the study established that a technology company can gain a competitive advantage by adopting BDA and understanding customer needs and usage patterns to improve product planning, product development, and market positioning. There was accompanying evidence from the responses of the participants. For example, participant P5 mentioned, “By

using the data we have within the product, we can hone what we're building and target that more, and therefore create more innovative stuff that we know our customers need because we see it in our data sets." Participant P9 confirmed, "If you have twenty features in your product and you see customers interacting with seven of them and not thirteen of them, you should understand that those seven features are most valuable to your customers."

Insights From Customer Journeys Can Enable Organizations to Be Proactive With Their Business Strategies. The research has indicated that having complete knowledge of a customer's product adoption and usage patterns helps a technology organization optimize expansion opportunities and reduce customer churn. The evidence exists in the participant responses from the interviews. Participant P10 emphasized "Understanding that customer journey and the customer better, as well as what is most used in the install base, and then seeing how you can apply that to new customers." Participant P2 confirmed,

Use the product usage behavior from BDA for future investments and the investment envelope to define the product roadmap for capturing future revenue. You can take resources and prioritize for that. If org does that, product market fit will be better, CSAT becomes better, NPS becomes better, which leads to a higher competitive advantage.

Participants mentioned that a data-driven organizational culture and overcoming data and technology fragmentation are needed. Participant P9 said, "Let's use data to see how you can make all twenty features valuable. That's how you gain a competitive advantage over your adversaries." The participant PC noted, "There can be challenges getting data moved between silos, getting that holistic picture for our customers across their environments is something that we have potential than some of our more single point product competitors."

The participant responses have indicated that overcoming the constraints helps the organization gain a competitive advantage and reach performance goals associated with the TOC framework (Hoyt, 2022; Rodgers et al., 2024; TOC Institute, 2021). The findings align with previous research in that understanding the business problem helps organizations apply a data-supported process inspired by TOC to gather data, extract information, and produce actionable insights to solve the problem and gain a competitive advantage (Rodgers et al., 2024). Past research also indicated that adopting data analytics had shown gains in competitive advantages in organizations, such as data-driven predictions (Manohar, 2021). The current findings, which suggest that culture is a factor, are supported by past research (Baker, 2022). In contrast to the current study, culture was not identified as a significant factor in past research (Aldossari et al., 2023).

Recommendations for Practice

BDA is a complex technology, and organizations face hurdles while embracing it. The study aimed to identify the constraints hindering BDA adoption in a technology company and mitigate them to gain a competitive advantage and achieve improved performance results.

Based on the finding that 15 of 17 participants identified leadership support as a primary constraint in Theme 1, organizations should implement a three-tier leadership engagement strategy comprising executive sponsorship, alignment of middle managers, and the development of champions among front-line managers. Organizations require leadership support, cultural transformation, and skilled resources to drive data-driven decisions and achieve performance goals, which aligns with the study's findings. The current study also aligns with past research that has noted leadership support in SMEs as a strong and influential factor for BDA adoption (Aldossari et al., 2023). For the successful implementation of BDA technology, executive

management support is essential in organizations to secure resources and allocate budgets. An organizational culture that supports data-driven decision-making is crucial for transitioning from traditional decision-making methods to a methodology that leverages insights from data analysis. Transformational change management strategies, including leadership support and employee training, are crucial for transitioning an organization to a data-driven culture. The current study builds upon findings from a previous study, which highlighted that change management initiatives incorporating training at all organizational levels and leadership support were crucial for steering employees toward embracing a data-oriented culture (Rauf et al., 2024). The finding is strengthened by another research work that noted that enterprises must train employees to gain skills in BD to be effective in their decision-making, ultimately helping the company achieve a strategic advantage (Wolseley et al., 2024). Evidence stems from a strategic management framework known as the resource-based view (Chaudhuri et al., 2024; Tawil et al., 2024), which emphasizes the importance of internal resources in achieving a sustained competitive advantage. Internal resources comprise skilled personnel with knowledge in data analysis and a culture of data-driven decision-making. With experienced employees, organizations can benefit from heterogeneity and immobility, whereas other organizations or competition cannot reach the same levels. Competition cannot attain the same levels as the value and rarity that employees bring to the organization, which are unique, as well as the cost or difficulty of replicating or acquiring such resources.

Given that 12 of 17 participants highlighted data silos in Theme 2, organizations should prioritize data consolidation initiatives, particularly focusing on fragmentation resulting from acquisitions, which was identified as a unique finding in this study. Companies have to overcome their data silos and technology fragmentation in BDA with investments (Aldossari et al., 2023;

Alexandre Terlizzi et al., 2024; Alharthi et al., 2017; Konanahalli et al., 2022), so that the data is consolidated, tools are standardized, and help pave the way for predictive analytics with AI and ML (Gupta et al., 2014; Pandey & Bist, 2024; Rajaraman, 2016; Saraswathi et al., 2022). These steps help organizations become more efficient, achieve performance outcomes, and gain a competitive advantage.

These recommendations align with the TOC framework's (Hoyt, 2022; Rodgers et al., 2024; TOC Institute, 2021) second step of exploiting the constraint by recommending that organizations provide maximum resources and attention to leadership development and cultural transformation initiatives. The resource-based view theory (Chaudhuri et al., 2024) discussed earlier in the literature review supports the recommendation for employee training, as skilled personnel represent immobile competitive advantages.

Recommendations for Future Research

This qualitative exploratory study aimed to identify the organizational constraints that impact the adoption of BDA for strategic decision-making and investigate how these impediments can be mitigated to achieve performance goals and gain a competitive advantage at a technology company.

In qualitative studies, the sample size is often small, sometimes limited to a single organization with a small number of participants, as was the case in the current study. Generalization of the results to a broader population of all technology companies cannot be reached. Future studies should consider quantitative research to generalize across technology companies by studying a broader sample (Wolseley et al., 2024). Future work should employ a quantitative approach with a broader sample to test the generalizability of the four identified constraint themes across different organizational sizes, geographic regions, and technology

sectors. The current study was conducted in the San Francisco Bay Area in the USA. Future researchers should consider conducting similar research with technology companies in a different location within the USA, a different country, or a different sector to determine if the results are identical or different (M. U. Khan & Fatima, 2024). Given the limitations of this study, which only interviewed a product group at a single technology company in the San Francisco Bay Area, future research should consider other groups, such as information technology and engineering groups, to determine if the findings align with this research work.

The unique finding linking data silos to organizational acquisitions necessitates a dedicated investigation. Future research should specifically examine how mergers and acquisitions impact BDA adoption constraints using a case study methodology. Future studies should test the applicability of TOC's five-step process (TOC Institute, 2021) as a prescriptive framework for BDA adoption, moving beyond constraint identification to empirically validate constraint exploitation and elevation strategies.

The next logical step in this area of research is to expand BDA to utilize AI, including Generative AI and NLP. Embracing AI offers numerous advantages for organizations in terms of business performance and innovation (Chaudhuri et al., 2024; Tawil et al., 2024). Businesses can harness the power of BD and AI to boost productivity and performance, ultimately driving innovation. As the findings have shown, technologies like BDA need leadership support for resources and investment in the organization, and the same is true for AI. As some participants stated in the study, utilizing customer product adoption data to predict which new features current or potential customers might be interested in and building them paves the way for a competitive advantage and achieving optimal performance results.

Conclusions

This qualitative research study explored what organizational constraints impact the adoption of BDA for strategic decision-making and investigated how these impediments can be mitigated to reach performance goals and gain a competitive advantage at a technology company.

This study's primary contribution was to demonstrate that the BDA adoption constraints identified by a product group at a technology company were fundamentally organizational rather than technical, with leadership support and cultural transformation representing the critical path to achieving a competitive advantage through data-driven decision-making. The convergence of TOC framework predictions and findings validates that identifiable bottlenecks indeed constrain organizational performance in BDA adoption. The study's four-theme model provides a practical roadmap for technology leaders to address barriers using TOC's five-step methodology systematically. By extending the TOC application from manufacturing to the technology organization contexts, this research bridges theoretical frameworks with contemporary digital transformation challenges, providing both scholarly contributions and practical guidance for industry leaders navigating BDA adoption.

Organizational constraints deeply impact the adoption of BDA for strategic decision-making. The study demonstrates that the constraints are multifaceted and present themselves at various levels in a company, creating hurdles for BDA implementation and usage. The constraints include the following. Absence of leadership support and a data-driven culture make it challenging to prioritize resources and budgets for BDA initiatives. Organizations prioritize budgets and resources for immediate revenue-generating product features versus BDA projects. Shortage of data literacy skills and resistance to change from the current decision-making

scheme necessitate an organizational transformation to adopt a data-driven culture. Organizations have different business units, and data fragmentation restricts complete data analysis for strategic decision-making. Regulatory and privacy constraints are permanent barriers that cannot be overcome but must be worked within the organization for compliance.

To successfully mitigate constraints and reach performance goals, organizations must plan for a comprehensive methodology encompassing leadership commitment and organizational transformation. This research study establishes that constraints cannot be alleviated with isolated actions but require an organizational change comprising executive sponsorship, standardization and consolidation of data and technologies, and cultural shift. Top-down commitment from leadership that enforces data-driven decision-making as a priority for the organization is essential. Embedding data collection analysis in product development and consolidation of data to overcome silos and common data analytic tools is vital. Mandatory data literacy programs are crucial to drive a culture change.

Adopting BDA in an organization provides a competitive advantage mainly through understanding consumer product adoption and usage, followed by data-driven product planning. The research demonstrates that companies gain a competitive advantage when implementing BDA for optimizing product market fit, enabling market differentiation, predicting consumer needs, and accelerating decision-making. Understanding customer usage patterns helps organizations invest resources in high-value product features, reduce customer churn, and create new opportunities and unique value propositions. Reducing the time to insights for strategic decision making helps gain a competitive advantage. Organizational transformation to adopt a data-driven culture helps overcome constraints and gain a competitive advantage, making it a strategic theme. Data silos and technology fragmentation span from being a barrier to becoming

an opportunity when addressed. Apart from different functions within the technology company, acquisitions exacerbate the data silos, and when tackled by consolidating the data and tools, lead to a competitive advantage.

The study successfully addresses the identified problem and answers the research questions by showing that organizational constraints create significant barriers to BDA adoption, impacting competitive advantage and performance. The research provides evidence through thick responses from participants on how the constraints are percolated at different levels of the organization. The research achieves its purpose by identifying the constraints that affect the adoption of BDA, documenting the conditions under which the constraints can be mitigated to gain a competitive advantage and reach performance goals. The study provides actionable insights for technology company leaders through recommendations. The study's findings support the premise that organizational constraints severely impact the adoption of BDA while providing a roadmap for overcoming the constraints to achieve strategic benefits. Past research highlighted leadership support in SMEs as a strong influential factor for BDA adoption (Aldossari et al., 2023). Resources, strategic prioritization, and cost factors are aligned with this implication identified in past research (Baker, 2022). From the data silos and technology fragmentation area, the current research aligns with past works that tools and technology are a factor in BDA adoption (Aldossari et al., 2023; Alexandre Terlizzi et al., 2024; Alharthi et al., 2017; Konanahalli et al., 2022). The participant responses have indicated that overcoming the constraints helps the organization gain a competitive advantage and reach performance goals associated with the TOC framework (Hoyt, 2022; Rodgers et al., 2024; TOC Institute, 2021). The findings align with the theoretical framework, and past research has shown performance improvements in services and supply chain logistics (da Silva Stefano et al., 2024; Khakifirooz et

al., 2024). The findings support previous research in that understanding the business problem helps organizations apply a data-supported process inspired by TOC to gather data, extract information, and produce actionable insights to solve the problem and gain a competitive advantage (Rodgers et al., 2024). This research establishes a foundation for future inquiry into constraint-based approaches to technology adoption, suggesting that organizational transformation frameworks may be more predictive of success than traditional technology acceptance models in complex enterprise environments.

References

Abankwa, K. (2023). *Big data analytics: Adoption readiness of small and midsize banks* (DBA) (Publication No. 2806706957) [Doctoral dissertation, Grand Canyon University]. ProQuest Dissertations & Theses Global. https://www.proquest.com/dissertations-theses/big-data-analytics-adoption-readiness-small/docview/2806706957/se-2?accountid=25320

Abbas, I., Khan, A., & Bibi, M. (2025). The nexus between sustainable business performance and green HRM in mediation with green innovation & moderation of organizational support & data-driven culture. *Market Forces*, 20(1), 135-156. https://doaj.org/article/91c07aa650234a0dbdb8ca2554141091

Abraham, D. M., & P, P. (2025). A methodological framework for descriptive phenomenological research. *Western Journal of Nursing Research*, 47(2), 125–134. CINAHL Complete. https://doi.org/10.1177/01939459241308071

Ackoff, R. L. (1989). From data to wisdom. *Journal of Applied Systems Analysis*, *16*(1), 3–9.

Adeleke, A. (2020). A case study of the marketing tools coffee shop owners use to sustain businesses. Open Journal of Business and Management, 8(2), 726-753. https://doi.org/10.4236/ojbm.2020.82044

Adewusi, A. O., Okoli, U. I., Adaga, E., Olorunsogo, T., Asuzu, O. F., & Daraojimba, D. O. (2024). Business intelligence in the era of big data: A review of analytical tools and competitive advantage. *Computer Science & IT Research Journal*, 5(2), 415–431.

Ahmed, S. F., Abduljabbar, B. T., & Hussein, A. A. A. (2021). Strategic intelligence and sustainable competitive advantage of small and medium enterprises: An exploratory study in Iraq. *Academy of Strategic Management Journal*, 20, 1–12.

Akter, S., Bandara, R., Hani, U., Fosso Wamba, S., Foropon, C., & Papadopoulos, T. (2019). Analytics-based decision-making for service systems: A qualitative study and agenda for future research. *International Journal of Information Management*, 48, 85–95. https://doi.org/10.1016/j.ijinfomgt.2019.01.020

Akter, S., & Wamba, S. F. (2016). Big data analytics in E-commerce: A systematic review and agenda for future research. *Electronic Markets*, *26*(2), 173–194. https://doi.org/10.1007/s12525-016-0219-0

Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113–131. https://doi.org/10.1016/j.ijpe.2016.08.018

Akyıldız, S. T., & Ahmed, K. H. (2021). An overview of qualitative research and focus group discussion. *International Journal of Academic Research in Education*, *7*(1), 1–15.

Al-Dmour, H., Saad, N., Basheer Amin, E., Al-Dmour, R., & Al-Dmour, A. (2023). The influence of the practices of big data analytics applications on bank performance: Filed study. *VINE: The Journal of Information & Knowledge Management Systems, 53*(1), 119–141. https://doi.org/10.1108/VJIKMS-08-2020-0151

Aldossari, S., Mokhtar, U. A., & Abdul Ghani, A. T. (2023). Factor influencing the adoption of big data analytics: A systematic literature and experts' review. *SAGE Open*, *13*(4), 1–25. https://doi.org/10.1177/21582440231217902

Alexandre Terlizzi, M., Tashiro de Oliveira, F. E., & de Rezende Francisco, E. (2024). Practices and barriers for big data projects: A case study on a large insurance company. *Journal of*

Business & Projects / Revista De Gestão E Projetos, *15*(1), 1–35. https://doi.org/10.5585/gep.v15i1.24673

Alharthi, A., Krotov, V., & Bowman, M. (2017). Addressing barriers to big data. Business Horizons, 60(3), 285–292. https://doi.org/10.1016/j.bushor.2017.01.002

Ali, A., Varma, U., & Pandya, S. (2024). Qualitative vs quantitative: The difference in the key sections of doctoral dissertations - a comparative analysis and a summary of findings. *International Journal of Doctoral Studies*, 19, 1–24. https://doi.org/10.28945/5330

Aljaž, T. (2024). Leveraging ChatGPT for enhanced logical analysis in the theory of constraints thinking process. *Organizacija*, 57(2), 202-214. https://doi.org/10.2478/orga-2024-0014

Al Rob, M. A., Mohd Nor, M. N., & Salleh, Z. (2024). The Role of Training in Big Data Analytics Adoption: An Empirical Study of Auditors Using the Technology Acceptance Model. *Electronic Journal of Business Research Methods*, 22(2), 30–45. Business Source Complete. https://doi.org/10.34190/ejbrm.22.2.3752

Alsalamah, A., & Callinan, C. (2021). Adaptation of Kirkpatrick's four-level model of training criteria to evaluate training programmes for head teachers. *Education Sciences*, 11, 116. https://research.ebsco.com/linkprocessor/plink?id=69af7a81-b243-358b-ba43-47bc8bd84ca0

Alshar, M. M., Sao, A., Sharma, M., Kadyan, S., Rao, V. S., & Anitha Vijayalakshmi, B. (2025). Leveraging AI to Personalize HR Marketing Campaigns: A Data-Driven Approach. *2025 3rd International Conference on Intelligent Systems, Advanced Computing and Communication (ISACC), Intelligent Systems, Advanced Computing and Communication (ISACC)*, 2025 3rd International Conference On, 225–230. IEEE Xplore Digital Library. https://doi.org/10.1109/ISACC65211.2025.10969174

Alsirhani, A., Ezz, M., & Mostafa, A. M. (2022). Advanced authentication mechanisms for identity and access management in cloud computing. *Computer Systems Science & Engineering*, 43(3), 967–984. https://doi.org/10.32604/csse.2022.024854

Al Teneiji, A. S., Abu Salim, T. Y., & Riaz, Z. (2024). Factors impacting the adoption of big data in healthcare: A systematic literature review. *International Journal of Medical Informatics*, 187, 105460. https://doi.org/10.1016/j.ijmedinf.2024.105460

Alvarez-Romero, C., Martínez-García, A., Bernabeu-Wittel, M., & Parra-Calderón, C. L. (2023). Health data hubs: An analysis of existing data governance features for research. *Health Research Policy and Systems*, 21(1), 70. https://doi.org/10.1186/s12961-023-01026-1

Amalina, F., Targio Hashem, I. A., Azizul, Z. H., Fong, A. T., Firdaus, A., Imran, M., & Anuar, N. B. (2020). *Blending big data analytics: Review on challenges and a recent study*, 8, 3629-3645. IEEE. https://doi.org/10.1109/ACCESS.2019.2923270

Anaya, L., & Qutaishat, F. (2022). ERP systems drive businesses towards growth and sustainability. *Procedia Computer Science*, 204, 854–861. https://doi.org/10.1016/j.procs.2022.08.103

Anna, N. E. V., & Mannan, E. F. (2020). Big data adoption in academic libraries: A literature review. *Library Hi Tech News*, 37(4), 1–5. https://doi.org/10.1108/LHTN-11-2019-0079

Anton, E., Oesterreich, T. D., Aptyka, M., & Teuteberg, F. (2023). Beyond Digital Data and Information Technology: Conceptualizing Data-Driven Culture. *Pacific Asia Journal of the Association for Information Systems*, 15(3), 1–36. Supplemental Index. https://doi.org/10.17705/1pais.15301

Antonsen, L. K., Lassen, A. T., Nielsen, D., & Østervang, C. (2024). Navigating healthcare systems: A qualitative study on socially marginalized patients' experiences of hospital

transition and support by social nurses. *Scandinavian Journal of Caring Sciences*, 38(2), 387–397. https://doi.org/10.1111/scs.13236

Araz, O. M., Choi, T., Olson, D. L., & Salman, F. S. (2020). Role of analytics for operational risk management in the era of big data. *Decision Sciences*, 51(6), 1320–1346. https://doi.org/10.1111/deci.12451

Arulsamy, A. S., Singh, I., Kumar, M. S., Panchal, J. J., & Bajaj, K. K. (2023). Employee training and development enhancing employee performance – A study. *Samdarshi*, 16(3), 1–11.

Aseeri, M., & Kang, K. (2022). Big data, oriented-organizational culture, and business performance: A socio-technical approach. *Problems and Perspectives in Management*, 20(4), 52–66. Directory of Open Access Journals. https://doi.org/10.21511/ppm.20(4).2022.05

Aseeri, M., & Kang, K. (2023). Organizational culture and big data socio-technical systems on strategic decision making: Case of Saudi Arabian higher education. *Education and Information Technologies*, 28, 8999-9024. https://doi.org/10.1007/s10639-022-11500-y

Ashaari, M. A., Singh, K. S. D., Abbasi, G. A., Amran, A., & Liebana-Cabanillas, F. (2021). Big data analytics capability for improved performance of higher education institutions in the era of IR 4.0: A multi-analytical SEM & ANN perspective. *Technological Forecasting & Social Change*, 173, 121119. https://doi.org/10.1016/j.techfore.2021.121119

Asigbee, F. M., Ranck, L., Pruitt, A. S., Pines, R. L., Silva, C., Barrett, L., Petras, J. K., & Ray, M. (2025). Qualitative Study Examining the Effects of the COVID-19 Pandemic on the Homelessness Community Using PhotoVoice: Methodology and Lessons Learned.

International Journal of Qualitative Methods, 24, 1–11. Academic Search Complete. https://doi.org/10.1177/16094069251353434

Asthana, S., Mukherjee, S., Phelan, A. L., & Standley, C. J. (2024). Governance and public health decision-making during the COVID-19 pandemic: A scoping review. *Public Health Reviews (2107-6952)*, 45, 1–11. https://doi.org/10.3389/phrs.2024.1606095

Awan, U., Shamim, S., Khan, Z., Zia, N. U., Shariq, S. M., & Khan, M. N. (2021). Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance. *Technological Forecasting & Social Change*, 168, 120766. https://doi.org/10.1016/j.techfore.2021.120766

Azam, M., & Ahmad, K. (2024). Adoption of big data analytics for sustainability of library services in academic libraries of Pakistan. *Library Hi Tech*, 42(5), 1457–1476. https://doi.org/10.1108/LHT-12-2022-0584

Azeem, M., Ahmed, M., Haider, S., & Sajjad, M. (2021). Expanding competitive advantage through organizational culture, knowledge sharing and organizational innovation. *Technology in Society*, 66, 101635. https://doi.org/10.1016/j.techsoc.2021.101635

Azeem, M., Haleem, A., Bahl, S., Javaid, M., Suman, R., & Nandan, D. (2022). Big data applications to take up major challenges across manufacturing industries: A brief review. *Materials Today: Proceedings*, 49, 339–348. https://doi.org/10.1016/j.matpr.2021.02.147

Azzi, R., Kilany Chamoun, R., Serhrouchni, A., & Sokhn, M. (2025). Unlocking the Potential of Data: Toward a Secure and Privacy-Preserving Blockchain-Based Health Data Governance Framework. *Blockchain: Research and Applications*. ScienceDirect. https://doi.org/10.1016/j.bcra.2025.100318

Badshah, A., Daud, A., Alharbey, R., Banjar, A., Bukhari, A., & Alshemaimri, B. (2024). Big data applications: Overview, challenges and future. *Artificial Intelligence Review*, 57(11), 290. https://doi.org/10.1007/s10462-024-10938-5

Bag, S., Dhamija, P., Singh, R. K., Rahman, M. S., & Sreedharan, V. R. (2023). Big data analytics and artificial intelligence technologies based collaborative platform empowering absorptive capacity in health care supply chain: An empirical study. *Journal of Business Research*, 154, 113315. https://doi.org/10.1016/j.jbusres.2022.113315

Bag, S., Pretorius, J. H. C., Gupta, S., & Dwivedi, Y. K. (2021). Role of institutional pressures and resources in the adoption of big data analytics powered artificial intelligence, sustainable manufacturing practices and circular economy capabilities. *Technological Forecasting & Social Change*, 163, 120420. https://doi.org/10.1016/j.techfore.2020.120420

Baker, D. R. (2022). Influencing factors of big data adoption in the utility industry (DBA) (Publication No. 2711754632) [Doctoral dissertation, Grand Canyon University]. ProQuest Dissertations & Theses Global. https://www.proquest.com/docview/2711754632/7C317ADD275478CPQ/1?accountid=25320&sourcetype=Dissertations%20&%20Theses

Balla, D., Simon, C., & Maliosz, M. (2020). Adaptive scaling of Kubernetes pods. *NOMS 2020 - 2020 IEEE/IFIP Network Operations and Management Symposium, Network Operations and Management Symposium, NOMS 2020 - 2020 IEEE/IFIP*, 1–5. https://doi.org/10.1109/NOMS47738.2020.9110428

Banmairuroy, W., Kritjaroen, T., & Homsombat, W. (2022). The effect of knowledge-oriented leadership and human resource development on sustainable competitive advantage

through organizational innovation's component factors: Evidence from Thailand's new S-curve industries. *Asia Pacific Management Review*, 27(3), 200–209. https://doi.org/10.1016/j.apmrv.2021.09.001

Bansal, P., Smith, W. K., & Vaara, E. (2018). New ways of seeing through qualitative research. *Academy of Management Journal, 61*(4), 1189–1195. https://doi.org/10.5465/amj.2018.4004

Bari, M. D., & Ara, A. (2024). The impact of machine learning on prescriptive analytics for optimized business decision-making. *Anjuman, the Impact of Machine Learning on Prescriptive Analytics for Optimized Business Decision-Making (April 15, 2024),* https://doi.org/10.62304/ijmisds.v1i1.112

Bari, M. H., Arif, N. U. M., Hasan, M. M., & Maraj, M. A. A. (2024). Comparative analysis of digital payment platforms and E-commerce giants: A five-year performance and strategic development study of Visa, Mastercard, Amazon, and eBay. *Global Mainstream Journal of Innovation, Engineering & Emerging Technology, 3*(01), 1.

Barry, L., Holloway, J., & McMahon, J. (2024). “It’s up to the teacher”: A qualitative study of teachers’ use of autism EBPs. Irish Educational Studies, 43(4), 1157–1173. Education Research Complete. https://doi.org/10.1080/03323315.2023.2200021

Batko, K., & Ślęzak, A. (2022). The use of big data analytics in healthcare. *Journal of Big Data*, 9(1), 3. https://doi.org/10.1186/s40537-021-00553-4

Bhat, W. A. (2018). Long-term preservation of big data: Prospects of current storage technologies in digital libraries. *Library Hi Tech*, 36(3), 539–555. https://doi.org/10.1108/LHT-06-2017-0117

Billups, F. D. (2024). Qualitative data collection tools: Design, development, and applications. SAGE Publications, Inc. https://doi.org/10.4135/9781071878699

Boakye, E. A., Zhao, H., & Ahia, B. N. K. (2022). Emerging research on blockchain technology in finance; a conveyed evidence of bibliometric-based evaluations. *Journal of High Technology Management Research*, 33(2), 100437. https://doi.org/10.1016/j.hitech.2022.100437

Bouncken, R. B., Czakon, W., & Schmitt, F. (2025). Purposeful sampling and saturation in qualitative research methodologies: Recommendations and review. *Review of Managerial Science*, 1–37. https://doi.org/10.1007/s11846-025-00881-2

Boutera, B., Brahim, D., Belgacem, A., & Faouzi, L. (2024). Methodological Considerations When Determining Sample Size in Qualitative Research. *Pakistan Journal of Life & Social Sciences*, 22(2), 12202–12209. Business Source Complete. https://doi.org/10.57239/PJLSS-2024-22.2.00873

Bragazzi, N. L., Dai, H., Damiani, G., Behzadifar, M., Martini, M., & Wu, J. (2020). How big data and artificial intelligence can help better manage the COVID-19 pandemic. *International Journal of Environmental Research and Public Health*, 17(9), 3176. https://doi.org/10.3390/ijerph17093176

Brenchley, A. (2024). Graphic paper: Promoting generalization in qualitative nursing research using the multiple case narrative approach: A methodological overview. *Journal of Research in Nursing*, 29(8), 609–614. https://doi.org/10.1177/17449871241298790

Britto, J. S. (2020). Exploring cloud-based big data analytics in healthcare organizations (DBA) (Publication No. 2443565768). [Doctoral dissertation, University of Maryland Global Campus]. ProQuest Dissertations & Theses Global.

https://www.proquest.com/dissertations-theses/exploring-cloud-based-big-data-analytics/docview/2443565768/se-2?accountid=25320

Bronzo, M., Barbosa, M. W., de Sousa, P. R., Torres Junior, N., & Valadares de Oliveira, M. P. (2024). Leveraging supply chain reaction time: The effects of big data analytics capabilities on organizational resilience enhancement in the auto-parts industry. *Administrative Sciences* (2076-3387), 14(8), 181. https://doi.org/10.3390/admsci14080181

Brown, P. A., & Anderson, R. A. (2023). A methodology for preprocessing structured big data in the behavioral sciences. *Behavior Research Methods*, 55(4), 1818–1838. https://doi.org/10.3758/s13428-022-01895-4

Caffrey, C. (2023). *Conceptual framework*. Salem Press.

Caputo, F., Keller, B., Möhring, M., Carrubbo, L., & Schmidt, R. (2023). Advancing beyond technicism when managing big data in companies' decision-making. *Journal of Knowledge Management*, 27(10), 2797–2809. https://doi.org/10.1108/JKM-10-2022-0794

Catyanadika, P. E., Sabani, A., & Leenders, M. A. (2024). Exploring Data Veracity Management in a Post-Truth Business Environment: An Integrative Literature Review and Future Research Direction. *Journal of Database Management (JDM)*, 35(1), 1–46.

Chand, S. P. (2025). Methods of data collection in qualitative research: Interviews, focus groups, observations, and document analysis. *Advances in Educational Research and Evaluation,* 6(1), 303–317.

Chaudhuri, R., Chatterjee, S., Vrontis, D., & Thrassou, A. (2024). Adoption of robust business analytics for product innovation and organizational performance: The mediating role of

organizational data-driven culture. *Annals of Operations Research*, 339(3), 1757–1791. https://doi.org/10.1007/s10479-021-04407-3

Choudhury, P., Allen, R. T., & Endres, M. G. (2021). Machine learning for pattern discovery in management research. *Strategic Management Journal (John Wiley & Sons, Inc.)*, 42(1), 30–57. Business Source Complete. https://doi.org/10.1002/smj.3215

Choudhury, S., Fishman, J., McGowan, M., & Juengst, E. (2014). *Big data, open science and the brain: Lessons learned from genomics*. Frontiers Media S.A. https://doi.org/10.3389/fnhum.2014.00239

Christalle, E., Zeh, S., Hahlweg, P., Kriston, L., Härter, M., Zill, J., & Scholl, I. (2022). Development and content validity of the Experienced Patient-Centeredness Questionnaire (EPAT)—A best practice example for generating patient-reported measures from qualitative data. *Health Expectations*, 25(4), 1529–1538. CINAHL Complete. https://doi.org/10.1111/hex.13494

Christian, K., Johnstone, C., Larkins, J., & Wright, W. (2022). Seeking Approval from Universities to Research the Views of Their Staff. Do Gatekeepers Provide a Barrier to Ethical Research? *Journal of Empirical Research on Human Research Ethics*, 17(3), 317–328. Academic Search Complete. https://doi.org/10.1177/15562646211068316

Chummee, P. (2025). Causal Influences of Big Data Analytics Adoption for Small and Medium-Sized Enterprises in the Eastern Economic Corridor (EEC) of Thailand. International Journal of Sociologies and Anthropologies Science Reviews, 6(6), 1–18. https://doi.org/10.60027/ijsasr.2026.8235

Ciola, E. (2020). Financial sector bargaining power, aggregate growth and systemic risk. *Journal of Economic Interaction and Coordination*, 15(1), 89–109. https://doi.org/10.1007/s11403-019-00270-5

Clancy, R., O'Sullivan, D., & Bruton, K. (2023). Data-driven quality improvement approach to reducing waste in manufacturing. *TQM Journal*, 35(1), 51–72. https://doi.org/10.1108/TQM-02-2021-0061

Coman, A., & Ronen, B. (1995). Information technology in operations management: A theory-of-constraints approach. *International Journal of Production Research*, 33(5), 1403. https://doi.org/10.1080/00207549508930217

Correia, J., Costa, C. A. P., & Santos, M. Y. (2019). *Challenging SQL-on-hadoop performance with Apache Druid*. Springer Verlag, 2019, 149-161. https://doi.org/10.1007/978-3-030-20485-3_12

Coşkun, E., Gezici, B., Aydos, M., Tarhan, A. K., & Garousi, V. (2022). ERP failure: A systematic mapping of the literature. *Data & Knowledge Engineering*, 142, 102090. https://doi.org/10.1016/j.datak.2022.102090

Cottu, P., Scott, D. R., Solà-Morales, O., Spears, P. A., & Taylor, L. (2022). *The emerging role of real-world data in advanced breast cancer therapy: Recommendations for collaborative decision-making*. Elsevier. https://doi.org/10.1016/j.breast.2021.12.015

Court, D., Jesko, P., Tim, M., Jonathan, G., & Spillecke, D. (2015). Marketing & sales: Big data, analytics, and the future of marketing & sales. *McKinsey & Company,* https://www.mckinsey.com/~/media/mckinsey/business%20functions/marketing%20and%20sales/our%20insights/ebook%20big%20data%20analytics%20and%20the%20future%20of%20marketing%20sales/big-data-ebook.pdf

Creswell, J. W., & Poth, C. N. (2018). *Qualitative inquiry and research design: Choosing among five approaches* (4th ed.). Thousand Oaks, CA: Sage publications.

Cui, Y., Saba, F. F., Afzal, A., Awais, M., & Akram, Z. (2022). *The influence of big data analytic capabilities building and education on business model innovation*. Frontiers Media S.A. https://doi.org/10.3389/fpsyg.2022.999944

Cvetkoska, V., Eftimov, L., & Kitanovikj, B. (2023). Enchanting performance measurement and management with data envelopment analysis: Insights from bibliometric data visualization and analysis. *Decision Analytics Journal*, 9, 100367. https://doi.org/10.1016/j.dajour.2023.100367

Dahlbom, P., Siikanen, N., Sajasalo, P., & Jarvenpää, M. (2020). Big data and HR analytics in the digital era. *Baltic Journal of Management*, 15(1), 120–138. https://doi.org/10.1108/BJM-11-2018-0393

Daněk, A., & Urgošíková, M. (2024). Qualitative research design in education: tools, challenges, and practical implications. *Ad Alta: Journal of Interdisciplinary Research*, 14(2), 385–389. Academic Search Complete. https://doi.org/10.33543/j.1402.385389

Dash, S., Sushil, K. S., Sharma, M., & Kaushik, S. (2019). *Big data in healthcare: Management, analysis and future prospects*. SpringerOpen, 6(1), 1-25. https://doi.org/10.1186/s40537-019-0217-0

da Silva Stefano, G., Pacheco Lacerda, D., Isabel Wolf Motta Morandi, M., Augusto Cassel, R., & Denicol, J. (2024). How important is the theory of constraints to supply chain management? an assessment of its application and impacts. *Computers & Industrial Engineering*, 198, N.PAG. https://doi.org/10.1016/j.cie.2024.110717

Delen, D., & Zolbanin, H. M. (2018). The analytics paradigm in business research. *Journal of Business Research*, 90, 186–195. https://doi.org/10.1016/j.jbusres.2018.05.013

De Mauro, A., Greco, M., & Grimaldi, M. (2016). A formal definition of big data based on its essential features. *Library Review*, 65(3), 122–135. https://doi.org/10.1108/LR-06-2015-0061

De Rijck, P. (2023). *The impact of a company's (big) data analytics capability on firm performance, decision-making, and management control* (Ph.D.) [Doctoral Dissertation, University of Antwerp]. https://hdl.handle.net/10067/1930700151162165141

Dhar, V., Sun, C., & Batra, P. (2019). *Transforming finance into vision: Concurrent financial time series as convolutional nets*. Mary Ann Liebert, Inc. 7(4), 276-285. https://doi.org/10.1089/big.2019.0139

Dhulavvagol, P. M., & Totad, S. G. (2023). Performance Enhancement of Distributed System Using HDFS Federation and Sharding. *Procedia Computer Science*, 218, 2830–2841. Science Direct. https://doi.org/10.1016/j.procs.2023.01.254

Dierckx de Casterlé, B., De Vliegher, K., Gastmans, C., & Mertens, E. (2021). Complex Qualitative Data Analysis: Lessons Learned From the Experiences With the Qualitative Analysis Guide of Leuven. *Qualitative Health Research*, 31(6), 1083–1093. CINAHL Complete. https://doi.org/10.1177/1049732320966981

Dixon-Woods, M., Campbell, A., Chang, T., Martin, G., Georgiadis, A., Heney, V., Chew, S., Van Citters, A., Sabadosa, K. A., & Nelson, E. C. (2020). A qualitative study of design stakeholders' views of developing and implementing a registry-based learning health system. *Implementation Science*, 15(1), 1–11. https://doi.org/10.1186/s13012-020-0976-1

Dominik Balazka & Dario Rodighiero. (2020). Big Data and the Little Big Bang: An Epistemological (R)evolution. *Frontiers in Big Data, 3.* Directory of Open Access Journals. 3, 31. https://doi.org/10.3389/fdata.2020.00031

Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data – evolution, challenges and research agenda. *International Journal of Information Management*, 48, 63–71. https://doi.org/10.1016/j.ijinfomgt.2019.01.021

Dun & Bradstreet. (2024). *Software Publishers Companies in the United States of America.* https://www.dnb.com/. Retrieved October 25, 2024, from https://www.dnb.com/business-directory/company-information.software_publishers.us.html

Dunmade, A. O., & Hamzat, S. A. (2022). Relevance of big data analytics in Nigerian academic libraries: University of Ilorin library experience. *Mousaion*, 40(1), 1–13. https://doi.org/10.25159/2663-659X/8361

Eachempati, P., & Srivastava, P. R. (2022). Applications of Big Data Analytics in Investment Management: A Review and Future Research Agenda Using TCM Framework. *Journal of Database Management*, 33(1), 1-32. Gale Academic OneFile. https://doi.org/10.4018/JDM.299557

Elia, G., Raguseo, E., Solazzo, G., & Pigni, F. (2022). Strategic business value from big data analytics: An empirical analysis of the mediating effects of value creation mechanisms. *Information & Management*, 59(8), 103701. ScienceDirect. https://doi.org/10.1016/j.im.2022.103701

Eliot, T. S. (2011). *The complete poems and plays of TS Eliot*. Faber & Faber.

Ellili, N., Nobanee, H., Alsaiari, L., Shanti, H., Hillebrand, B., Hassanain, N., & Elfout, L. (2023). The applications of big data in the insurance industry: A bibliometric and

systematic review of relevant literature. *Journal of Finance and Data Science*, 9, 100102. Directory of Open Access Journals. https://doi.org/10.1016/j.jfds.2023.100102

Elragal, A., & Klischewski, R. (2017). Theory-driven or process-driven prediction? Epistemological challenges of big data analytics. *Journal of Big Data*, 4, 1–20. https://doi.org/10.1186/s40537-017-0079-2

Ergun, O., Hopp, W. J., & Keskinocak, P. (2023). A structured overview of insights and opportunities for enhancing supply chain resilience. *IISE Transactions*, 55(1), 57–74. https://doi.org/10.1080/24725854.2022.2080892

Fatieieva, A. (2020). Information systems in the enterprise's management. *Economics.Finances.Law*, 6(1), 11–15. https://doi.org/10.37634/efp.2020.6(1).2

Faulkner, S. S., & Faulkner, C. A. (2019). *Research methods for social workers: A practice-based approach*. Oxford University Press.

Flyverbom, M., Deibert, R., & Matten, D. (2019). The governance of digital technology, big data, and the internet: New roles and responsibilities for business. *Business & Society*, 58(1), 3–19. https://doi.org/10.1177/0007650317727540

Fong, J. H., Koh, B. S. K., Mitchell, O. S., & Rohwedder, S. (2021). Financial literacy and financial decision-making at older ages. *Pacific-Basin Finance Journal*, 65, 101481. https://doi.org/10.1016/j.pacfin.2020.101481

Fusch Ph D, P. I., & Ness, L. R. (2015). Are we there yet? Data saturation in qualitative research.

Galetsi, P., Katsaliaki, K., & Kumar, S. (2019). Values, challenges and future directions of big data analytics in healthcare: A systematic review. *Social Science & Medicine*, 241, 112533. https://doi.org/10.1016/j.socscimed.2019.112533

Galetsi, P., Katsaliaki, K., & Kumar, S. (2020). Big data analytics in health sector: Theoretical framework, techniques and prospects. *International Journal of Information Management*, 50, 206–216. https://doi.org/10.1016/j.ijinfomgt.2019.05.003

Ghanad, A. (2023). An overview of quantitative research methods. *International Journal of Multidisciplinary Research and Analysis*, 6(08), 3794–3803. https://doi.org/10.47191/ijmra/v6-i8-52

Ghasemaghaei, M., & Calic, G. (2020). Assessing the impact of big data on firm innovation performance: Big data is not always better data. *Journal of Business Research*, 108, 147–162. https://doi.org/10.1016/j.jbusres.2019.09.062

Gökalp, M. O., Gökalp, E., Kayabay, K., Koçyiğit, A., & Eren, P. E. (2022). The development of the data science capability maturity model: A survey-based research. *Online Information Review*, 46(3), 547–567. https://doi.org/10.1108/OIR-10-2020-0469

Goundar, P. R. (2025). Researcher Positionality: Ways to Include it in a Qualitative Research Design. *International Journal of Qualitative Methods*, 24, 1–7. Academic Search Complete. https://doi.org/10.1177/16094069251321251

Gozalo-Brizuela, R., & Garrido-Merchan, E. C. (2023). ChatGPT is not all you need. A state of the art review of large generative AI models. *arXiv Preprint arXiv:2301.04655*

Grander, G., da Silva, L. F., & Santibañez Gonzalez, E. D. R. (2021). Big data as a value generator in decision support systems: A literature review. *Revista de Gestão*, 28(3), 205–222.

Gravili, G., Hassan, R., Avram, A., & Schiavone, F. (2023). Big data and human resource management: Paving the way toward sustainability. *European Journal of Innovation Management*, 26(7), 552–590. https://doi.org/10.1108/EJIM-01-2023-0048

Gujar, P., Panyam, S., & Paliwal, G. (2025). AI Integrated Product Development: Building Sustainable Competitive Advantage. *IEEE Engineering Management Review, Engineering Management Review, IEEE, IEEE Eng. Manag. Rev.*, 53(1), 73–81. IEEE Xplore Digital Library. https://doi.org/10.1109/EMR.2024.3475408

Gupta, M., Borole, P., Hebbar, P., Mehta, R., & Nayak, N. (2014). *Cross market modeling for query-entity matching*, 285-286. https://doi.org/10.1145/2567948.2577277

Haarhaus, T., & Liening, A. (2020). Building dynamic capabilities to cope with environmental uncertainty: The role of strategic foresight. *Technological Forecasting & Social Change*, 155, 120033. https://doi.org/10.1016/j.techfore.2020.120033

Habimana, Y., Moseti-Morara, I., & Odero, D. (2020). An adoption model for a big data analytics system for improving healthcare services in Burundi's public hospitals. *East African Journal of Science, Technology and Innovation*, 1(2). https://doi.org/10.37425/eajsti.1.2.90

Hadjielias, E., Christofi, M., Christou, P., & Hadjielia Drotarova, M. (2022). Digitalization, agility, and customer value in tourism. *Technological Forecasting & Social Change*, 175, 121334. https://doi.org/10.1016/j.techfore.2021.121334

Halim, H. A., Waqas, A., Hanifah, H., & Ahmad, N. H. (2024). *Strategic foresight and big data analytics as antecedents of SMEs' sustainable competitive advantage: Role of AI utilization*. Global Business and Management Research: An International Journal.

Hamad, F., Al-Fadel, M., & Fakhouri, H. (2023). The provision of smart service at academic libraries and associated challenges. *Journal of Librarianship & Information Science*, 55(4), 960–971. https://doi.org/10.1177/09610006221114173

Han, X., Gstrein, O. J., & Andrikopoulos, V. (2024). When we talk about big data, what do we really mean? Toward a more precise definition of big data. *Frontiers in Big Data*, 7, 1441869. https://doi.org/10.3389/fdata.2024.1441869

Hands, A. S. (2022). Integrating quantitative and qualitative data in mixed methods research: An illustration. *Canadian Journal of Information & Library Sciences*, 45(1), 1–20. https://doi.org/10.5206/cjilsrcsib.v45i1.10645

Hang, L., & Tat, H. H. (2023). Application of job analysis in recruitment based on big data technology: Take F company as an example. *Proceedings of the 2nd International Conference on Big Data Economy and Digital Management, BDEDM 2023, January 6-8, 2023,* https://doi.org/10.4108/eai.6-1-2023.2330356

Harris, J. G., & Davenport, T. H. (2017). Competing on analytics, updated, with a new introduction: The new science of winning. (pp. 1). Harvard University.

Harris, R. J. (2018). *The evaluation of constraints within information technology departments concerning the statistical and analytical problems of big data* (DBA) (Publication No. 2090948570) [Doctoral dissertation, National University]. ProQuest Dissertations & Theses Global. https://www.proquest.com/dissertations-theses/evaluation-constraints-within-information/docview/2090948570/se-2?accountid=25320

Hassan, M., Awan, F. M., Naz, A., deAndrés-Galiana, E. J., Alvarez, O., Cernea, A., Fernández-Brillet, L., Fernández-Martínez, J. L., & Kloczkowski, A. (2022). *Innovations in genomics and big data analytics for personalized medicine and health care: A review*. MDPI, 23(9), 4645. https://doi.org/10.3390/ijms23094645

Hasson, F., Keeney, S., & McKenna, H. (2025). Revisiting the Delphi technique—Research thinking and practice: A discussion paper. *International Journal of Nursing Studies*, 168, 105119. APA PsycInfo. https://doi.org/10.1016/j.ijnurstu.2025.105119

He, Q., Liu, J., Gan, J., & Qian, Z. (2019). Systemic financial risk and macroeconomic activity in China. *Journal of Economics and Business*, 102, 57–63. https://doi.org/10.1016/j.jeconbus.2018.10.002

He, W. (2025). Medical Data Large-scale Processing Technology Based on March Algorithm. *Procedia Computer Science*, 259, 572–580. Supplemental Index. https://doi.org/10.1016/j.procs.2025.04.006

Heliana, L., & Wahyuni, H. (2024). *Big data analysis in human resources decision making: Optimizing workforce management*

Hennessy, M., Bleakley, A., & Ellithorpe, M. E. (2023). Evaluating and tracking qualitative content coder performance using item response theory. *Quality & Quantity: International Journal of Methodology*, 57(2), 1231–1245. Springer Nature Journals. https://doi.org/10.1007/s11135-022-01397-7

Hennink, M., & Kaiser, B. N. (2022). Sample sizes for saturation in qualitative research: A systematic review of empirical tests. *Social Science & Medicine*, 292, 114523. https://doi.org/10.1016/j.socscimed.2021.114523

Henry, E. A., Oladapo, A. P., Chukwuekem, D. O., & Abiodun, E. A. (2024). *Theoretical frameworks supporting IT and business strategy alignment for sustained competitive advantage*, 6(4), 1273-1287.

Hirschlein, N., & Dremel, C. (2021). How to realize business value through a big data analytics capability–results from an action design research approach. *ICIS 2021 Proceedings, 3*

Hong, J., Dreibholz, T., Schenkel, J. A., & Hu, J. A. (2019). An overview of multi-cloud computing. Paper presented at the *Web, Artificial Intelligence and Network Applications: Proceedings of the Workshops of the 33rd International Conference on Advanced Information Networking and Applications (WAINA-2019)* 33, 1055–1068.

Hooper, R. (2023). Big data: What is it and how can academic libraries use it? *Alabama Libraries*, 60(2), 3.

Hoyt, B. R. (2022). Theory of constraints: From theory to practice. *Pathways to Research in Business & Economics*, 1–20. https://research.ebsco.com/linkprocessor/plink?id=2cd5cb23-3d69-3f1b-b175-04dfec6779bd

Hussinki, H., Ritala, P., Vanhala, M., Kianto, A., & Mero, J. (2025). Effects of Big Data Analytics on Firm Innovativeness: The Role of a Data-Driven Culture. *Knowledge & Process Management*, 32(4), 161–173. Complementary Index. https://doi.org/10.1002/kpm.70000

Huy, P. Q., & Phuc, V. K. (2023). Big data in relation with business intelligence capabilities and e-commerce during COVID-19 pandemic in accountant's perspective. *Future Business Journal*, 9(1), 40. Springer Nature Journals. https://doi.org/10.1186/s43093-023-00221-4

Islam, A. Y. M. A., Ahmad, K., Rafi, M., & JianMing, Z. (2021). Performance-based evaluation of academic libraries in the big data era. *Journal of Information Science*, 47(4), 458–471. https://doi.org/10.1177/0165551520918516

Islam, M. S. U., & Roknuzzaman, M. (2021). Big data management in the libraries of Bangladesh: Perceptions, issues and challenges. *Bangladesh Journal of Library and Information Science*, 2(3), 162–207.

Islam, N., Islam, K., & Islam, M. (2023). Exploring the Potential of Big Data Analytics in Improving Library Management in Indonesia: Challenges, Opportunities, and Best Practice. *Internet Reference Services Quarterly*, 27(2), 111–120. CINAHL Complete. https://doi.org/10.1080/10875301.2023.2184900

Javan Jafari Bojnordi, A., Zahedian Nezhad, M., Bagheri, R., Bazrafshan, M., & Sohrabi, B. (2025). Identifying, ranking and analyzing obstacles to big data analytics implementation in the healthcare industry using an ISM approach. *Discover Health Systems*, 4(1), 1–25. CINAHL Complete. https://doi.org/10.1007/s44250-025-00204-y

Jiang, G., Cai, X., Feng, X., & Liu, W. (2023). Effect of data environment and cognitive ability on participants' attitude towards data governance. *Journal of Information Science*, 49(3), 740–761. Business Source Complete. https://doi.org/10.1177/01655515211019000

Jiang, Z., Zhu, Z., & Pan, S. (2024). Data governance in multimodal behavioral research. *Multimodal Technologies & Interaction*, 8(7), 55. https://doi.org/10.3390/mti8070055

Karakoç, M., & Şik, E. (2021). THEORY OF CONSTRAINTS: THE APPLICATION OF WINE PRODUCTION FACILITY. *Omer Halisdemir Universitesi Iktisadi ve Idari Bilimler Fakültesi Dergisi*, 14(2), 378–395. Business Source Complete. https://doi.org/10.25287/ohuiibf.703440

Kasiraju, N. (2024). *Strategic use of big data for customer experience and protection in US financial institutions: A systematic review*. (2024-85918-191). https://search.ebscohost.com/login.aspx?direct=true&AuthType=sso&db=psyh&AN=2024-85918-191&site=eds-live&scope=site&custid=natuniv

Khakifirooz, M., Fathi, M., & Dolgui, A. (2024). Theory of AI-driven scheduling (TAIS): A service-oriented scheduling framework by integrating theory of constraints and AI.

International Journal of Production Research, 1–35. https://doi.org/10.1080/00207543.2024.2424976

Khan, M. A., Uddin, M. F., & Gupta, N. (2014). Seven v's of big data understanding big data to extract value. *Proceedings of the 2014 Zone 1 Conference of the American Society for Engineering Education*, 1–5. https://doi.org/10.1109/ASEEZone1.2014.6820689

Khan, M. U., & Fatima, I. (2024). The role of big data analytics capability in the telecommunication sector of Pakistan: The chain mediating effect of data integration capability and data-driven decision making. *Quality & Quantity: International Journal of Methodology*, 59(1), 51–85. https://doi.org/10.1007/s11135-024-01923-9

Khan, S., Khan, H. U., & Nazir, S. (2022). Systematic analysis of healthcare big data analytics for efficient care and disease diagnosing. *Scientific Reports*, 12(1), 1–21. Directory of Open Access Journals. https://doi.org/10.1038/s41598-022-26090-5

Khan, W., Kumar, T., Zhang, C., Raj, K., Roy, A. M., & Luo, B. (2023). SQL and NoSQL Database Software Architecture Performance Analysis and Assessments—A Systematic Literature Review. *Big Data and Cognitive Computing*, 7(2), 97–97. Directory of Open Access Journals. https://doi.org/10.3390/bdcc7020097

Khan, Z. F., & Alotaibi, S. R. (2020). Applications of artificial intelligence and big data analytics in m-health: A healthcare system perspective. *Journal of Healthcare Engineering, 2020*, 8894694. https://doi.org/10.1155/2020/8894694

Knight, F., Bourassa, M. W., Ferguson, E., Walls, H., de Pee, S., Vosti, S., Martinez, H., Levin, C., Woldt, M., Sethurman, K., & Bergeron, G. (2022). Nutrition modeling tools: A qualitative study of influence on policy decision making and determining factors. *Annals*

of the New York Academy of Sciences, 1513(1), 170–191. https://doi.org/10.1111/nyas.14778

Koltai, T., & Tamás, A. (2022). Performance evaluation of teams in business simulation games with weight restricted data envelopment analysis models. *International Journal of Management Education (Elsevier Science), 20*(3), N.PAG. https://doi.org/10.1016/j.ijme.2022.100688

Konanahalli, A., Marinelli, M., & Oyedele, L. (2022). Drivers and challenges associated with the implementation of big data within UK facilities management sector: An exploratory factor analysis approach. *IEEE Transactions on Engineering Management*, 69(4), 916–929. https://doi.org/10.1109/TEM.2019.2959914

Koot, M., Mes, M. R. K., & Iacob, M. E. (2021). A systematic literature review of supply chain decision making supported by the Internet of things and big data analytics. *Computers & Industrial Engineering*, 154, N.PAG. https://doi.org/10.1016/j.cie.2020.107076

Koshksaray, A. A., Quach, S., Trinh, G., Keivani, S. B., & Thaichon, P. (2023). Brand competitiveness antecedents: The interaction effects of marketing and R&D expenditure. Journal of Retailing and Consumer Services, 75, 103532. ScienceDirect. https://doi.org/10.1016/j.jretconser.2023.103532

Krotov, V., & Johnson, L. (2023). Big web data: Challenges related to data, technology, legality, and ethics. Business Horizons, 66(4), 481–491. ScienceDirect. https://doi.org/10.1016/j.bushor.2022.10.001

Kumar, A., Arya, N., & Sharma, P. K. (2023). A Research on the Impact of Big Data Analytics on the Telecommunications Sector. *International Conference on Information and Communication Technology for Intelligent Systems*, 121–128.

Kushwaha, A. K., Kumar, P., & Kar, A. K. (2021). What impacts customer experience for B2B enterprises when using AI-enabled chatbots? Insights from big data analytics. *Industrial Marketing Management*, 98, 207–221. https://doi.org/10.1016/j.indmarman.2021.08.011

Kwasu, E. A., Ombui, K. A., & Siele, E. (2024). Leveraging technological research methodologies to improve employee performance in organizations. *East African Journal of Business & Economics*, 7(2), 51–65. https://doi.org/10.37284/eajbe.7.2.2279

Ladeira, M. B., Oliveira, M. P. V. D., Sousa, P. R. D., & Barbosa, M. W. (2021). Firm's supply chain agility enabling resilience and performance in turmoil times. *International Journal of Agile Systems and Management*, 14(2), 224–253. https://doi.org/10.1504/IJASM.2021.118068

Lee, C. K. M., Ng, K. K. H., Jiao, R. J., & Yang, Z. (2022). Editorial notes: Emerging intelligent automation and optimisation methods for adaptive decision making. *Advanced Engineering Informatics*, 51, 101500. https://doi.org/10.1016/j.aei.2021.101500

Li, L., Lin, J., Ouyang, Y., & Luo, X. (2022). Evaluating the impact of big data analytics usage on the decision-making quality of organizations. *Technological Forecasting & Social Change*, 175, 121355. https://doi.org/10.1016/j.techfore.2021.121355

Lim, W. M. (2025). What Is Qualitative Research? An Overview and Guidelines. Australasian Marketing Journal, 33(2), 199–229. Supplemental Index. https://doi.org/10.1177/14413582241264619

Lincoln, Y. S., & Guba, E. G. (1985). Naturalistic Inquiry. SAGE Publications. https://doi.org/10.1016/0147-1767(85)90062-8

Liu, T., Junchao, F., Luo, H., & Guo, K. (2023). Transforming Supply Chain Management with Big Data Analytics: A Pathway to Competitive Advantage. 2023 International

Conference on Data Science & Informatics (ICDSI), Data Science & Informatics (ICDSI), 2023 International Conference on, ICDSI, 217–222. IEEE Xplore Digital Library. https://doi.org/10.1109/ICDSI60108.2023.00050

Liu, Z., Mahinder Singh, H. S., & Shibli, F. A. (2025). What is a recognized mechanism for transforming big data analytics into firm performance? A meta-analysis from cultural view. Humanities & Social Sciences Communications, 12(1), 1–20. Directory of Open Access Journals. https://doi.org/10.1057/s41599-024-04284-8

Lokesh, S., Chakraborty, S., Pulugu, R., Mittal, S., Pulugu, D., & Muruganantham, R. (2022). AI-based big data analytics model for medical applications. *Measurement: Sensors*, 24, 100534. ScienceDirect. https://doi.org/10.1016/j.measen.2022.100534

Lukić, J. (2017). The impact of big data technologies on competitive advantage of companies. *Facta Universitatis, Series: Economics and Organization,* 255. https://doi.org/10.22190/FUEO1703255L

Lutfi, A., Alsyouf, A., Almaiah, M. A., Alrawad, M., Abdo, A. A. K., Al-Khasawneh, A., Ibrahim, N., & Saad, M. (2022). Factors influencing the adoption of big data analytics in the digital transformation era: Case study of Jordanian SMEs. *Sustainability (2071-1050),* 14(3), 1802. https://doi.org/10.3390/su14031802

Lysaght, T., Lim, H. Y., Xafis, V., & Ngiam, K. Y. (2019). AI-assisted decision-making in healthcare: The application of an ethics framework for big data in health and research. *Asian Bioethics Review*, 11(3), 299–314. https://doi.org/10.1007/s41649-019-00096-0

Mahmoudian, M., Zanjani, S. M., Shahinzadeh, H., Kabalci, Y., Kabalci, E., & Ebrahimi, F. (2023). An overview of big data concepts, methods, and analytics: Challenges, issues, and opportunities. *2023 5th Global Power, Energy and Communication Conference*

(GPECOM), Power, Energy and Communication Conference (GPECOM), 2023 5th Global, 554–559. https://doi.org/10.1109/GPECOM58364.2023.10175760

Maley, J. F., Dabic, M., & Moeller, M. (2021). Employee performance management: Charting the field from 1998 to 2018. *International Journal of Manpower*, 42(1), 131–149. https://doi.org/10.1108/IJM-10-2019-0483

Mangaroska, K., Martinez-Maldonado, R., Vesin, B., & Gaševic, D. (2021). Challenges and opportunities of multimodal data in human learning: The computer science students' perspective. *Journal of Computer Assisted Learning*, 37(4), 1030–1047. https://research.ebsco.com/linkprocessor/plink?id=529b3a6b-4029-3443-bf0e-7651c85d87bf

Manohar, P. (2021). Impact of adopting big data analytics on strategic decisions: A Delphi study using the technology–organization–environment (TOE) framework (Ph.D.) (Publication No. 2456453062) [Doctoral dissertation, Capella University]. ProQuest Dissertations & Theses Global. https://www.proquest.com/docview/2456453062?pq-origsite=gscholar&fromopenview=true&sourcetype=Dissertations%20&%20Theses

Manroop, L., Malik, A., & Milner, M. (2024). The ethical implications of big data in human resource management. *Human Resource Management Review*, 34(2), N.PAG. https://doi.org/10.1016/j.hrmr.2024.101012

Maroufkhani, P., Iranmanesh, M., & Ghobakhloo, M. (2023). Determinants of big data analytics adoption in small and medium-sized enterprises (SMEs). *Industrial Management & Data Systems*, 123(1), 278–301. https://doi.org/10.1108/IMDS-11-2021-0695

May, T. A., Koskey, K. L. K., & Provinzano, K. (2024). Developing and validating the preschool nutrition education practices survey. *Journal of Nutrition Education & Behavior*, 56(8), 545–555. https://doi.org/10.1016/j.jneb.2024.03.009

Mazzei, M. J., & Noble, D. (2017). Big data dreams: A framework for corporate strategy. *Business Horizons*, 60(3), 405–414. https://doi.org/10.1016/j.bushor.2017.01.010

Mc Donnell, N., Howley, E., & Duggan, J. (2020). Dynamic virtual machine consolidation using a multi-agent system to optimise energy efficiency in cloud computing. *Future Generation Computer Systems*, 108, 288–301. https://doi.org/10.1016/j.future.2020.02.036

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019a). Big data analytics and firm performance: Findings from a mixed-method approach. *Journal of Business Research*, 98, 261–276. https://doi.org/10.1016/j.jbusres.2019.01.044

Mikalef, P., Boura, M., Lekakos, G., & Krogstie, J. (2019b). Big data analytics capabilities and innovation: The mediating role of dynamic capabilities and moderating effect of the environment. *British Journal of Management*, 30(2), 272–298. https://doi.org/10.1111/1467-8551.12343

Mikalef, P., & Krogstie, J. (2020). Examining the interplay between big data analytics and contextual factors in driving process innovation capabilities. *European Journal of Information Systems*, 29(3), 260–287. https://doi.org/10.1080/0960085X.2020.1740618

Mikalef, P., Krogstie, J., Pappas, I. O., & Pavlou, P. (2020). Exploring the relationship between big data analytics capability and competitive performance: The mediating roles of dynamic and operational capabilities. *Information & Management*, 57(2), N.PAG. https://doi.org/10.1016/j.im.2019.05.004

Mohajan, H. K. (2020). *Quantitative research: A successful investigation in natural and social sciences*. Editura Fundatiei Romania de Maine. https://doi.org/10.26458/jedep.v9i4.679

Monday, T. U. (2020). Impacts of interview as research instrument of data collection in social sciences. *Journal of Digital Art & Humanities*, 1(1), 15–24. https://doi.org/10.33847/2712-8148.1.1_2

Moreno, J., Fernandez, E. B., Serrano, M. A., & Fernandez-Medina, E. (2019). Secure development of big data ecosystems. *IEEE Access, 7*, 96604–96619. https://doi.org/10.1109/ACCESS.2019.2929330

Morozov, V. A. (2020). Corporate culture management methods in enterprise management. *Management and Business Administration, NA*(1), 137–143. https://doi.org/10.33983/2075-1826-2020-1-137-143

Mu, S., Cui, M., & Huang, X. (2020). Multimodal data fusion in learning analytics: A systematic review. *Sensors, 20*(23), 6856. http://doi.org/10.3390/s20236856

Muhammad, N. K. (2022). A conceptual framework for big data analytics adoption towards organization performance in Malaysia. *International Journal of Information & Knowledge Management (22318836)*, 12(1), 54–62. https://ir.uitm.edu.my/id/eprint/65775

Muhunzi, D., Kitambala, L., & Mashauri, H. L. (2024). Big data analytics in the healthcare sector: Opportunities and challenges in developing countries. A literature review. Health *Informatics Journal*, 30(4), 14604582241294217. MEDLINE. https://doi.org/10.1177/14604582241294217

Murphy, J., Vallières, F., Bentall, R. P., Shevlin, M., McBride, O., Hartman, T. K., McKay, R., Bennett, K., Mason, L., Gibson-Miller, J., Levita, L., Martinez, A. P., Stocks, T. V. A.,

Karatzias, T., & Hyland, P. (2021). Psychological characteristics associated with COVID-19 vaccine hesitancy and resistance in Ireland and the United Kingdom. *Nature Communications*, 12(1) https://doi.org/10.1038/s41467-020-20226-9

Naeem, M., Ozuem, W., Howell, K., & Ranfagni, S. (2024). Demystification and Actualisation of Data Saturation in Qualitative Research Through Thematic Analysis. *International Journal of Qualitative Methods*, 23, 1–17. Academic Search Complete. https://doi.org/10.1177/16094069241229777

Natividade Joergensen, P., & Zaggl, M. (2024). The role of data science and data analytics for innovation: A literature review. *Journal of Business Analytics, 7*(4), 207–223. https://doi.org/10.1080/2573234X.2024.2365917

Nesca, M., Katz, A., Leung, C., & Lix, L. (2022). A scoping review of preprocessing methods for unstructured text data to assess data quality. *International Journal of Population Data Science*, 7(1), 1757. Directory of Open Access Journals. https://doi.org/10.23889/ijpds.v7i1.1757

Nespeca, V., Comes, T., Meesters, K., & Brazier, F. (2020). Towards coordinated self-organization: An actor-centered framework for the design of disaster management information systems. *International Journal of Disaster Risk Reduction*, 51, 101887. https://doi.org/10.1016/j.ijdrr.2020.101887

Niknejad, N., Ismail, W., Bahari, M., Hendradi, R., & Salleh, A. Z. (2021). Mapping the research trends on blockchain technology in food and agriculture industry: A bibliometric analysis. *Environmental Technology & Innovation*, 21, 101272. https://doi.org/10.1016/j.eti.2020.101272

Niu, Y., Ying, L., Yang, J., Bao, M., & Sivaparthipan, C. B. (2021). Organizational business intelligence and decision making using big data analytics. *Information Processing & Management, 58*(6), N.PAG-N.PAG. Education Research Complete. https://doi.org/10.1016/j.ipm.2021.102725

Noble, H., & Smith, J. (2025). Ensuring validity and reliability in qualitative research. *Evidence-Based Nursing.*

Nowicka, J., Pauliuchuk, Y., Ciekanowski, Z., Fałda, B., & Sikora, K. (2024). The use of data analytics in human resource management. *European Research Studies*, 27(2), 203–215. https://doi.org/10.35808/ersj/3380

Núñez-Cacho Utrilla, P. V., Grande-Torraleja, F., Moreno Albarracín, A. L., & Ortega-Rodríguez, C. (2023). Advance employee development to increase performance of the family business. *Employee Relations, 45*(7), 27–45. https://doi.org/10.1108/ER-03-2022-0151

Oladokun, B. D., Aboyade, M. A., & Aboyade, W. A. (2023). Global challenge and opportunities for libraries and big data. *Library Hi Tech News*

Ospanova, G., & Kukharenko, E. (2021). *Building a model of the integrity of information resources within an enterprise management system*

Ostapenko, Y. P. (2021). Management of tax burden on value-added tax at the enterprise level. *Accounting & Finance / Oblìk Ì Fìnansi*, (91), 70–75. https://doi.org/10.33146/2307-9878-2021-1(91)-70-75

Oyewobi, L., Okanlawon, T., Medayese, S., Ogunbode, E., & Jimoh, R. (2024). Is pursuing a PhD without theoretical and conceptual framework a journey without roadmap?

Environmental Technology and Science Journal, 15(2), 138–149. https://doi.org/10.4314/etsj.v15i2.15

Pan, Y., & Zhang, L. (2021). Roles of artificial intelligence in construction engineering and management: A critical review and future trends. *Automation in Construction*, 122, 103517. https://doi.org/10.1016/j.autcon.2020.103517

Panda, S. (2021). Usefulness and impact of big data in libraries: An opportunity to implement embedded librarianship. *Technological Innovations and Environmental Changes in Modern Libraries*

Pandey, M., & Bist, A. S. (2024). *A study of big data analytics: Tools, applications, and information value chain*. IEEE. https://doi.org/10.1109/ICAIT61638.2024.10690840

Papi, F. G., Hübner, J. F., & de Brito, M. (2022). A blockchain integration to support transactions of assets in multi-agent systems. *Engineering Applications of Artificial Intelligence*, 107, 104534. https://doi.org/10.1016/j.engappai.2021.104534

Park, G., & Song, M. (2020). Predicting performances in business processes using deep neural networks. *Decision Support Systems*, 129, 113191. https://doi.org/10.1016/j.dss.2019.113191

Partners, N. (2017). *NewVantage partners releases 5th annual big data executive survey for 2017*

Patgiri, R. (2019). *A taxonomy on big data: Survey.* https://doi.org/10.48550/arxiv.1808.08474

Pattnaik, M., & Shah, T. R. (2023). Role of big data to boost corporate decision making. *2023 2nd International Conference on Edge Computing and Applications (ICECAA), Edge Computing and Applications (ICECAA), 2023 2nd International Conference On,* 105–111. https://doi.org/10.1109/ICECAA58104.2023.10212179

Patton, M. Q. (1990). *Qualitative evaluation and research methods*. SAGE Publications, inc.

Peng, J., & Bao, L. (2023). Construction of enterprise business management analysis framework based on big data technology. *Heliyon*, 9(6). https://doi.org/10.1016/j.heliyon.2023.e17144

Peters, M. A. (2024). From 2-D Pyramid to Generative Network: Reimagining the DIKW Hierarchy as a Biodigital Network Intelligent Ecosystem. *Psychosociological Issues in Human Resource Management*, 12(2), 7-17. Gale Academic OneFile.

Phung, T. M. T., Tran, Q. N., Nguyen, N. H., & Nguyen, T. H. (2021). Financial decision-making power and risk taking. *Economics Letters*, 206. https://doi.org/10.1016/j.econlet.2021.109999

Ponnusamy, V. K., Kasinathan, P., Madurai Elavarasan, R., Ramanathan, V., Anandan, R. K., Subramaniam, U., Ghosh, A., & Hossain, E. (2021). A comprehensive review on sustainable aspects of big data analytics for the smart grid. *Sustainability* (2071-1050), 13(23), 13322. https://doi.org/10.3390/su132313322

Porter, M. E. (1996). Competitive advantage, agglomeration economies, and regional policy. *International Regional Science Review*, 19(1-2), 85–90. https://doi.org/10.1177/016001769601900208

Powless, S., & Jarquin, N. M. (2023). Theory of constraints & consumer behavior: A comparative analysis between developed & advanced developing cultures. *Journal of Applied Business & Economics*, 25(5), 49–60. https://doi.org/10.33423/jabe.v25i5.6511

Pregoner, J. D. (2024). Research Approaches in Education: A Comparison of Quantitative, Qualitative and Mixed Methods. *IMCC Journal of Science*, 4(2), 12–17. Academic Search Complete.

Raban, D. R., & Gordon, A. (2020). The evolution of data science and big data research: A bibliometric analysis. *Scientometrics*, 122(3), 1563–1581. https://doi.org/10.1007/s11192-020-03371-2

Rahaman, M. A., & BARI, M. H. (2024). Predictive analytics for strategic workforce planning: A cross-industry perspective from energy and telecommunications. *International Journal of Business Diplomacy and Economy, 3*(2), 14–25.

Rahul, K., Banyal, R. K., & Arora, N. (2023). A systematic review on big data applications and scope for industrial processing and healthcare sectors. *Journal of Big Data*, 10(1) https://doi.org/10.1186/s40537-023-00808-2

Raj, A., Dwivedi, G., Sharma, A., Lopes de Sousa Jabbour, A. B., & Rajak, S. (2020). *Barriers to the adoption of industry 4.0 technologies in the manufacturing sector: An inter-country comparative perspective.* https://doi.org/10.1016/j.ijpe.2019.107546

Rajaraman, V. (2016). Big data analytics. *Resonance: Published by the Indian Academy of Sciences*, 21(8), 695–716. https://doi.org/10.1007/s12045-016-0376-7

Ranjan, J., & Foropon, C. (2021). Big data analytics in building the competitive intelligence of organizations. *International Journal of Information Management*, 56, N.PAG. https://doi.org/10.1016/j.ijinfomgt.2020.102231

Rauf, M. A., Shorna, S. A., Joy, Z. H., & Rahman, M. M. (2024). *Data-driven transformation: Optimizing enterprise financial management and decision-making with big data*. All Academic Research 2024-06-15.

Reggio, G., & Astesiano, E. (2020). *Big-data/analytics projects failure: A literature review*. IEEE. https://doi.org/10.1109/SEAA51224.2020.00050

Ren, S. (2022). *Optimization of enterprise financial management and decision-making systems based on big data*. Hindawi Limited. https://doi.org/10.1155/2022/1708506

Renugadevi, N., Saravanan, S., & Naga Sudha, C. M. (2023). Revolution of Smart Healthcare Materials in Big Data Analytics. *Materials Today: Proceedings*, 81, 834–841. ScienceDirect. https://doi.org/10.1016/j.matpr.2021.04.256

Riazi, A. M. (2025). Inference in Qualitative Research: An Overlooked Index of Quality. *Journal of Modern Research in English Language Studies*, 12(special issue), 147–164. Directory of Open Access Journals. https://doi.org/10.30479/jmrels.2025.3839

Rodgers, M., Mukherjee, S., Melamed, B., Baveja, A., & Kapoor, A. (2024). Solving business problems: The business-driven data-supported process. *Annals of Operations Research, 332*(1-3), 705–741. https://doi.org/10.1007/s10479-023-05770-z

Rogo, E. J. (2024). Exploring Qualitative Research. *Journal of Dental Hygiene*, 98(4), 56–61. CINAHL Complete.

Rybicka, K. (2019). Usage of big data technology in controlling. *Research in World Economy, 10*(4), 92. https://doi.org/10.5430/rwe.v10n4p92

Sajid, H. A., Habib, N., Chaudhry, S. A., & Naveed, S. (2020). *Effectiveness of performance management system for employee performance through engagement*. SAGE Publishing. https://doi.org/10.1177/2158244020969383

Sakr, S., & Elgammal, A. (2016). Towards a comprehensive data analytics framework for smart healthcare services. *Big Data Research*, 4, 44–58. https://doi.org/10.1016/j.bdr.2016.05.002

Salawu, R., Shamsuddin, A., Bolatitio, S., & Masibo, S. (2023). Theoretical and conceptual frameworks in research: Conceptual clarification. *European Chemical Bulletin*, 12(12), 2103–2117.

Salman, M. A., Mondal, K., Kobir, M. S., Khusi, K. K., Rifat, M., & Ghani, S. I. (2025). Harnessing big data analytics for industry 4.0: A hybrid architecture of revolutionary technologies and predictive implementation in manufacturing. *International Journal of System Assurance Engineering and Management*, 1–18. Springer Nature Journals. https://doi.org/10.1007/s13198-025-03045-3

Salman, M. S., Abdullah, M. K. J., & Sahid, S. N. Z. (2020). Big data analytic concepts in libraries: A systematic. *Sciences, 9*(2), 345–362. https://doi.org/10.6007/IJARPED/v9-i2/7381

Sarabi, A. S., Zamani, M., Ranjbar, S., & Rahmatian, F. (2023). Innovation – But with Risk: The Strategic Role of IT in Business Risk Management. *Cyberspace Studies*, 7(2), 253–275. Directory of Open Access Journals. https://doi.org/10.22059/jcss.2023.101605

Saraswathi, S., Deepa, G., Vennila, G., Parthasarathy, S., & Ramadoss, B. (2022). A survey on big data: Infrastructure, analytics, visualization and applications. *International Journal of Industrial Engineering*, 29(5), 618–648. https://doi.org/10.23055/ijietap.2022.29.5.7643

Sardi, A., Sorano, E., Cantino, V., & Garengo, P. (2023). Big data and performance measurement research: Trends, evolution and future opportunities. *Measuring Business Excellence*, 27(4), 531–548. https://doi.org/10.1108/MBE-06-2019-0053

Schuiling, S. J. (2020). *Feasible and desirable approaches to overcoming barriers to small and medium-sized enterprise adoption of big data analytics* (DBA) (Publication No. 2434507902) [Doctoral dissertation, Capella University]. ProQuest Dissertations &

Theses Global. https://www.proquest.com/dissertations-theses/feasible-desirable-approaches-overcoming-barriers/docview/2434507902/se-2?accountid=25320

Schwöbel, S., Marković, D., Smolka, M. N., & Kiebel, S. (2024). Joint modeling of choices and reaction times based on Bayesian contextual behavioral control. *PLoS Computational Biology, 20*(7), e1012228. MEDLINE Complete. https://doi.org/10.1371/journal.pcbi.1012228

Sebele-Mpofu, F. (2021). *The sampling conundrum in qualitative research: Can saturation help alleviate the controversy and alleged subjectivity in sampling?* https://doi.org/10.11114/ijsss.v9i5.5294

Sedkaoui, S., Khelfaoui, M., & Kadi, N. (2021). *Big data analytics: Harnessing data for new business models*. Apple Academic Press.

Senger, B., MacDonald, Q., Pencer, A., Crocker, C. E., Hughes, J., & Tibbo, P. G. (2025). Referral pathways to early intervention services for psychosis and their influence on perceptions of care: An interpretive phenomenological analysis. *Early Intervention in Psychiatry*, 19 (1). APA PsycInfo. https://doi.org/10.1111/eip.13553

Shahbaz, M., Gao, C., Zhai, L., Shahzad, F., Luqman, A., & Zahid, R. (2021). Impact of big data analytics on sales performance in pharmaceutical organizations: The role of customer relationship management capabilities. *PloS One*, 16(4), e0250229. https://doi.org/10.1371/journal.pone.0250229

Shahzad, K., & Khan, S. A. (2024). Factors influencing the adoption of big data in libraries: A systematic literature review of peer-reviewed articles from 2013 to 2023. *Electronic Library*, 42(5), 722–740. https://doi.org/10.1108/EL-02-2024-0057

Shamim, M. M. I., & Khan, M. H. (2022). Cloud computing and AI in analysis of worksite. *Nexus, 1*(03)

Shamim, S., Zeng, J., Khan, Z., & Zia, N. U. (2020). Big data analytics capability and decision making performance in emerging market firms: The role of contractual and relational governance mechanisms. *Technological Forecasting & Social Change*, 161 https://doi.org/10.1016/j.techfore.2020.120315

Shamim, S., Zeng, J., Shariq, S. M., & Khan, Z. (2019). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capabilities view. *Information & Management*, 56(6), 103135. https://doi.org/10.1016/j.im.2018.12.003

Sivarajah, U., Kamal, M. M., Irani, Z., & Weerakkody, V. (2017). Critical analysis of big data challenges and analytical methods. *Journal of Business Research*, 70, 263–286. https://doi.org/10.1016/j.jbusres.2016.08.001

Sivarajah, U., Kumar, S., Kumar, V., Chatterjee, S., & Li, J. (2024). A study on big data analytics and innovation: From technological and business cycle perspectives. *Technological Forecasting & Social Change*, 202, N.PAG-N.PAG. Supplemental Index. https://doi.org/10.1016/j.techfore.2024.123328

Smith, G. (2020). Data mining fool's gold. *Journal of Information Technology*, 35(3), 182–194. https://doi.org/10.1177/0268396220915600

Sørstrøm, A. K., Ludvigsen, M. S., & Kymre, I. G. (2025). Facilitating planned home death: A qualitative study on home care nurses' experiences of enablers and barriers. *Journal of Advanced Nursing (John Wiley & Sons, Inc.)*, 81(1), 340–352. Complementary Index. https://doi.org/10.1111/jan.16171

Stahl, N. A., & King, J. R. (2020). Expanding Approaches for Research: Understanding and Using Trustworthiness in Qualitative Research. Journal of Developmental Education, 44(1), 26–28. JSTOR Journals. https://doi.org/10.2307/45381095

Stake, R. E. (1995). The art of case study research. Thousand Oaks, CA: Sage. Paper presented at the *Sixth International Conference on Self-Study of Teacher Education Practices.*

Stake, R. E. (2005). Qualitative case studies. in N. K. denzin and Y. S. lincoln (eds.) . *The Sage Handbook of Qualitative Research,* 443–466.

Statista. (2022). Big data market size revenue forecast worldwide from 2011 to 2027. https://www.statista.com/statistics/254266/global-big-data-market-forecast/

Stimpfel, A. W., Leep-Lazar, K., Mercer, M., & DeMarco, K. (2025). "Scheduling Is Everything": A Qualitative Descriptive Study of Job and Schedule Satisfaction of Staff Nurses and Nurse Managers. *Western Journal of Nursing Research*, 47(10), 912–923. Complementary Index. https://doi.org/10.1177/01939459251330280

Stobierski, T. (2019). The advantages of data-driven decision-making. Harvard Business School.

Sun, S., Cegielski, C. G., Jia, L., & Hall, D. J. (2018). Understanding the factors affecting the organizational adoption of big data. *Journal of Computer Information Systems*, 58(3), 193–203. https://doi.org/10.1080/08874417.2016.1222891

Tabesh, P., Mousavidin, E., & Hasani, S. (2019). Implementing big data strategies: A managerial perspective. *Business Horizons*, 62(3), 347–358. https://doi.org/10.1016/j.bushor.2019.02.001

Taecharungroj, V. (2023). 'What can ChatGPT do?' analyzing early reactions to the innovative AI chatbot on Twitter. *Big Data and Cognitive Computing*, 7(1) https://doi.org/10.3390/bdcc7010035

Taherdoost, H. (2022). What are different research approaches? Comprehensive review of qualitative, quantitative, and mixed method research, their applications, types, and limitations. *Journal of Management Science & Engineering Research*, 5(1), 53–63. https://doi.org/10.30564/jmser.v5i1.4538

Taifi, N. (2022). The primordial role of business intelligence and real time analysis for big data: Finance-based case study. *Journal of Intelligence Studies in Business*, 12(2), 36–53. https://search.ebscohost.com/login.aspx?direct=true&AuthType=sso&db=edb&AN=162311636&site=eds-live&scope=site&custid=natuniv

Tanasescu, L. G., Vines, A., Bologa, A. R., & Vîrgolici, O. (2024). Data analytics for optimizing and predicting employee performance. *Applied Sciences*, 14(8). https://doi.org/10.3390/app14083254

Tawil, A. H., Mohamed, M., Schmoor, X., Vlachos, K., & Haidar, D. (2024). Trends and challenges towards effective data-driven decision making in UK small and medium-sized enterprises: Case studies and lessons learnt from the analysis of 85 small and medium-sized enterprises. *Big Data and Cognitive Computing*, 8(7). https://doi.org/10.3390/bdcc8070079

Taylor, P. (2023). *State of big data/AI adoption in organizations worldwide, 2018 to 2023.* Statista. Retrieved March 2, 2025, from https://www.statista.com/statistics/742993/worldwide-survey-corporate-disruptive-technology-adoption/

Tegtmeyer, J. (2022). Building a dissertation conceptual and theoretical framework: A recent doctoral graduate narrates behind the curtain development. *Perspectives on Urban Education*, 20(1), 1–13.

https://search.ebscohost.com/login.aspx?direct=true&AuthType=sso&db=edo&AN=162661333&site=eds-live&scope=site&custid=natuniv

Tersine, R. J., & Hummingbird, E. A. (1995). Lead-time reduction: The search for competitive advantage. *International Journal of Operations & Production Management*, 15(2), 8–18. https://doi.org/10.1108/01443579510080382

Thanabalan, P., Vafaei-Zadeh, A., Hanifah, H., & Ramayah, T. (2025). Big Data Analytics Adoption in Manufacturing Companies: The Contingent Role of Data-Driven Culture. *Information Systems Frontiers*, 27(3), 1061–1087. Complementary Index. https://doi.org/10.1007/s10796-024-10491-0

Thomas, G. (2021). How to do your case study. https://us.sagepub.com/

TOC Institute. (2021). *Theory of Constraints Institute.* https://www.tocinstitute.org/. Retrieved December 14, 2023, from https://www.tocinstitute.org/eliyahu-goldratt.html

Tornatzky, L. G., Fleischer, M., & Chakrabarti, A. K. (1990). *Processes of technological innovation*. Lexington books.

Tosi, D., Kokaj, R., & Roccetti, M. (2024). 15 years of Big Data: A systematic literature review. *Journal of Big Data*, 11(1). Springer Nature Journals. https://doi.org/10.1186/s40537-024-00914-9

Trieu, V. (2017). Getting value from business intelligence systems: A review and research agenda. *Decision Support Systems*, 93, 111–124. https://doi.org/10.1016/j.dss.2016.09.019

Türkyilmaz, G. S., & Üçok, D. I. (2024). Antecedents and consequences of healing organisations: a qualitative study. *International Journal of Management Economics &*

Business / Uluslararası Yönetim İktisat ve İşletme Dergisi, 20(3), 706–720. Academic Search Complete. https://doi.org/10.17130/ijmeb.1451619

Tzanova, S. (2020). Changes in academic libraries in the era of open science. *Education for Information*, 36(3), 281–299. https://research.ebsco.com/linkprocessor/plink?id=99514d25-7b5a-38be-bb9d-7dec7e744187

Upadhyay, P., & Kumar, A. (2020). The intermediating role of organizational culture and internal analytical knowledge between the capability of big data analytics and a firm's performance. *International Journal of Information Management, 52.* https://doi.org/10.1016/j.ijinfomgt.2020.102100

Van Manen, M. (1990). *Researching lived experience: Human science for an action sensitive pedagogy*. New York, NY: State University of New York Press.

Van Manen, M. (2016). *Phenomenology of practice*. New York, NY: Routledge.

Van Rijmenam, M., Erekhinskaya, T., Schweitzer, J., & Williams, M. (2019). Avoid being the turkey: How big data analytics changes the game of strategy in times of ambiguity and uncertainty. *Long Range Planning*, 52(5), 101841. https://doi.org/10.1016/j.lrp.2018.05.007

Vasanth, S., Saravanan, G., S, K., & A, M. K. (2024). Data Governance in the Big Data Era: A Scalable Framework for Effective Management and Regulatory Compliance. *2024 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES),* 1–5. IEEE Xplore Digital Library. https://doi.org/10.1109/ICSES63760.2024.10910410

Venkatesh, S. (2019). Big data - can it make a big impact in the insurance sector? *Journal of the Insurance Institute of India*, 6(4), 92–97. https://research.ebsco.com/linkprocessor/plink?id=4a230829-74b9-3f2b-84c0-e372960d87c3

Villamin, P., Lopez, V., Thapa, D. K., & Cleary, M. (2025). A Worked Example of Qualitative Descriptive Design: A Step-by-Step Guide for Novice and Early Career Researchers. *Journal of Advanced Nursing*, 81(8), 5181–5195. MEDLINE Complete. https://doi.org/10.1111/jan.16481

Wang, W. Y. C., & Wang, Y. (2020). Analytics in the era of big data: The digital transformations and value creation in industrial marketing. *Industrial Marketing Management*, 86, 12–15. https://doi.org/10.1016/j.indmarman.2020.01.005

Wiener, M., Saunders, C., & Marabelli, M. (2020). Big-data business models: A critical literature review and multiperspective research framework. *Journal of Information Technology*, 35(1), 66–91. https://doi.org/10.1177/0268396219896811

Williams, R. A., Duman, G. M., Kongar, E., & Tenney, D. (2024). Understanding Business Intelligence Implementation Failure From Technology, Organization, and Process Perspectives. *IEEE Engineering Management Review, Engineering Management Review*, IEEE, IEEE Eng. Manag. Rev., 52(1), 151–176. IEEE Xplore Digital Library. https://doi.org/10.1109/EMR.2023.3331247

Willig, C. (2017). Interpretation in qualitative research. *The SAGE Handbook of Qualitative Research in Psychology*, 2, 274–288. https://doi.org/10.4135/9781526405555.n16

Wolseley, N. N., Salahuddin, L., Aboobaider, B. M., Raja Ikram, R. R., Hashim, U. R., & Rahim, F. A. (2024). Socio-technical factors influencing big data analytics adoption in

healthcare. *International Journal of Electrical & Computer Engineering (2088-8708),* 14(4), 4745–4758. https://doi.org/10.11591/ijece.v14i4.pp4745-4758

Wurster, F., Di Gion, P., Goldberg, N., Hautsch, V., Hefter, K., Herrmann, C., Langebartels, G., Pfaff, H., & Karbach, U. (2024). Roger's diffusion of innovations theory and the adoption of a patient portal's digital anamnesis collection tool: Study protocol for the MAiBest project. *Implementation Science Communications, 5*(1), 74. Springer Nature Journals. https://doi.org/10.1186/s43058-024-00614-8

Yakut Çayir, M., & Saritaş, M. T. (2017). Computer-assisted qualitative data analysis: A descriptive content analysis (2011 - 2016). *Necatibey Faculty of Education Electronic Journal of Science & Mathematics Education*, 11(2), 518–544. https://search.ebscohost.com/login.aspx?direct=true&AuthType=sso&db=ehh&AN=128030298&site=eds-live&scope=site&custid=natuniv

Yang, Q., & Tang, Y. (2023). Big data-based human resource performance evaluation model using Bayesian network of deep learning. *Applied Artificial Intelligence*, 37(1), 1–24. https://doi.org/10.1080/08839514.2023.2198897

Yaseen, H. K., & Obaid, A. M. (2020). Big Data: Definition, Architecture & Applications. In JOIV: *International Journal on Informatics Visualization* (Vol. 4, Issue 1, pp. 45–51). https://joiv.org/index.php/joiv/article/view/292

Yin, R. K. (2016). *Qualitative research from start to finish*. Guilford Publications.

Yin, R. K. (2018). Case study research and applications: Design and methods.

Yu, J., Taskin, N., Nguyen, C. P., Li, J., & Pauleen, D. (2022). Investigating the determinants of big data analytics adoption in decision making: An empirical study in New Zealand,

China, and Vietnam. *Pacific Asia Journal of the Association for Information Systems,* 14(4), 62–99. https://doi.org/10.17705/1pais.14403

Yu, W., Wong, C. Y., Chavez, R., & Jacobs, M. A. (2021). Integrating big data analytics into supply chain finance: The roles of information processing and data-driven culture. *International Journal of Production Economics, 236.* https://doi.org/10.1016/j.ijpe.2021.108135

Zakria, B. R., Khurshid, A., & Jan, S. U. (2024). *Big data analytics implementation and practices in medical institute libraries of Pakistan*. De Gruyter. https://doi.org/10.1515/libri-2023-0084

Zargoush, M., Ghazalbash, S., Hosseini, M. M., Alemi, F., & Perri, D. (2025). Machine learning driven diabetes care using predictive-prescriptive analytics for personalized medication prescription. *Scientific Reports*, 15(1), 1–13. Academic Search Complete. https://doi.org/10.1038/s41598-025-12310-1

Zhang, X., Chu, Z., Ren, L., & Xing, J. (2023). Open innovation and sustainable competitive advantage: The role of organizational learning. *Technological Forecasting & Social Change*, 186, 122114. ScienceDirect. https://doi.org/10.1016/j.techfore.2022.122114

Zhao, Y. (2024). Development of big data assisted effective enterprise resource planning framework for smart human resource management. *PLoS ONE,* 19(5), 1–28. https://doi.org/10.1371/journal.pone.0303297

Zhou, Y., & Li, H. (2019). Asset diversification and systemic risk in the financial system. *Journal of Economic Interaction and Coordination,* 14(2), 247–272. https://doi.org/10.1007/s11403-017-0205-4

Zotoo, I. K., Lu, Z., & Liu, G. (2021). Big data management capabilities and librarians' innovative performance: The role of value perception using the theory of knowledge-based dynamic capability. *The Journal of Academic Librarianship*, 47(2), 102272. https://doi.org/10.1016/j.acalib.2020.102272

Appendix A: Interview Questions

Table A1

List of Interview Questions

Question No.	Interview Question	Linked Research Question
1.	What is your title and role in the organization?	None: Demographics
2.	How long have you been in the executive management role in this specific organization?	None: Demographics
3.	What is your view of Big Data Analytics?	RQ1, RQ2, RQ3
4.	Under what conditions is a data-driven organization successful?	RQ1, RQ2, RQ3
5.	What are examples of impactful results you see in your organization when using Big Data Analytics?	RQ1, RQ2, RQ3
6.	a. How do you use Big Data Analytics in your organization? b. Can you share details on what drives or influences the use of Big Data Analytics in your organization?	RQ1, RQ2, RQ3
7.	In what ways do you think your group is ready to embrace and expand the use of Big Data Analytics?	RQ1, RQ2, RQ3
8.	What are the challenges in using Big Data Analytics in your organization?	RQ1, RQ2, RQ3
9.	What organizational constraints deter the adoption of Big Data Analytics?	RQ1
10.	What are the opportunities for using Big Data in your organization?	RQ1, RQ2, RQ3
11.	Provide an example of how Big Data Analytics impacts product planning and strategy.	RQ1, RQ2, RQ3
12.	To what extent do organizational constraints impact the adoption of Big Data Analytics in making strategic decisions?	RQ1
13.	Under what conditions does BDA adoption for strategic decision-making help your organization?	RQ3
14.	Under what conditions does BDA adoption for strategic decision-making help your organization gain a competitive advantage?	RQ3
15.	a. Under what conditions can the organizational constraints impeding the adoption of Big Data Analytics be mitigated? b. Under what conditions can the organizational constraints impeding the adoption of Big Data Analytics be mitigated to meet or exceed performance goals?	RQ2

Note. The table shows the list of questions that the researcher asked the participants during the interviews (Baker, 2022; R. J. Harris, 2018; Manohar, 2021).

Appendix B: Focus Group Questions

Table B1

List of Focus Group Questions

Question No.	Interview Question	Linked Research Question
1.	What is your view of Big Data Analytics?	RQ1, RQ2, RQ3
2.	Under what conditions is a data-driven organization successful?	RQ1, RQ2, RQ3
3.	What are examples of impactful results for an organization from Big Data Analytics?	RQ1, RQ2, RQ3
4.	a. How do you use Big Data Analytics in your organization? b. Can you share details on what drives or influences the use of Big Data Analytics in your organization?	RQ1, RQ2, RQ3
5.	In what ways do you think your group is ready to embrace and expand the use of Big Data Analytics?	RQ1, RQ2, RQ3
6.	What are the challenges in using Big Data Analytics in your organization?	RQ1, RQ2, RQ3
7.	What organizational constraints deter the adoption of Big Data Analytics?	RQ1
8.	What are the opportunities for using Big Data in your organization?	RQ1, RQ2, RQ3
9.	Provide details with an example of how Big Data Analytics impacted product planning and strategy in the organization.	RQ1, RQ2, RQ3
10.	To what extent do organizational constraints impact the adoption of Big Data Analytics for making strategic decisions?	RQ1
11.	Under what conditions does BDA adoption for strategic decision-making help your organization?	RQ3
12.	Under what conditions does BDA adoption for strategic decision-making help your organization gain a competitive advantage?	RQ3
13.	Under what conditions can the organizational constraints impeding the adoption of Big Data Analytics be mitigated?	RQ2
14.	Under what conditions can the organizational constraints impeding the adoption of Big Data Analytics be mitigated to meet or exceed performance goals?	RQ2
15.	How would you describe the maturity level of your organization when using BDA?	RQ1, RQ2, RQ3
16.	How would your organization compare to the industry in terms of using BDA?	RQ1, RQ2, RQ3

Note. The table shows the list of questions that the researcher asked the participants during the focus group sessions (Baker, 2022; R. J. Harris, 2018; Manohar, 2021).

Appendix C: Recruitment Email/Letter

My name is Sreenu Pillutla, and I am a doctoral student at National University. I am conducting a research study to find what organizational constraints impact the adoption of Big Data Analytics for strategic decision-making.

I am recruiting individuals who meet all of these criteria:

1. You are 21 years or older.
2. You are the vice president, senior director, director, leader, or manager of the organization.
3. You use Big Data Analytics in your organization.

If you decide to participate in this study, you will be asked to do the following activities:

1. Participate in an online interview via Zoom for 60 minutes
2. Participate in a focus group via Zoom for 60 minutes
3. Review interview summary via email for 10-15 minutes

During these activities, you will be asked questions about:

- The use of Big Data Analytics in the organization
- Constraints in using Big Data Analytics in the organization
- How can the constraints in using Big Data Analytics in the organization be mitigated

If you are interested in participating in this study, please contact me at (408)571-8432 or at S.Pillutla7267@o365.ncu.edu.

Thank you for considering participating in this voluntary research!

Sreenu Pillutla

Appendix D: Consent Form

My name is Sreenu Pillutla, and I am a doctoral student at National University (NU).

I'm asking you to participate in a research study about what organizational constraints impact the adoption of Big Data Analytics for strategic decision-making. The name of this research is "Adoption of Big Data Analytics for Strategic Decision Making in a Technology Organization: A Qualitative Study."

You may participate in this research if you meet all the following criteria:

1. You are 21 years or older.
2. You are the vice president, senior director, director, leader or manager of the organization.
3. You use Big Data Analytics in your organization.

I hope to include 15 people in this research.

Please read this form carefully and ask any questions you may have before agreeing to take part in this study.

What you will be asked to do: If you agree to participate in this study, you will be asked to do the following activities:

1. Participate in an interview over Zoom for 60 minutes. (Please let me know if you would prefer an interview conducted another way, such as in person or over the phone.)
2. Participate in a focus group over Zoom for 60 minutes. (Please let me know if you prefer a focus group conducted another way, such as in person or over the phone.)
3. Review interview summary via email for 10-15 minutes.

During these activities, you will be asked questions about:

- The use of Big Data Analytics in the organization
- Constraints in using Big Data Analytics in the organization
- How can the constraints in using Big Data Analytics in the organization be mitigated

Risks: There are minimal foreseeable risks or discomforts associated with this research. You can skip any question you do not wish to answer, skip any activity, or stop participation anytime.

Benefits: If you participate, there are no direct benefits to you. This research may increase the body of knowledge in the subject area of this research.

Recording: I would like to audio/video record your responses with Zoom during the interview. You can turn off the video function of the online meeting platform at any time.

Confidentiality: I will keep records of this study private and take reasonable measures to protect the security of all your personal information. In any report I make public, I will not include any information that will make it possible to identify you. I will securely store your data in a password-protected folder for 3 years. Then, I will delete electronic data and destroy paper data.

Taking part is voluntary: Participation in this study is entirely voluntary. You may quit at any time.

If you have questions, please ask them now. If you have questions later, contact me at S.Pillutla7267@o365.ncu.edu or at (408)571-8432.

If you have any questions or concerns regarding your rights as a subject in this study, you may contact the Institutional Review Board (IRB) via email at irb@nu.edu.

Appendix E: IRB Approval Letter

9388 Lightwave Ave.
San Diego, CA 92123
irb@nu.edu

Notice of Exemption

June 26, 2025

To: Sreenu Pillutla

Project Title: Adoption of Big Data Analytics for Strategic Decision Making in a Technology Organization: A Qualitative Study
NU IRB Number: IRB-FY24-25-859
Determination: Exempt from further review 45 CFR 46.101 Category 2.(ii). Research that only includes interactions involving educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures, or observation of public behavior (including visual or auditory recording) if at least one of the following criteria is met:
Any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation; or

Status: Active - Research activities may begin as of June 26, 2025

Dear Sreenu Pillutla:

The study referenced above has been reviewed by the National University IRB. The IRB has

determined your research is exempt from further review under 45 CFR 46.104, which means you will not need to renew your study and may begin your study effective immediately. However, if you find the need to change your study in any way, you will need to submit a modification to the IRB prior to implementing the changes. This will allow the IRB to determine whether or not the study still meets exemption criteria.

Please review your Post Approval Responsibilities here: Approved Documents Guidelines

For any questions regarding your protocol, please reach out to the IRB at irb@nu.edu.

Sincerely,

Dr. Joseph Marron, IRB Chair

Dr. Brianne Mongeon, Director, HRPP & IRB

Jenessa Eberhardt, Associate Director, HRPP & IRB