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Strategies to Implement Big Data Analytics in Telecommunications Organizations

Delton Aneato
Walden University

<u>Walden University</u>

College of Management and Technology

This is to certify that the doctoral study by

Delton Aneato

has been found to be complete and satisfactory in all respects,
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Review Committee
Dr. Ify Diala, Committee Chairperson, Doctor of Business Administration Faculty

Dr. Carol-Anne Faint, Committee Member, Doctor of Business Administration Faculty

Dr. Annie Brown, University Reviewer, Doctor of Business Administration Faculty

Chief Academic Officer and Provost
Sue Subocz, Ph.D.

Walden University
2020

Abstract

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MBA, London Metropolitan University, 1999

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Doctoral Study Submitted in Partial Fulfillment

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Abstract

Information Technology (IT) leaders who do not invest in big data projects may struggle to gain a competitive advantage and business insights to improve performance. Grounded in the Kotter's change and Six Sigma models, the purpose of this qualitative multiple case study was to explore strategies IT leaders used to implement big data analytics successfully. The participants comprised 4 IT leaders from 2 telecommunication organizations in the United States of America, who effectively used strategies to promote and maximize competitive advantage using big data analytics. Data were collected from semistructured interviews, company documents, and project-related documents and were analyzed using thematic analysis. Four themes emerged: communication, training, employee involvement in decisions, and teamwork strategy. A key recommendation emerging from these findings is for IT leaders to use successful communication strategies to communicate the vision and objectives effectively to all the different levels within the organization. The successful communication of strategy can help with the analysis of business trends and forecasts and improve overall organizational performance and competitive advantage. The implications for positive social change include the potential for job creation, thus catalyzing economic growth within communities.

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Dedication

I want to dedicate this study to my spiritual father and his son, God almighty, and Jesus Christ for their kindness and grace for my life. To my late parents Christopher and Maria, they would be very proud of the person I am today, a son that will never give up no matter the adversity ahead. To my beloved family members, my sisters, brother, nephew: Uzo, Julie, Marcellinus, Ozor. To the two queens that actively assisted in reviewing my research page after page, my niece Efua and my daughter Mercedes, who helped me achieve my desired goals. This study is also dedicated to my special friend and Australian mum, Professor Harrison. She kept encouraging me, pushing me on, and never let me quit even when it was challenging and painful for me to continue.

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Section 1: Foundation of the Study

Nearly half of organizational leaders invest in big data projects (Grover et al., 2018). Leaders who do not invest in big data projects may fail to recognize and leverage this information to gain a competitive advantage (Chrimes et al., 2017). With the advancement of technology and the dramatic cost reduction of technology for data acquisition, processing, and storage, the exponential growth of the amount of data in digital form to support business operations and decisions has increased. Therefore, organizational leaders need to find ways to collect vast amounts of data, process the data, and analyze and derive patterns to make business decisions to gain competitive advantage. The next steps are to identify strategies for implementing the right technology and process successfully and strategies for adoption to achieve this desired outcome.

Grover et al. (2018) indicated that big data adoption could have adverse effects after implementation. Thus, the low success rate in project implementation of big data can result in organizations' poor operational and financial performance. The purpose of this qualitative multiple case study was to explore strategies that Information Technology (IT) leaders in the telecommunications industry use to implement big data analytics successfully. Adopting big data analytics implementation strategies may benefit leaders to successfully achieve business goals to improve organizational performance while reducing operating costs.

Background of the Problem

Implementing big data analytics has the potential to improve a company's competitive advantage, growth, and performance. However, inefficient knowledge of implementation strategies of big data analytics can result in selecting the wrong technologies and skillsets (Matthias et al., 2017). Big data technology enables organizational leaders to have the ability to access, diagnose, and integrate the necessary information gathered through various data sources. Therefore, organizational leaders need to have the skills and techniques to collect and manage the data. Leaders also need to gain implementation experience and knowledge in using analytical methods and tools. The success of implementing big data analytics requires that leaders have the experience and knowledge of these strategies (Grover et al., 2018).

Big data analytics drive organizational intelligence among leaders to assist them with improving their business goals, such as more effective operations, satisfied customers, and high profits (Alsghaier et al., 2017). Potential benefits of using big data analytics within organizations exist, but organizations still fail to appropriate the value of such a possibility in practice (Sharma et al., 2014). In large organizations, 50% of big data-related projects are never completed (Grover et al., 2018). However, organizational leaders still require substantial guidance to realize the value generated by using big data analytics (Wang & Hajli, 2017). Therefore, organizational leaders should consider big data analytics seriously to heighten and evolve their development issues.

Problem Statement

Business leaders are not likely to benefit from using big data analytics if they do not recognize and leverage business patterns and trends to improve processes or reduce costs (Chrimes et al., 2017). Results from a 2016 survey indicated that 48% of organizational leaders invested in big data projects, but 60% of these organizational leaders struggled to gain a competitive advantage and business insights to improve performance (Grover et al., 2018). The general business problem is that leaders lack strategies to use big data analytics to recognize patterns for gaining business insights and to identify trends to improve processes or reduce costs, for increasing sustainability. The specific business problem is that some IT leaders in the telecommunications industry lack the strategies to implement big data analytics successfully.

Purpose Statement

The purpose of this qualitative multiple case study was to explore strategies that IT leaders in the telecommunications industry use to implement big data analytics successfully. The targeted population was comprised of four IT leaders in the telecommunications industry from two organizations that have successfully implemented big data analytics. The geographic area for this research was Seattle, Washington, and New York, New York. The implications for positive social change could include the potential to increase the sustainability of businesses, which may lead to increased jobs, revenue, and reducing unemployment in communities. Further implications for positive social change also include the potential improvement of the standard of living of the employees by providing permanent and well-paying jobs that enable employees to support their families and contribute to communities.

Nature of the Study

Researchers use three methods for conducting a research study: qualitative, quantitative, and mixed. Researchers can use a qualitative method when they seek a deeper understanding of peoples' motivations, attitudes, and behaviors (Barnham, 2015).

Researchers use a qualitative method to gain insights into participants' experiences and perspectives (Yin, 2018). Researchers can use the qualitative research method to explore and interpret nonnumeric data for exploring themes and patterns (Yazid, 2015). In contrast, the quantitative research method is an analytical process that researchers use to test hypotheses and measure results using numeric data. The mixed-method approach is appropriate when identifying relationships among variables using surveys to collect statistical data potentially through both open-ended and close-ended questions (Clinning & Marnewick, 2017). The quantitative or mixed-method approach was not appropriate for this study because the purpose of the study was to explore leadership strategies and not test theories by testing hypotheses. The qualitative research method is also used to reveal patterns in knowledge and ideas through an in-depth exploration of the problem. For these reasons, the qualitative research methodology was appropriate for this study to develop an in-depth understanding of the business phenomenon of the strategies organizational leaders used to successfully implement big data analytics.

I considered three qualitative research designs to address the specific business problem in this study: (a) ethnography, (b) phenomenological, and (c) case study. Researchers use an ethnographic design when exploring participants' personal effects, habits, and cultures (De Montigny, 2018). Using an ethnographic design allows the researcher to explore cultural customs or habits of participants (Hyland, 2016). Researchers use phenomenological designs to describe or interpret what participants may have in common as they perceive events or experience a phenomenon (Nigar, 2020). A researcher uses a phenomenological design to focus on the meanings of participants' experiencing a phenomenon to obtain detailed results revealing the essence of the experience (Bliss, 2016). The goal of this study was to collect and analyze data from multiple data sources such as multiple companies, interviews, companies' physical artifacts, and archival records. Hence, ethnographic and phenomenological designs were inappropriate for the study. A case study design is an in-depth study that allows a researcher to address the *what, why*, and *how* of a research question, focusing on the behavioral events of the participants' experiences (Yin, 2018). Researchers use a single case study design to describe a specific activity or event of an individual case (Turner & Danks, 2014).

Researchers use a multiple case study design to understand the differences and the similarities among the various cases (Turner & Danks, 2014). A researcher implementing a single case study design obtains evidence from a single case, but my research study involved multiple cases making a single case study design inappropriate. The multiple case study approach was also an appropriate design as it enabled me to address the purpose of my study of gathering, analyzing, and interpreting data to identify strategies IT leaders use when implementing big data analytic. I achieved my research objectives by using semistructured interviews of IT leaders and company documents as an additional source of information during this study. I explored detailed information from multiple cases while using different data types to identify specific strategies used by IT leaders to implement big data analytics.

Research Question

What strategies do IT leaders in the telecommunication industry use to successfully implement big data analytics?

Interview Questions

1. What, if any, strategies have you used to implement big data analytics in your organization successfully?
2. What role did you play in the implementation of the big data analytics system?
3. How do you evaluate the effectiveness of your big data analytics implementation strategies?
4. Based upon your experience, what are some of the specific organizational improvements and outcomes realized since the implementation of big data analytics in your organization?
5. What, if any, strategies have you used to address employee concerns before the implementation of big data analytics?
6. What key obstacles have you encountered with the implementation process and how did you resolve them?
7. In retrospect, what, if anything, would you have done differently during the implementation process?
8. What type(s) of training did you and your team receive before implementing a big data analytics system?
9. What additional information would you like to add to the current organization, and its strategy in implementing big data analytics?

Conceptual Framework

The composite conceptual framework for this study was Kotter's change theory for driving change augmented with the Six Sigma model for business process quality management design. Kotter developed his eight-step change model in 1995 (Kotter, 2007). Kotter (2012) argued that successful implementation of change requires change to progress through a series of eight phases (a) establish a sense of urgency regarding the need for change, (b) build a powerful coalition, (c) create a vision and strategy, (d) communicate the vision, (e) empower employees to act on the change vision, (f) plan and create for short- term wins, (g) consolidate improvements and produce more changes, and (h) institutionalize new approaches in the corporate culture. Kotter's theory, if used effectively, can help a leader overcome opposition to change within the company and thereby promote organizational transformation and adoption (Kotter, 2007). Kotter's model provides a potential lens for understanding the change management process used by the participating leaders to implement big data analytics. Change management used effectively can lead to behavioral change in the team and improve the organization's potential to achieve positive results during implementation (Baek, Chang, & Kim, 2019). Therefore, the management and the project team's fundamental objective during the implementation of big data analytics within their organization was to produce beneficial change.

Six Sigma is a framework first conceptualized in the 1980s as a model for continuous improvement of business processes (Samman & Ouenniche, 2016). Bill Smith developed the Six Sigma framework. Six Sigma is a means for finding and eliminating reasons for defects or errors, reducing cycle times and the operational cost, increase productivity, attain higher asset utilization and surpass customer expectations (Samman & Ouenniche, 2016). Two Six Sigma methodologies used are DMAIC (Define, Measure, Analyze, Improve, and Control) and DMADV (Define, Measure, Analyze, Design, and Verify), for the change process within an organization. DMAIC and DMADV techniques improve the business process effectively and productively. While both techniques have similar vital characteristics, they are not interchangeable and are used for different business processes or change initiatives. DMADV was applied to this study. DMADV describes the requirements of the consumer as they connect to a service or perhaps product. Five Six Sigma principles exist for DMADV: (a) define, (b) measure, (c) analyze, (d) design, and (e) verify (Samman & Ouenniche, 2016). Motorola adopted Six Sigma, a quality improvement program to enhance its quality, reduce costs, increase profitability, and to optimize business processes (Chen et al., 2017). The application of big data technology in an organization also improves business operations, financial performance, and an organization's competitive advantage. Therefore, company leaders could consider implementing big data analytics as an opportunity to eliminate waste from their current process, improve business processes, and improve organizational performance. As such, the composite framework of Kotter's change model and the Six Sigma model was expected to be an appropriate framework for exploring and understanding the strategies that IT leaders use when implementing big data analytics successfully.

Operational Definitions

The following are the necessary definitions used during the research study. The description of the definitions provides the association of the study to the terms used within academic and business practices.

Big Data Analytics: *Big data* is defined as data that is continually being generated from multiple sources and diverse data formats that are both structured and unstructured (Grover et al., 2018).

Change management: Change management is the mechanism, the process, and method to achieve change in business strategies, project plans, or organizational goals and objectives (Stouten et al., 2018).

Cloud computing: Cloud computing is multiple pools of hardware computers sharing software, resources, and enabled with IT services that are authorized to implement with minimal effort or with any contribution from the vendor (Botta, et al., 2016).

Data Analytics: The term *data analytics* describes the process by which leaders gather data together from a single source to create and represent the present and future state of the organization (King, 2016).

Organizational change: This is a process of moving from an initial stage to a desirable stage to which the company's position has changed as a result of leadership influence (Espedal, 2016).

Predictive analytics: Predictive analytics is the use of statistical techniques and forecast models to predict future insights or occurrences using past and present data (Nagarajan & Babu, 2019).

Six Sigma: Six Sigma is a data-driven methodology and a business management strategy, with a fundamental aim to diminish variation within a process that can result in failures or defects (Trakulsunti, & Antony, 2018).

Strategy: Strategy is defined as establishing the scope and direction to which organization leaders will adopt and execute to achieve their desired outcomes (Reimer et al., 2016).

Software development life cycle (SDLC): This is described as a framework defining tasks performed at each step in the software development process.

Structured data: This is data described by utilizing database tables stored in traditional relational database management systems (Zhan & Tan, 2018).

Unstructured data: This is data not easily described utilizing database tables, such forms of unstructured data include but are not limited to picture images, log files, photos, e-mails, crowd-sourcing systems, newsgroups, and sensor data (Zhan & Tan, 2018).

Assumptions, Limitations, and Delimitations

Assumptions, limitations, and delimitations perform a vital purpose in the evolution of peer-reviewed academic and professional research. These are guidelines that a researcher needs to adhere to when conducting research. I encountered four assumptions that correlate to the purpose and research question of the study, three evident limitations to be aware of during the research period, and four delimitations that preserved the credibility and reliability of this study.

Assumptions

Assumptions are weaknesses in a research study beyond the researcher's control (Guzys et al., 2015). I made the following assumptions in this study. The first assumption was that the participants answer the interview questions truthfully and accurately. The second assumption was that the participants had sound knowledge of their organization, understanding their mission, vision, and goals. The third assumption was I assumed that all participants were available for the interviews and that they would contribute to the research's quality through their answers. The fourth assumption was that the participants were honest with their answers and removed any possible biases when they provide their responses.

Limitations

Limitations are conditions, constraints, factors, and boundaries that confine the control of the researcher (Yin, 2018). The first limitation of this study was the sample size of two organizations and the minimum of four IT leaders, which limited the generalizability of the study. Limitations are factors and conditions that are beyond a researcher's control (Yin, 2017). Because the research was a multiple case study, the resulting information regarding strategies for implementing big data analytics may not apply to all other telecommunication organizations. Second, the results of the research study were limited by the IT leaders' experiences and knowledge of implementing big data analytical strategies to their current organization. Third, the organization had limited supporting documentation, but the provided documents supported the data collection process. It would have been advantageous to collect ample and recent documentation to guarantee the validity of the research further.

Delimitations

Delimitations are the boundaries that a researcher sets for the study and the definition of the scope (Babbie, 2015). Delimitations are those elements in research that the researcher can control. First, the multiple case study was delimited to only two cities: Seattle and New York, with a focus on the telecommunications sector. Second, a minimum of four IT leaders participated in the interviews. All participants also had a minimum of 5 years or more of experience used for this study. Third, I restricted two organizations with a gross profit of over 1 billion United States dollars. Fourth, given that the focus was on the strategy's IT leaders used to implement big data analytics successfully, the targeted group was individuals that possessed the experience and were responsible for implementing the projects once the organizational board had approved it.

Significance of the Study

The findings of this study could be valuable to business leaders because it helps identify effective strategies that leaders could adopt when implementing big data analytics to streamline their business and stimulate organizational growth while reducing costs. Business leaders perceive big data as having value but need guidance to establish a data-driven decision-making cultural strategy (Ahmed et al., 2017). Researchers can use information from multiple sources while using different data types to identify specific strategies to implement big data analytics successfully. More broadly, this study leads to a better understanding of successful big data implementation and what supports effective big data implementations.

Contribution to Business Practice

The study results may contribute to the effective practice of business by identifying strategies that could assist business leaders in implementing big data analytics successfully in organizations. A useful outcome of this study was to examine whether successful data analytics implemented provided market insights to effectively lead to an improvement in process and a reduction in cost. From a leader's perspective, the significance of big data analytics lies in the ability to provide information and knowledge of value, before making a business decision (Elgendy & Elragal, 2016). Using big data analytics, organizational leaders can make successful decisions with the availability of massive amounts of data to provide unprecedented opportunities (Comuzzi & Patel, 2016). Grover et al. (2018) indicated that the business insights generated from successfully implementing big data could create new business value chains in many parts of the business, such as new product and service innovation, business process improvement, organization performance improvement, and the creation of a positive brand image and reputation. Business leaders who use data-driven decision-making to implement big data analytics within their organization can gain and sustain a competitive advantage. Therefore, organizational leaders who reward their employees are likely to see an increase in employee participation and job satisfaction (Khalili, 2017).

Implications for Social Change

The implications for positive social change could include the potential for creating new job opportunities, higher wages, and creating a collaborative working environment for employees. Higher wages and benefits can improve the living standards of the employees and their families. When businesses thrive, their employees may gain better work compensation. Additional implications of the study for positive social change include the potential to increase the sustainability of businesses, which could lead to an increase in jobs, revenues, and possible reductions in unemployment for catalyzing economic growth within communities. Improved organizational performance using big data analytics can lead to an increase in employee wages, revenue, and financial performance for the organization (Grover et al., 2018). A revenue increase can attract more investors and improve stakeholders' confidence in the organization.

Employees may also benefit from an increase in their salaries and benefits, including shares or bonuses. More career opportunities exist for employees to improve their standards of living. Furthermore, the evidence needed to guide decisions and insights to maximize benefits for businesses and its stakeholders can be made possible by analytics methods.

A Review of the Professional and Academic Literature

The purpose of this qualitative multiple case study was to explore strategies that IT leaders in the telecommunications industry use to implement big data analytics successfully. Kotter's eight-step process model for organizational change augmented with the business process quality management design of Six Sigma were the underlying conceptual frameworks used to underpin the study. Organizational leaders are involved in the rapid evolution of big data technologies as the next big thing in innovation because of the benefits (Wamba et al., 2017). The potential of big data analytics is becoming increasingly valuable to an organization's ability to grow and be competitive in a variety of operations (Wamba et al., 2017). The literature review includes a review of literature related to (a) Kotter's change model, (b) Six Sigma the methodologies of DMAIC (Define, Measure, Analyze, Improve, and Control) and DMADV (Define, Measure, Analyze, Design, and Verify), (c) technology-organization-environment (TOE) conceptual framework, (e) big data analytics, (f) history of big data analytics, (g) big data analytics and competitive advantage, (h) the benefits of big data analytics, and (i) the challenges to implementing big data analytics.

To research literature regarding this topic, I read peer-reviewed and nonpeer-reviewed journal articles, publications of government agencies, and academic books. I searched for relevant academic articles and books using (a) Microsoft Academic, (b) Google Scholar, and (c) ABI/Inform, Business Source Complete, Emerald Management, ProQuest Central Database, SAGE Premier, and Science Direct databases using Walden University Library. I used seven keywords for searches: (a) *big data*, (b) *big data analytics*, (c) *successful strategies implemented*, (d) *competitive advantage*, (e) *kotter's change model,* (f) *Six Sigma and DMADV*, (g) *big data and telecommunication,* and (h) *big data and social change*. The study had 275 references, of which 247 (90%) were peer-reviewed articles and 237 (86%) were published within 5 years of my expected year (2020) of CAO approval of my completed study.

Kotter’s Change Model

Kotter's change model outlines fundamental steps to implementing change. Organizational leaders can choose to use the Kotter's change process model to understand possible limitations of initiating or implementing new programs (Kotter, 2007). The model continues to be a popular source for research in change management, providing researchers with an understanding of challenges and opportunities by applying each step of the model to a specific organizational need. Kotter created the eight-step change model in 1995 to support change management within organizations (Kotter, 2007). Kotter (2012) argued that successful implementation of change requires a series of eight phases (a) establish a sense of urgency regarding the need for change, (b) build a powerful coalition, (c) create a vision and strategy, (d) communicate the vision, (e) empower employees to act on the change vision, (f) plan and create short-term wins, (g) consolidate improvements and produce more changes, and (h) institutionalize new approaches in the corporate culture.

If used effectively, Kotter's theory can help a leader overcome opposition to change within the company and thereby promote organizational transformation and adoption (Kotter, 2007). His model provides a potential lens for understanding the change management process that the participating leaders used to implement big data analytics. Change management, if used effectively, can lead to behavioral change in the team and lead to positive final results during implementation (Baek et al., 2019). Therefore, the management and the project team's will experience change and transformation during the implementation of big data analytics within their organization.

Establishing a sense of urgency. The first step of this approach was for organizational leaders to establish a sense of urgency around implementing the new systems. The type of leader and the support they have for the proposed change was crucial to the success of the initiative. Transformational leaders are more likely to motivate their workers to produce requirements for new systems and processes (Muchiri et al., 2019). Change has a better chance of succeeding through a progressive leader who can inspire at different levels within the organization (Kotter & Schlesinger, 2008). The leader creates a sense of awareness for the organizational change to gain cooperation from the employees and their contribution to the overall outcome (Pollack & Pollack, 2015). There is a sense of urgency and necessity to communicate the change to all employees throughout the organization. A failure to create this sense of urgency could result in employees being resistant to change and becoming defensive (Kotter, 1996). Failure in implementing change can occur when leaders do not communicate their objectives with their leaders and employees at the beginning of a business transformation. Therefore, during the change process, effective communication helps to diminish resistance (Akan et al., 2016), which could otherwise hamper the successful implementation of new policies (Nilsen et al., 2016).

Build a powerful coalition. Identifying the team to assist with implementing the change is Kotter's second stage. The second stage involves having a coalition team to implement this transformation change strategy (Kotter, 1996). Transformational change within an organization can begin with a few individuals and a dynamic leader and this is essential to creating a powerful coalition for transformational change (Kotter, 2007). The team to participate in the change transformation includes members of the senior leadership, managers, and employees that are committed to the cause of improving the performance and financial stability of the organization (Kotter, 1996). However, for change to succeed, the team would have the experience, commitment, credibility, knowledge, and skills to influence and mobilize change within the organization.

The coalition size is also reliant on the headcount of the organization. Therefore, the larger the size of the coalition team, the higher the chances of success. When implementing change within an organization, coalition support is essential to ensure employees' good behavior, awareness, commitment, and cooperation (Johannsdottir et al., 2015). With a great leadership team, the coalition would likely be powerful enough to implement change. Organizational leaders that do not succeed in this stage are not able to form a coalition (Kotter, 2007). Implementing a change process requires the participation and contribution of senior leaders and teams to prepare and lead the employees through the change process (Johannsdottir et al., 2015).

Creating an organizational vision. The third stage includes the creation of an organizational vision and strategy (Kotter, 2007). An organization's vision represents the future strategic path (Grobler et al., 2019). The vision for an organization typically comes from the initial leader of change and can extend beyond a 5-year plan (Kotter, 2007). The coalition must have the same vision, strategy, and a coherent picture of the future for the organization to succeed (Kotter, 2007). A realistic vision can help organizational leaders and employees align their objectives and goals. The leader of change can consider the vision as a fundamental component to motivate and inspire fellow leaders and employees within the organization. The vision contributes to the guiding principles of decision-making for the change leader while building a clear statement of direction (Pollack & Pollack, 2015). The vision should be realistic, adaptable, communicated, focused, and achievable (Grobler et al., 2019). Overcomplicating the vision can lead to employees being less inspired (Kotter, 2007).

Communicate the vision. The fourth stage involves the communication of the vision. The change leader and coalition can sometimes fail to communicate their vision, thereby making the change process difficult for all employees to understand (Kotter, 2007). The fourth stage highlights the need for a transformation leader to effectively communicate the vision with both actions and words (Kotter, 2007). Underestimating the value of creating a communication strategy to convey the change could hurt the change process (Pollack & Pollack, 2015).

Little or no communication of the vision can also have a detrimental effect on motivating employees creating confusion and unclarity (Kotter, 2007). With proper communication of the vision to all, a positive chain reaction from the employees exists to the new change process. Creating avenues for employees to discuss and provide feedback is the best way to ensure that the vision is understood and communicated (Kotter & Schlesinger, 2008). Sharing the vision throughout the organization is an ingredient of a communication strategy for change management (Kotter, 2012). Positive and effective communication strategy for change management would remove any obstacles.

Empower employees to act on the change vision. In the fifth stage, Kotter described the consequences of obstacles that hinder the change process' new vision. For example, the organization's size could be an obstacle to implementing change (Baloh et al., 2018). However, organizational leaders are to remove more significant obstacles for effective implementation of the change process. Other examples of change obstacles include cultural change, performance appraisal systems, and lack of employee willingness to adapt to change (Kotter, 1996). It can be challenging to encourage the support and participation of employees during the change process (Grobler et al., 2019). Some employees might be more interested in compensation than the vision (Kotter & Schlesinger, 2008). When eliminating obstacles, it is necessary to build more integrated work processes and empower employees at different levels of the organization (Kotter & Schlesinger, 2008).

Plan and create short-term wins. Implementing a change process demands patience from the coalition (Grobler et al., 2019). The sixth step involves preparing to accept short-term wins (Kotter, 2007). The organizational willingness for change requires the engagement of leaders, managers, employees, new processes, and technology (Grobler et al., 2019). It would take a significant amount of time for an organizational leader to achieve transformation. However, progress is something that stakeholders demand to see. Quick wins provide credibility to the change process and reassurance to the stakeholders (Grobler et al., 2019). Leaders can bolster motivation to promote the team’s focus on short-term gains (Kotter, 2007). Short-term wins increase the teams' confidence, reduce complacency, and encourage detailed analytical thinking in implementing the vision and change process (Kotter & Schlesinger, 2008).

Consolidate improvements and produce more changes. Kotter's seventh step change process cautions against premature celebrations. Implementing change can take a toll on company costs and employee morale (Kotter & Schlesinger, 2008). Sometimes the transformation adoption can take 3 to 10 years before yielding the desired results (Kotter, 1996). Consequently, leaders must continuously sustain the drive and momentum of their employees (Grobler et al., 2019). Throughout this period, the culture within the organization was also likely to change. Organizational leaders must review the impact of the change process on the organizational culture (Willis et al., 2016a). The success of the change process requires the leadership team and employees to share the same culture, such as beliefs, assumptions, and values (Willis et al., 2016a). Having the same culture means that the leadership team and employees solve problems and manage the risks (Mouhamadou et al., 2017). A sense of belonging and unity across all teams was also an indicator of a thriving organizational culture.

Institutionalize new approaches in the corporate culture. The eighth and final step of Kotter's change process describes the conceptual model through which organizations can regulate the change process (Kotter, 2007). When undergoing a corporate change process, employees can develop a new behavior and strategy (Kotter, 1996). The employees' new behaviors become the organization's new shared values and culture. This culture can then lead to positive transformation when using Kotter's model (Kotter, 2007). Transformation occurs at different organizational levels and managerial behavioral change can also occur variably in most change initiatives.

The coalition should ensure that the management and employee accept and buy into the change initiative. The change initiative should also last the duration to achieve the expected outcome and increase employee confidence. Organizational success and work behaviors can be by-products of implementing a successful change process. Before implementing a new solution, such as big data analytics, the leader should have leadership buy-in. The leader should communicate the vision for a successful implementation throughout the organization. Members of the organization should form a coalition made up of leaders, managers, and employees who support and participate in the change process. When leaders are involved in the change process, a high probability exists that the implementation of the change, such as big data analytics, could be successful. The application of Kotter's model in this context explores strategies for successfully implementing big data, which requires a tremendous level of support from all management levels throughout the organization.

When implementing big data analytics, organizational leaders can introduce a change process that could lead to a cultural change, process improvements, and technical readiness within the organization. When implementing big data analytics, Kotter's change model can also allow for cultural alignment and effective communication within the organization. I can use Kotter's change process to explore strategies used to successfully implement big data analytics within the organizations in my study. The change process of implementing new systems requires a purposeful and successful leadership that can manage the changes related to both processes and people effectively. Using Kotter's change model, management can produce precise outcomes based on their experience, and leaders produce transformational change within the organization. Therefore, leaders and managers are vital to implementing change such as big data analytics.

Six Sigma the methodology of DMAIC and DMADV

Six Sigma is an approach to continuous improvement, improving customer satisfaction, encouraging leadership, raising profits, and competitive advantage over other businesses (Mouaky et al., 2018). Six Sigma is also a business theory focused on continuous improvement through the understanding of customers' needs, by analyzing business processes, and establishing proper measurement methods (Samman & Ouenniche, 2016). The Six Sigma method is a quality improvement strategy that attempts to improve efficiency (Basta et al., 2016). Smith developed the Six Sigma methodology at Motorola as a model for business process improvement in 1980 (Mouaky et al., 2018).

Many other organizational leaders implemented Six Sigma within their organizations after its remarkable success at General Electric (Mouaky et al., 2018). Six Sigma is an innovative and adaptive methodology used to improve the efficiency and effectiveness of business processes (Sony & Naik, 2019). Six Sigma uses two sets of methodologies, DMAIC (Define, Measure, Analyze, Improve, and Control) and DMADV (Define, Measure, Analyze, Design, and Verify), to examine and discuss different aspects of business processes (Sony & Naik, 2019). DMAIC and DMADV make use of statistical tools and facts to look for answers to quality-related issues and concentrate on achieving the financial stability of an organization (Sony & Naik, 2019). Despite the unique distinctions of the methodologies, DMAIC and DMADV overlap during the application process and share the same end goal of business processes improvements (Sony & Naik, 2019).

DMAIC and DMADV methodologies are data-intensive and based only on hard facts. Implementing the Six Sigma model requires the training to obtain the skill rating of green belts, black belts, and black master belts aimed at reducing defects during the improvement process. The DMAIC methodology includes these project stages: (a) defining specific processes, (b) measure data and use metrics to track effectiveness and evaluate efficiencies, (c) analyze data and clarify goals, (d) improve change and better alignment with corporate goals, and (e) control ongoing improvement in processes (Sony & Naik, 2019). This methodology can be used to find variations of processes by analyzing and eliminating waste (Soundararajan & Janardhan, 2019). The DMADV methodology includes these project stages: (a) defining specific processes of a product or service, (b) measure requirements and response, (c) analyze requirements to customer goals and needs, (d) design the improvement of business processes, and (e) verify models to check customer requirements are met along with ongoing improvements (Sony & Naik, 2019).

Six Sigma's DMAIC has gained popularity across the world, from Fortune 500 multinationals to small organizations in new business sectors such as banking and healthcare (Mouaky et al., 2018). However, the methodology addresses four key initiatives: cost, profitability, productivity, and quality (Soundararajan & Janardhan, 2019). For the successful implementation of Six Sigma, a quality improvement strategy is essential. Six Sigma has five principles to establish a quality improvement strategy: (a) define, (b) measure, (c) analyze, (d) improve, and (e) control, also known as the DMAIC roadmap (Basta et al., 2016).

Define. The term *define* is the principle of the DMAIC which involves the identification of the right project, the classification of the scope, and the definition of the goals and objectives (Sharma et al., 2018). The defined phase involves preparing the project's purpose, scope, and charter (Samman & Ouenniche, 2016). In the define phase, leaders can also identify customer needs, process capabilities, and customer objectives for the project-based improvement efforts (Soundararajan & Janardhan, 2019). The definition phase should have a problem statement, an understanding of how to measure the project through performance metrics, and have a high-level end to end process diagram (Samman & Ouenniche, 2016). The process of defining projects is scientific; selected projects have higher buy-in from all stakeholders (Sharma et al., 2018). Leaders should define and assign a value to every project or initiative designed to solve problems (Nagi & Altarazi, 2017).

Measure. The measuring process requires teams to identify their immediate problems before collecting the data on the faulty process or root cause of the problem (Soundararajan & Janardhan, 2019). The measuring stage involves measuring the characteristics that lead to improvement (Soundararajan & Janardhan, 2019). For example, in retail sales product performance and customer satisfaction metrics to measure the performance (Soundararajan & Janardhan, 2019). Establishing performance metrics to monitor and measure key performance indicators such as project objectives, scope, and goals is also necessary. The resulting output of the measuring phase should describe immediate processes, identify problem areas with the aid of data to support, and process capability (Samman & Ouenniche, 2016).

Analyze. During this phase, the team identifies the cause of the problem through data collection and verifies the root causes of defects and wastes (Soundararajan & Janardhan, 2019). In healthcare, once the data collection process is complete, leaders analyze the data to obtain insights using a baseline before beginning the new processes (PonceVega, 2018). Initially, analyzing the data will help the primary care leader identify the problems and causes of poor quality of the practice (PonceVega, 2018). The results from the data analyzed can provide the primary care leader with ways to improve the practice. However, by using the Six Sigma method, leaders have a structure that would provide them ways to identify outcomes needed promptly.

Improve. In this phase, resources are assigned to define, design, analyze, and implement solutions to improve the process (Soundararajan & Janardhan, 2019). The solution implemented is expected to eliminate or minimize the discovered defects (PonceVega, 2018). Techniques and tools that exist, such as brainstorming and corrective action matrix, can be utilized to spur the advancement of solutions to eliminate or minimize waste or identify defects (Sharma et al., 2018). The improvement process requires teams to verify and implement solutions as a permanent or remedial fix. The idea was that the solution implemented by teams should improve and innovate current processes.

Control. The control process phase has the team support and maintains the solutions on an ongoing basis (Srinivasan et al., 2016). The process requires retaining the gains achieved through documentation, standardization, and observing the work practices and processes in place (Westgard & Westgard, 2017). For example, the Motorola team used Six Sigma to identify processes that affected customer satisfaction and introduced ways to reduce defects and wastes. The control phase requires teams to document their findings on how to sustain improvements and provide process improvements (Samman & Ouenniche, 2016). Sharma et al. (2018) described the control stage as the phase of monitoring newly implemented solutions. The monitoring process would require the project team to apply statistical process control graphs and quality management tools to ensure that performance improvements are maintained (Srinivasan et al., 2016).

DMADV describes the requirements of the consumer as they connect to a service or product. The application of DMADV methodology supports service or product improvements or the creation of a completely new product or service. The DMADV acronyms stand for five principles (a) define, (b) measure, (c) analyze, (d) design, and (e) verify (Mouaky et al., 2018). The define, measure, and analysis stages share the same characteristics as in the DMAIC methodology with differences in the last two stages, design, and verify stages. DMAIC and DMADV methodologies have similar vital qualities, but they are not interchangeable and utilized for various business processes or maybe change initiatives (Sony & Naik, 2019).

Design. In the design phase, prototypes from the choices outlined in the analysis phase create the basis for the stage (Sony & Naik, 2019). The design phase looks at designing project plans that suit the desired outcome. The teams can decide on what design best meets the requirements and expectations. They would also examine the performance expectations of the DMADV process (Sony & Naik, 2019). The design phase can involve a detailed and high-level design or both. Finalizing the multiple elements of the designing would lead to the creation of a prototype model (Sony & Naik, 2019). The design phase ensures that the production of the designs is possible so that the organization is confident that the product can be delivered within budget and with the design parameters (Li, Laux, & Antony, 2018). The design phase continues developing new product or process that satisfies the organizations' requirements. In the design phase, it involves the redesigning or creating of new products to enhance organizational leaders' satisfaction.

Verify. The last stage methodology is continuously checking the validity of the product to ensure that it is valid, complete, and satisfies the expected requirements (Sony & Naik, 2019). At this stage, if the results are unsatisfactory to the design of the new product, meaning the product does not meet the required capability, then DMADV method should be started again (Li et al., 2018). The verify phase validates the design model or plans with other stakeholders on whether it would be useful in the operating conditions intended for it to operate. The DMADV method results are highly conceptual, but reviewing the best practices and information learned for possible use in other areas is beneficial. The customers' feedback can still be given, and adjustments made before implementation (Li et al., 2018). DMADV method keeps track of continuous customer feedback on the product or service performance to adjust. A pilot and production exercise are conducted after the verification and validity of the process has passed the selected success criteria (Sony & Naik, 2019). The verify step of the DMADV method includes an implementation plan that stipulates how the new process would transition into routine operation. The intent of this phase includes facilitating the buy-in of the stakeholders, including the design of controls and a transition plan before concluding the DMADV process (Sony & Naik, 2019). The application of the DMADV methodology is made over a more extensive period of many months or even years. The result is a product or service that aligns with customer expectations and wants.

Using Six Sigma methods and tools, organizational leaders can define and analyze areas of their business that require improvement. Organizational leaders can implement Six Sigma for continuous improvement that aligns with organizational vision and goals. Organizational leaders need a transparent methodology to support them in implementing big data analytics effectively. Six Sigma methods within an organization can lead to leaders developing a quality management system. DMAIC assesses present processes, products, or services that must be changed. At the same time, DMADV evaluates new processes, products, or services that have no precedent. Implementing big data analytics not only has a similarly structured set of principles for Six Sigma, but it should also provide leaders with the opportunity to measure the results of achieved initiatives. When implementing a big data analytics solution, organizational leaders should use Six Sigma to identify opportunities to improve business processes. Organizational leaders need a methodology to maintain the successful implementation of the project and effective big data analytics with the organization. Additionally, organizational leaders should measure the organization's immediate baseline performance before re-measuring the performance after implementing the big data solution.

Organizational leaders can leverage Six Sigma to improve quality and increase productivity across all operations. Proper use of the Six Sigma method allows for the identification and elimination of defects as well as streamlined business processes (Basta et al., 2016). Six Sigma creates unique support of people within an organization to help reduce waste and improve quality. These individuals become experts and lead the organization through business process improvements. For example, improving the coordination between medical specialists and physicians for primary care requires a strategy to reduce redundant appointments and waste time when seeking a specialist (Basta et al., 2016). Primary care leaders must ensure that data analysis drives Six Sigma interventions.

I used Six Sigma to explore the components of successful big data analytics implementation strategies. Implementing a big data analytics strategy should comprise of the five principles of DMADV: (a) defining the problem, (b) electing key performance indicator measures, (c) analysis of the data, (d) the implementation of new solutions, and (e) verifying the effectiveness of the solution. The outcome of implementing a successful strategy should reveal an improvement in enhanced operational efficiency, achieving a competitive advantage, and customer satisfaction. Leaders should use Six Sigma to learn about their customers' needs. They should also analyze their business processes and initiate precise measurement methods for continuous improvement, which should align with their organizational objectives and goals.

Technology-Organization-Environment (TOE) Conceptual Framework

The technology, organization, environment (TOE) model was first introduced by Tornatzky and Fleischer (1990) to improve the process of adopting new technology. The TOE framework discusses the adoption of technology by an organization (Jia et al., 2017). The TOE model also assists organizational leaders to consider various strategies adopting technology, analyze them, and select the appropriate method (Tornatzky & Fleischer, 1990). Gupta and Saini (2017) discovered that the TOE model could better understand the adoption and innovation of technology within an organization. For that reason, the TOE model can gauge an organization's level of success in technology innovation adoption and the decisions made across a wide array of systems, including developmental and technical contexts. The TOE model can help organizational leaders collect and analyze data from multiple perspectives to manage the implementation decisions and innovation process (Tornatzky & Fleischer, 1990).

A researcher would use the TOE framework to explain how to adapt the technology within an organization (Jia et al., 2017). The TOE framework consists of both internal and external factors to forecast the probability of successful technology implementation (Awa, & Ojiabo, 2016). The model posits technology, organization, and environment as the three contexts that influence organizational leaders in the adoption of innovation (Feldman et al., 2016). More specifically, TOE considers the characteristics of the technology in question, the organizational readiness to change, and the organization's environmental health to initiate the adoption of innovation (Tornatzky & Fleischer, 1990). First, technology focuses on how technology practices and structures influence the adoption process (Puklavec et al., 2018). The technology includes elements such as (a) complexity, (b) competencies, (c) relative advantage, and (d) efficiency (Kinuthia, 2015). Other technology elements can include (a) compatibility, (b) infrastructure, (c) security, (d) software, and (e) security.

Second, the organization category can reveal some organizational attributes that could aid or stifle innovation adoption (Puklavec et al., 2018). Such characteristics may consist of the culture, leadership structure, size of the organization, goals, and objectives (Puklavec et al., 2018). The organizational context comprises the scope, organizational culture, leadership support, and the availability of skilled resources (Awa, & Ojiabo, 2016). The organizational context also relates to the organization (Awa & Ojiabo, 2016).

Last, the environment reveals the organization's ecosystem, that is, the various stakeholders involved in the decision making to innovate, secure resources, and implement the solution (Puklavec et al., 2018). Stakeholders may include but are not limited to (a) the community, (b) suppliers, (c) the government, (d) customers, and (e) competitors. Environmental conditions include (a) trust, (b) consumer readiness, (c) external pressure, (d) competitive pressure, and (e) regulatory policies (Awa, & Ojiabo, 2016; Chatzoglou & Chatzoudes, 2016; Jia et al., 2017; Tornatzky & Fleischer, 1990). The environmental context is the world in which organizational leaders manage their affairs within the industry in which they operate, manage their competitors, and the government (Awa, & Ojiabo, 2016).

In attempting to predict the success of new technology adoption (Awa, & Ojiabo, 2016; Chatzoglou & Chatzoudes, 2016), the TOE model can encourage the researcher to take a broader view of how the adoption takes place (Shaltoni, 2017). The model also offers a way to study the determinants of adopting big data analytics with an organization. However, limitations to using the TOE model exist, which makes it inappropriate for this study. Some limitations include not addressing individual factors, such as issues relating to organizational leaders' attributes like leadership buy-ins (Shaltoni, 2017). A leader can be the primary decision-maker of new technology adoption and may reduce any resistance from other leaders to adopting the new technology. This could vary depending on the industry in question. Small businesses have a different strategy from a larger organization.

Besides, the TOE model does not offer a set of factors that could affect the adoption of technology (Aboelmaged & Hashem, 2018). Awa and Ojiabo (2016) stated that organizational and environmental factors of a TOE framework do not influence technology adoption as much as the technology factor. It merely categorizes factors within their respective contexts, where the adoption process can take place (Aboelmaged & Hashem, 2018). Therefore, specific determinants identified within the three contexts may vary across different studies. Despite these purported weaknesses, the TOE model provides a starting point for many studies when analyzing and considering suitable factors for understanding the innovation adoption decision because it has consistent empirical support.

Although the TOE model offers a lens to study the determinants of successfully adopting big data analytics, the focus of this study was on identifying strategies to successfully implement big data analytics. The TOE model does not focus on exploring strategies, nor does it leave space for studying the specifics which this type of study demands. Instead, TOE provides the taxonomy for classifying factors in their particular condition and the adoption of technology (Jia et al., 2017). While considering the objectives of this study, the TOE model does not focus on exploring strategies that leaders can use to implement big data analytics successfully. Therefore, the TOE model would not be a suitable conceptual framework for this study.

Big Data Analytics

Big data is defined as data that is continually being generated from multiple sources and diverse data formats that are both structured and unstructured (Grover et al., 2018). Big data provides leaders with the potential to mine useful business information for their organization (Balachandran & Prasad, 2017). Leaders can get a holistic view of their performance through the translation and consumption of structured and unstructured data from multiple sources (Grover et al., 2018). Big data can help leaders identify relationships, patterns, and insights from different types of data to help them determine their organization's performance. The use of big data by leaders can help improve organizational growth by using business insights aimed at becoming market leaders.

Wamba et al. (2015) defined big data analytics as a holistic approach to capturing, managing, processing, and analyzing data. A common method of data classification/sorting is the 5V's (i.e., volume, velocity, variety, value, and veracity). Big data creates business insights for delivering sustainability, performance, value, and establishing competitive advantages over its competitors (Wamba et al., 2015). The first characteristic is *volume*, which refers to the ever-growing magnitude of data; *velocity* refers to the continuous generation of data at an unparalleled pace; and *variety* is the different types of data formats, ranging from structured, semistructured, to unstructured data (Grover et al., 2018). *Value* refers to the worth of hidden insights in data, and *veracity* refers to the biases, noise, trustworthiness, and messiness in data (Yaqoob et al., 2016). The emergence of networked businesses from social media outlets, including Facebook and Instagram, has dramatically increased the volume, variety, velocity, value, and veracity of structured, semistructured, and unstructured data (Yaqoob et al., 2016). Traditional data analytics is the ability to process and store structured and semistructured data in conventional databases, while big data analytics can store and process structured, semistructured, and unstructured data from multiple sources.

Studying the origin of big data applications is vital in understanding the conceptual background, vision, and trend of big data (Yaqoob et al., 2016). Big data analytics has spawned into a massive industry of data. However, before its existence, standalone applications existed with a single processing unit to reflect business users' actions with the computation speed of a local host machine (Abolfazli et al., 2014). Moreover, leaders used these standalone machines (a PC or server) with no existing network, but with software that stored the data, performed several calculations, and produced results for further analysis. The ability to run data analytics software locally on a standalone machine was a significant source of empowerment to leaders, and this led to an increase in the purchase of standalone corporate machines in the 1960s and 1970s, and then the era of personal computers (PCs) in the 1980s (Kacprzyk & Zadrożny, 2001).

Structured data has a high degree of order and use by organizational leaders, such that it can be stored in a relational database seamlessly, readily available for straightforward analysis, and search engines (Adnan & Akbar, 2019). Examples of structured data include numbers, groups of words, and dates stored in a relational database (Adnan & Akbar, 2019). Semistructured data does not conform to the formal structure associated with relational databases (Woo et al., 2019). An example of semistructured data is XML which is used to transfer data from one destination to another. XML is a language used for data exchange and representation (Nassiri et al., 2018). Unstructured data cannot be stored in rows and columns in a relational database and has no identifiable structure (Wu & Lin, 2018). Examples of unstructured data include archived documents in a file folder, e-mail messages, photos, videos, and images (Adnan & Akbar, 2019).

Three types of advanced analytical techniques exist in big data: (a) predictive analysis, which is responsible for developing models based on past data for future prediction; (b) descriptive analysis, which is a model that reports on the past; and (c) prescriptive analysis, which uses models to specify optimal actions and behaviors (Grover et al., 2018). Advanced analytical techniques provide a forward-looking view, enabling leaders to anticipate and execute future opportunities based on real-time insights discovered from current events, ongoing business processes, and high-volume streaming data sources (Grover et al., 2018). Technology is a crucial and complementary strategic asset to big data analytics. While much of the literature surrounding big data analytics is relatively new, big data analytics is a robust process by which leaders can unearth social and potentially immense economic value to gain a competitive advantage (Grover et al., 2018).

Technological advancements with the combination of advanced analytical techniques can enable organizational leaders to realize the benefits of using big data analytics (Balachandran & Prasad, 2017). According to Grover et al. (2018), big data analytics is applying statistical technology, processing, and advanced analytical techniques to big data to advance a competitive advantage. IDC forecasts that in 2019, big data technology and services markets will grow at a 23.1% compound annual rate, reaching $48.6 billion (Grover et al., 2018). Several big data technologies exist in the market. Some include Hadoop and NoSQL technologies that provide leaders with access to real-time, centralized data collected from different sources (Grover et al., 2018). Using advanced technology, leaders can embrace unique opportunities to capitalize on big data analytics to gain a competitive advantage (Grover et al., 2018). Big data analytics is a strategic asset used by leaders to guide their decision-making and improve business processes and outcomes.

The concept of big data evolved at the beginning of the 21st century, and it remains an essential business component for successful leaders to use. The field of data analytics is also an essential subcomponent of big data analytics. Big data analytical tools and techniques are in high demand by organizational leaders because of some of the perceived benefits that it can provide to organizations. Therefore, organizational leaders should implement big data analytics to realize these opportunities. Leaders in different business sectors leverage big data technologies to analyze the vast and voluminous data sets to gain industry insights and patterns. From these insights, leaders can find new opportunities to improve their business efficiently and attain a competitive advantage.

History of Big Data Analytics

Big data analytics began with the introduction of standalone computers in businesses in the 1980s (Yaqoob et al., 2016). Leaders conducted data analytics using spreadsheets or less-advanced technologies installed on standalone machines for the sole purpose of identifying business trends (Yaqoob et al., 2016). Leaders would commonly use desktop software to perform data analytics on standalone applications with no Internet access for the sole purpose of collecting useful information for the organization. By the mid-1990s, standalone applications hosted on local machines presented some challenges for leaders to accurately perform data analysis (Yaqoob et al., 2016) as the applications were unable to support the excessive processing loads of data for analysis (Abolfazli et al., 2014).

The late 1990s saw an exponential increase in the volume of data generated globally (Balachandran & Prasad, 2017). The volume of data increased rapidly as a result of the globalization of the world's economy, the emergence and ubiquity of the Internet, social media networks, and new product introduction of mobile devices (Amankwah-Amoah, 2016). The telecommunication sector experienced and contributed to the increase in the volume of data growth during their introduction of a new technology shift from an analog to a digital platform (Asamoah et al., 2017). Data growth is exponential, from (a) 281 petabytes in 1986, (b) to 471 petabytes in 1993, (c) to 2.2 exabytes in 2000, (d) to 65 exabytes in 2007, and (e) to 667 exabytes in 2010 (Hilbert & Lopez, 2011).

Other factors existed, including business transformation and the introduction of new processes, products, and practices that influenced the growth of data in the world. Some industry sectors experienced business change and transformation that resulted in leaders adjusting to these new demands for higher data quality, fast access to data for decision making, new data visualization tools, and more data privacy and protection (Baber et al., 2019). The management of a vast amount of data within organizations was becoming a challenging risk, and leaders would have to devise ways of collecting, processing, and analyzing the data.

By the new millennium, business needs and requirements changed, and leaders found that the data analytical tools of the time had limitations in providing the right information. Leaders also experienced challenges with harvesting, managing, and processing vast amounts of data through nontraditional systems and capabilities (Chandy et al., 2017). Big data analytics evolved because of the ever-changing business needs and its perceived benefits to leaders in the processing capacity of vast volumes of data (Balachandran & Prasad, 2017). With the successful implementation of big data analytics, leaders have the potential to generate economic value in different industry sectors such as healthcare, retail, manufacturing, telecom, banking, and government administration (Elgendy & Elragal, 2016).

The first adopters of big data analytics were a startup and online organizations such as Facebook, eBay, Google, Target, Amazon, and LinkedIn; these organizations made big data analytics part of their organizations' core foundation and strategy (Ertemel, 2015). At Target, a retail organization, leaders used big data analytics with their loyalty card program data to track customers' buying patterns and to predict what consumers would probably buy in the future (Wamba et al., 2017). At Amazon, almost 35% of goods purchased by consumers on Amazon.com were a result of personalized recommendations targeted at each consumer (Wills, 2014).

Other organizations from different industries also implemented big data. General Electric also invested in big data analytics to (a) improve their operational efficiency of 1500 gas turbines, (b) optimize their network, (c) improve their dispatch service, and (d) better coordinate the distribution of gas and power systems (Wamba et al., 2017). In healthcare, hospital leaders in Paris utilized a prescient examination of workers to determine what number of patients will visit in any period and to empower them to foresee the number of employees to support the patients (Alexandru, Radu, & Bizon, 2018). Alexandru et al. (2018) discovered that leaders were able to create a balanced supply of hospital employees to support patients' demands through big data. The outcome of using big data led to a shortage in the supply of hospital staff, with shorter waiting times for patients, and lower labor costs to the hospital.

In summary, big data analytics was introduced as a process to assist leaders with a solution to resolve the problem associated with collecting, processing, and analyzing vast amounts of data. Big data analytics provides strategic business value that offers insights to identifying trends and algorithms to predict outcomes. Big data analytics can potentially generate business value for organizations, and *how* and *what* business value is still a work in progress. The creation of big data analytics began with the introduction of numerous new tools and techniques to replace the existing ones so that leaders achieved similar or better business outcomes. With the ever-increasing use of social media in the United States, a strong case exists to understand how massive amounts of collected data add business value, like increased productivity and profitability. Organizations would need to understand what benefits and challenges they may encounter.

Big Data Analytics and Competitive Advantage

Many organizational leaders have shifted to data-driven decision-making due to the advantages of big data analytics (Adrian et al., 2018). Two fundamental advantages of implementing big data analytics are (a) competitive advantage and (b) cost savings (Mohan, 2016). The term *competitive advantage* refers to an organization's ability to be better than its competitors or others. Organizational leaders use their competitive advantage to build more economic value than their competitors (Manzoor et al., 2019). Mobile and Internet activities can generate large amounts of structured, semistructured, and unstructured data (digitalized data), which organizational leaders can analyze to achieve a competitive advantage in their market through better business efficiency (Curry, 2016).

Organizational leaders who apply big data analytics within their organization can create a sustainable competitive advantage (Matthias et al., 2017). An organization can attain a competitive advantage when organizational leaders create value for its buyers that exceeds the organization's original cost (Porter, 2020). Leaders who invest in big data analytics have a 36% chance of improving their superiority over their competitors in areas such as operating efficiency and revenue growth (Anthony et al., 2015).

Leaders use big data to leverage information in their organizations, giving them access to achieve a competitive advantage against competitors through improved performance and decision making. For example, Walmart implemented an in-house design search engine that used big data for semantic analysis called Polaris (Raguseo & Vitari, 2018). The Polaris system relies on text analysis, from big data and machine learning to produce relevant search results (Raguseo & Vitari, 2018). After the Polaris system's implementation, the number of completed purchases online at Walmart increased from 10% to 15%, thus creating a sustainable competitive advantage over their rivals (Jayanand et al., 2015). Leaders should continue to search for new avenues or opportunities to achieve continuous advantages and improvements.

Organizations can benefit from the use of information from big data analytics to reduce costs, save time, and make business decisions or prepare better product offers (Bumblauskas et al., 2017). Big data tools and techniques can help leaders achieve cost savings through data processing and storage of vast volumes of information at a lower price than a conventional database (Mohan, 2016). Big data technologies such as Hadoop, MongoDB, and Apache Cassandra, can provide substantial cost advantages (Balachandran & Prasad, 2017). Hadoop, MongoDB, and Apache Cassandra are open source platforms (Wang et al., 2018). These technology platforms all share similar capabilities focused on storing and processing vast volumes of data for advanced analytics.

Spotify, LinkedIn, and Netflix are some organizations that utilize big data technologies such as Hadoop, MongoDB, and Apache Cassandra (Boncea et al., 2017).

For example, Spotify leverages Hadoop to store and process vast amounts of structured, semistructured, and unstructured data; LinkedIn built a search learning platform called LearnIn from MongoDB, and Netflix utilizes an administration and management platform built with Apache Cassandra (Boncea et al., 2017). These open-source platforms allow organizations and their leaders to analyze their data effectively and efficiently.

Organizational leaders can leverage big data open-source platforms to create their custom big data applications for advanced data analytics (Boncea et al., 2017). Open source big data platforms can also support integration with one another to form a single solution. For example, the Hadoop platform can blend data from different sources to produce business models that the MongoDB platform will process and produce valuable business insights in real-time (Boncea et al., 2017). Leaders can also utilize the MongoDB platform for real-time operational processing of data (Lahmer & Zhang, 2016). MongoDB and Hadoop are big data tools that leaders can use for data partitioning and consistency (Boncea et al., 2017). These platforms are very similar tools, but with differences in processing and storing big data to provide leaders with big data analytics options.

In healthcare, leaders can adopt big data analytics to understand directional trends and patterns within the data collected. The information helps leaders identify relationships and connections, which can result in better care, ultimately saving lives, and reducing labor costs and expenses (Alexandru et al., 2018). Organizational leaders can use big data analytics to design and offer cheaper and better-tailored medical products based on patient data (Alexandru et al., 2018). Big data analytics is a technology enterprise component that leaders use to gain new insights and business value to make better decisions. Leaders with knowledge of big data technologies should select the right tool, skills, and team structure which would be necessary to implement big data analytics effectively (Elgendy & Elragal, 2016).

Organizational leaders can select big data technologies based on their organizational goals and objectives to perform advanced data analytics. Before selecting a tool, a leader should evaluate the advantages and disadvantages of each big data technology solution for compatibility with their business requirements. The alignment of their business requirements with a big data technology solution could increase business benefits and opportunities. Leaders also gain business insights from the data they analyze because data contain connections with distinct relationships and patterns that can translate into new business insights. Leaders should select an appropriate big data technology that would support the collection and analysis of vast amounts of data to foster better business decisions.

Benefits of Big Data Analytics

The increasing availability of big data analytics and big data platforms helps organizational leaders collect and analyze data in search of valuable business information and insights that can help improve their products and services. These opportunities exist in an organizational leaders' ability to blend and analyze different kinds of data to gain the benefits from big data analytics and big data platforms. Balachandran and Prasad (2017) identified four benefits of big data analytics: (a) faster and better decision-making, (b) new products and services, (c) product recommendations, and (d) fraud detection.

Organizational leaders seek to make faster and better decision-making strategies with big data analytics (Elgendy & Elragal, 2016). From a leader's perspective, the significance of big data analytics lies in the ability to provide information and knowledge of value, before making a business decision (Elgendy & Elragal, 2016). Big data analytics can enable faster data analysis and decision-making through advanced data visualization (Elgendy & Elragal, 2016). Organizational leaders should seize the opportunities offered by big data analytics to gain possible insights and benefits to unlocking economic value. Therefore, organizational leaders should implement big data analytics to realize benefits such as understanding customer intelligence and unveil previously unseen patterns that support competitive advantage and sustainability.

Organizational leaders using big data analytics can create new services and products (Bartosik-Purgat & Ratajczak-Mrożek, 2018). Leaders adopting big data technologies can improve products and services, reduce organizational costs, execute innovations faster, and make better decisions (Davenport, 2014). For example, leaders at the Babolat organization introduced a new product feature to improve a tennis player's performance by connecting devices and sensors onto the handles of a tennis racket (Porter & Heppelmann, 2015). The tennis player can track and analyze specific metrics such as the ball speed, ball spin, and the impact location of the ball on the racket in real-time using big data technology (Porter & Heppelmann, 2015). New product features can increase a product's value, marketability, and profitability for an organization. Organizational leaders should first implement such features on a trial basis to understand the consumers' appetite in the market before conducting a full rollout (Bartosik-Purgat &

Ratajczak-Mrożek, 2018). Measuring and evaluating the benefits of a new product launch occurs after the trial is over. This strategy would assist leaders in making any changes before the official product launch. The most frequently recognized benefits from big data technologies are related to assisting leaders in introducing better services and new products.

Leaders from online businesses who adopt big data analytics can find it a valuable strategy because it provides a significant and economical way to process vast amounts of consumer data. For example, Walmart improved its online shoppers' ability to complete a purchase from 10% to 15% using a big data platform called Polari (Raguseo, 2018). Polari is a semantic analysis search engine that relies on text analysis and machine learning to produce relevant search results to assist online shoppers on Walmart's website (Raguseo, 2018). When consumers utilize the Internet or mobile devices, they provide a great deal of information to organizations, including (a) websites frequently visited, (b) types of information viewed, and (c) the types of products or services of interest (Ahsan & Rahman, 2016). Consumers can leave traces of the information viewed when browsing online sites (Davenport, 2014). Leaders can also gain access and process this information using big data analytics to prepare personal offers to the consumer (Almeida, 2017). Organizational leaders can also use this information generated to target the consumers to sign up for loyalty programs (Bartosik-Purgat & Ratajczak-Mrożek, 2018). Using this consumer, online information leads to renewed sales, improved customer services, market intelligence, and target marketing (Raguseo, 2018).

Organizational leaders are using big data analytics for fraud detection and prevention. With the aid of new computing technology, data analysts can quickly store and process vast volumes of information. Leaders can use in-memory processing and cloud technology to lower their risk of making poor decisions (Bologa et al., 2013). In health insurance, organizational leaders utilize big data analytics to detect abnormal claims quicker by automatically narrowing the segment with potentially fraudulent applications or detecting new patterns of fraud (Bologa et al., 2013). Other organizational leaders are using big data analytics for fraud detection and prevention. In the social media sector, big data technology is utilized to detect fraudulent activities because fraud schemes can lurk in the vast amounts of data (Tang & Karim, 2019).

In summary, organizational leaders use big data analytics to help direct their strategy to maximize profits, reduce costs, introduce a new product, minimize fraud, and support their decision-making processes. Big data technologies allow business leaders to make proactive, knowledge-driven decisions on future trends. Data analysts collect and process data in real-time, store data remotely in the cloud, and have faster access to data from anywhere and anytime at a reduced cost. Cloud-based big data analytics provides a low-end cost infrastructure that organizations would otherwise have to construct themselves. The combined low-cost cloud technology footprint can foster organizations to stay competitive by providing benefits, including cost-effectiveness, ease of management, rapid elasticity, on-demand service, and resource pooling. Implementation success can reinforce management trust and confidence in the chosen technology and strategy. Nevertheless, despite the benefits and opportunities associated with big data analytics, the implementation can create challenges. Organizational leaders should understand these challenges.

Challenges to Implementing Big Data Analytics

Big data analytics can yield beneficial information, but some challenges exist such as (a) managing large sets of data, (b) data silos, (c) data centralization, (d) data protection and privacy, (e) management training, (f) having the right skills to conduct analysis such as data scientists, (g) cost of implementation, and (h) organizational cultural change (Saldžiūnas & Skyrius, 2017). Michael and Miller (2013) argued that leaders would face challenges using big data analytics when trying to understand (a) how much data to collect and store, (b) how long should the data be maintained, (c) whether the data would be secure, and (d) how much this would cost.

Managing large datasets. As the volume of data increases, challenges may arise, with leaders discovering ways to manage the continued growth in data collected to yield more benefits (Saldžiūnas & Skyrius, 2017). For example, law enforcement agencies and other organizations rely on video data generated from closed-circuit television (CCTV) from surveillance used in criminal investigations (Michael & Miller, 2013). Leaders are challenged with deciding whether it is cost-effective to allow the closed-circuit television to run continuously or to capture only selective scenes (Michael & Miller, 2013). The large amounts of video data generated are unstructured data collected, processed, and stored using big data technology (Michael & Miller, 2013).

Managing and storing video data can be expensive because it contains large amounts of unstructured data (Michael & Miller, 2013). The decision is left with the operator to decide how much of the data to manage and store. Unstructured data are time-consuming to process, manage, and can be expensive to store for analysis using big data analytics (Michael & Miller, 2013). A mobile network operator is a telecommunications operator or a telecom carrier. In mobile network operators (MNO), leaders in the telecommunications industry have experience managing large amounts of structured and semistructured data. However, a problem exists with having data silos because of the nature of their business (Saldžiūnas & Skyrius, 2017).

The purpose of this qualitative multiple case study is to explore strategies that IT leaders in the telecommunications industry use to implement big data analytics successfully. The digitized economy brings about the ability to use and manage large datasets in real-time or a delayed period using big data technology and using big data analytics is essential to achieving organizational competitive advantage. Managing large datasets with big data analytics can be a strategic goal for an organization and, if appropriately addressed, can lead to developing and unlocking new perspectives from the analysis.

Data silos. The term *data silos* describe the isolation or segregation of data collection (Leonard et al., 2018). While the term *centralized data* describes a typical nonsilo environment that consists of multiple integrated systems with a complete dataset of unstructured, semistructured, and structured data (Saldžiūnas & Skyrius, 2017). The term *professional silos* describe the process by which barriers can exist within an organization between departments, leading to isolation amongst individuals who are supposed to be working collaboratively in the same team rather than working individually

(Kitchens et al., 2018). The phenomenon can be better known as divisional rivalry, departmental politics, or turf wars (Kitchens et al., 2018). Silos generally occur when leaders fail to provide themselves and their employees with a compelling reason and purpose to work together (Kitchens et al., 2018). Dismantling silo processes or systems into integrated processes or systems can be advantageous, enhancing an organization's external and internal performance.

In the telecommunication sector, data silos are a frequent occurrence, especially in mobile network operators (MNO) (Saldžiūnas & Skyrius, 2017). The data from a mobile network operator originates from many disparate systems and sources such as (a) device data, (b) cell site data, (c) network data, and (d) back-office data (Saldžiūnas & Skyrius, 2017). The data are scattered in standalone systems throughout the organization, making data analysis difficult (Saldžiūnas & Skyrius, 2017). Data not centralized within an organization can present challenges for organizational leaders to produce business insights when using big data analytics (Saldžiūnas & Skyrius, 2017).

The downside of having a predominantly silo data environment could result in the existence of data duplication in multiple data locations (Saldžiūnas & Skyrius, 2017). Data could be of less value without cleansing, transforming, integrating, and aggregating the data before analyzing it to discover insights (Saggi & Jain, 2018). Having a silo data environment could lead to data inaccuracy, duplicate data, and no single source of truth for an organization. A data environment that encompasses different data sources from the whole organization is complete and most valuable. Data silo environments are also not sufficiently reliable to use in making organizational decisions because of possible errors, duplications, and missing data (Saldžiūnas & Skyrius, 2017).

Higher costs are associated with maintaining several silo data sources in multiple data locations and controversy could arise amongst teams when leaders try to translate and reconcile duplicates (Saldžiūnas & Skyrius, 2017). An advantage of having data silos is that leaders can have the flexibility and freedom to analyze the data faster individually (Saldžiūnas & Skyrius, 2017). The silo data environment can provide the leader with a limited singular perspective (Saldžiūnas & Skyrius, 2017). However, to enable leaders to discover unlimited new business insights, data silos must not exist, and the data should be centrally located and available for use. While many organizations recognize that data silos are a problem, undoing the problem can be challenging because of the possible legacy systems that may exist or an entrenched organizational culture of separating data. Changing the mindset of employees would require organizational leaders to adopt a data centralization and sharing strategy approach. Introducing big data analytics can help organizational leaders get an overall view of their company data.

Data centralization. In MNO organizations, billing systems are in a central location where leaders can securely access the information to conduct analytics centrally (Saldžiūnas & Skyrius, 2017). Other systems, such as device and cell tower site information, can be located in separate systems elsewhere throughout the organization, making data analysis of the entire data challenging for leaders to derive a comprehensive view of their organization (Saldžiūnas & Skyrius, 2017). When an organization has a centrally located data environment, it can benefit from cost savings because of its uniform data structure standards, a centrally located data environment with no duplicate data, and an integrated security system (Saldžiūnas & Skyrius, 2017). The linking of data silos for intergenerational research can have benefits concerning time and cost (Leonard et al., 2018). Leaders could make better decisions for their organization if the data collected were centrally hosted, structured, and easily accessible to conduct big data analytics. Despite the organizational benefit of a centrally hosted data environment to support leaders in making better decisions, consumers have concerns regarding the lack of sufficient regulatory legislation, adequate security protocols to protect, and prevent a data breach on consumers' personal information (Saldžiūnas & Skyrius, 2017). A data centralization strategy can avoid the duplication of data sets and provide new perspectives from multiple analyses of the same data set using big data analytics. However, a data centralization strategy can also promote a data-sharing culture within an organization, that could lead to access to insights to support a competitive advantage with a better financial performance outcome.

Data protection and data privacy. Data protection and data privacy measures promote and justify the laws and regulations set by the regulators. Data protection and data privacy of any data collected by an organization create a concern for consumers, and it can also create challenges for organizational leaders to manage. In Europe, for example, legal reforms on data protection and privacy exists to protect an individual's data from being sold or misused (Vayena et al., 2018). The European Union enforces general data protection legislative laws that all organizations must abide by (Vayena et al., 2018). The General Data Protection Regulation (GDPR) is a statutory law established to increase data protection and privacy controls on consumer data used by any organization using big data (Vayena et al., 2018). GDPR legislative law exists to tackle and control the probable pressure on organizations to attempt to commercialize and monetize the use of the data (Vayena et al., 2018). The GDPR prompted most companies, inside and outside of Europe, to review their data protection laws to avoid substantial economic penalties in case of a data breach.

In Lithuania, by law, MNOs organizations are legally expected to store service data for a minimum of 6 months to address any future billing related inquiries, issues, or disputes for services provided and to provide information to the appropriate authorities (Saldžiūnas & Skyrius, 2017). The National Data Protection Regulators of the European Union are responsible for imposing significant fines of up to 2% of the global turnover on offenders of the data protection laws (Mullock, 2012). Regulatory bodies monitor and control organizations and their employees regarding adherence to data privacy laws and application of security measures within their organizations to protect consumer data (Vayena et al., 2018). Protecting the data also comes with various challenges and an additional cost for organizational leaders. Costs exist with protecting consumer data and these costs could include the cost of implementing a high-grade data security solution to a secure storage location (Vayena et al., 2018).

The term *data security* describes the proper handling and protection of data (Sultan et al., 2018). Before organizational leaders can adopt big data analytics, they need to understand the associated requirements in ensuring data security and data privacy are part of their overall implementation solution (Sultan et al., 2018). For example, during the data collecting, processing, and management stages of the big data process, the data are encrypted and secured to avoid any tampering or manipulation (Sultan et al., 2018). Data encryption is also applied when the data are at rest or in transit to protect the integrity of the data (Sultan et al., 2018). Only authorized staff members should have data access (Sultan et al., 2018). Organizational leaders who choose to invest in big data analytics should adhere to data protection laws and have security measures to protect, control, access, and monitor data usage. In the healthcare sector, specific security protocols exist to manage and protect patient confidentiality and data. In hospitals, proactive and durable policies exist to protect patient data in the form of confidentiality clauses, including high-grade security software in systems (Vayena et al., 2018). Patients are also increasingly demanding access to their data (Vayena et al., 2018). Consequently, hospitals are using the internet through their portal sites to provide patients with the necessary access to their health information and other useful data in a secure manner (Vayena et al., 2018). A data secured environment would minimize the opportunity of a possible data breach. Stricter checks on data privacy controls and regulations are required to combat and prevent any breach in consumer data.

The term *data breach* describes the unintentional or intentional penetration of a secure system using agents to access private and confidential information or data to an untrusted secure environment (Sultan et al., 2018). A data breach from an internal or an external source occurs when digital agents search and exploit erroneous or insecure security protocols by using software agents to introduce malware into the intended systems (Kude et al., 2017). A data breach is an act of compromising an organization's security to gain unauthorized access to its systems and protected data (Shamsi & Khojaye, 2018). Carphone Warehouse, a telecommunications dealer in the UK, had over 90,000 credit and debit card information of their customers stolen (Bush, 2016). In 2015, several banks in the UK, such as Barclays, HSBC, Lloyds Banking Group, NatWest, Nationwide, and Santander, also had their data breached (Bush, 2016). In the U.S., in 2016, a data breach occurred involving a malware attack and the malware software designed was targeted to extract credit card information as customers swiped their cards at Home Depot's in-store registers (Krebsonsecurity, 2014). The outcome of a data breach can be expensive and exorbitant for an organization because the regulatory bodies impose a hefty financial penalty and demand payouts to the parties impacted (Kude et al., 2017). Organizational leaders pursuing a compensation strategy rather than fixing vulnerable areas in their security after a data breach could find it to be challenging and expensive. Organizational leaders pay huge fines if found guilty of violating the data protection laws (Kude et al., 2017). For example, Adobe, Sony, Home Depot, and Target all paid out compensation packages to reestablish customer relations and reputation after a data breach (Kude et al., 2017). Ultimately the organizations that provide compensation to millions of customers after a data breach incur a high expense and have to restore consumer confidence (Kude et al., 2017). When implementing big data analytics in their organization for better decision-making, leaders can choose to implement compensation strategies or adopt security and data protection strategies. Guidelines are available to assist leaders in selecting the appropriate big data technology, undergoing the necessary training needed to conduct proper analysis, and hiring the right skilled resources required to analyze and interpret the information better.

Management training. Another challenge to implementing big data analytics is that leaders need to acquire the analytical capability to conduct a proper analysis of the information collected using big data analytical tools. Interpreting the information from big data analytical tools can be challenging if leaders do not have the required training or skills (Sharma et al., 2014). Leaders should be able to describe the output produced by using big data tools to identify strategic or operational patterns and make the right decisions to create value (Sharma et al., 2014). Leaders derive new business insights from using big data analytical tools. When a leader is unable to translate the data collected in this manner, the information produced often has little or no value to the organization (Saldžiūnas & Skyrius, 2017). A common mistake some leaders make when using big data analytics is to focus mainly on the data collection and transformation instead of on how to use the data to develop business models and insights that might create a competitive advantage (Alharthi et al., 2017). Therefore, leaders should undergo the necessary training before proceeding with implementing big data analytics within the organization. Leaders should hire a data scientist to assist with the implementation and operational use of big data analytics technology.

Brynjolfsson, Hitt, and Kim conducted a study that found that organizations that managed with big data increased output and productivity levels by 6%, compared to other organizations that invested in only traditional internal and external data collection with fundamental analysis (Brynjolfsson et al., 2011). The result of the study revealed that several growing organizations implemented a data-driven culture. Tambe (2014) also discovered that organizational leaders who use big data could benefit from up to 3% growth in productivity and performance than organizational leaders that do not use it. Organizations that possess employees with the knowledge and technical skills to translate the data into business insights have a competitive advantage over their rivals. It would appear that analytical skills, a driven-data culture, and proficient leaders are necessary ingredients for a successful organization. In such organizations, opportunities exist for leaders to learn new skills and for employees to harness their potential benefits of big data analytics for the sole purpose of increasing efficiency and effectiveness with the organization. Training and workplace learning efforts are also seen as the objective goals of the organization.

Employees of an organization using big data analytics would also require training to conduct analytics. Analytics are the methods that specialists use to derive meaning from raw big data to make data-based decisions (Giacumo & Breman, 2016). These methods include gathering, cleaning, organizing, and analyzing data from several sources to answer business questions or problems (Giacumo & Breman, 2016). This process is called talent or people analytics and can be used to answer desired questions with descriptive, predictive, or even present prescriptive recommendations (Ahmad et al., 2019). The resources, culture, and talent that an organization possesses can help or hinder its efforts to build an analytical organization (Giacumo & Breman, 2016). Organizational teams must work together to leverage data assets in order to derive value from big data.

Leaders and employees with analytical skills can be powerful business tools for an organization.

Nevertheless, as Giacumo and Breman (2016) stated, a more exceptional analytical ability will not significantly improve an organization's performance if data is not employed to make better decisions. As such, a cultural change for leaders who have historically made decisions based on intuition retrained to tap into data-driven decision-making. Training leaders and employees who move beyond operational analysis, who become capable of predicting trends, and outcomes in different areas of the organization can improve decision making and performance (Giacumo & Breman, 2016). In the past, under traditional analysis, it has been harder to understand trends or measure how certain organization investments drive results.

Leaders that have historically made decisions based on intuition may be required to undergo training to educate themselves to use big data analytics to make a change in their practice by tapping into data-driven decision-making. Therefore, organizational leaders should invest in skilled leaders, vast IT skilled resources to realize an increase in productivity, and a progressive path for the organization. System and process changes with the introduction of big data analytics would require front line participation of professionals and specialists hired in the workplace to be well equipped and participate in the projects for a successful outcome. Finally, skilled leaders and employees need to be brought into the organizational structure, either through training or hiring, because of the value they would bring to the organization. To implement big data analytics, an organization requires skilled leaders, skilled technical resources and a sizable budget.

Data scientists. The data scientist is a resource needed during and after the implementation of big data analytics (Saldžiūnas & Skyrius, 2017). The term *data scientist* describes an individual that uses analytical technology, statistics, systemic capabilities, and scientific rigor to ensure that answers to data questions are accurate (Saldžiūnas & Skyrius, 2017). Data scientists are experts in using big data technologies such as Hadoop, MongoDB, and Apache Cassandra (Asamoah et al., 2017). The data scientist focuses on analytical modeling, data science, business analysis, and data management for the leader (Asamoah et al., 2017). Data scientists specialize in a niche area of the business and can often work with different teams within an organization (Ceri, 2018). A data scientist's experience can include applying business ideas, business analytics, and technology to solve strategic and operational challenges (Rodolfa et al., 2019). Big data leverages both data and science to create new insights

A shortage of data scientists is an issue with big data analytics, given that so many organizations are now seeking to implement big data analytics and hire people with data analytics expertise (Malaka & Brown, 2015). Data scientists unlock knowledge from big data, using analytical methods and technologies. They utilize programming languages and statistical skills, to complete their advanced analytical analyzes, such as data mining and predictive analytics (Vicario & Coleman, 2020). Data scientists interpret and analyze results to discover business insights generated from big data technology (Bailer & Fisher, 2020). Organizational leaders can benefit from improving their decision-making capabilities across multiple business domains, including operations, finance, infrastructure, and planning.

A data scientist's skill set includes both non-technical and technical skills, making it a high-demand resource (Hu et al., 2018). In combining these technical skills, such as business intelligence analytics, mathematics, statistics, and data analytics, a data scientist can effectively extract useful findings from big data (Carbone et al., 2016). The primary focus of a data scientist is to interpret data into new data insights to create new products and services (Carbone et al., 2016). The relevance of a data scientist in an organization is a necessity for the business to transform and use disruptive technology. In 2015, in the United States, a shortage of data scientists skills existed within the market (Rodolfa et al., 2019). Therefore, leaders can find it challenging to hire data scientists and successfully transition into big data analytics. Researchers from the Data Warehouse Institute found that 46% of the 325 respondents surveyed indicated that there was inadequate staffing existed, which meant that there was a shortage of data scientists to implement big data analytics (Rodolfa et al., 2019).

Organizational leaders will also need to hire other highly skilled and experienced professionals, such as chief data officers (Miller, 2014). Hired professionals will require extensive data knowledge and be highly specialized (Miller, 2014). Data scientists work with leaders from across the organization pre and post-implementation of big data analytics (Miller, 2014). They can connect data in ways that reveal insights and deliver business answers in an effective manner (Patil, 2011). Consequently, a data scientist is a vital member of a team within an organization to uncover patterns and correlations through the analysis of massive amounts of data from various sources. Data scientists are technically proficient and possess a broad business acumen in the industry. Given the highly variable skill requirements for a data scientist, it can be challenging to hire an individual with all the skill sets to fit the profile (Asamoah et al., 2017). The data scientist is a conglomeration of skills over a wide swath of technological and business landscape, including advanced analytics, creativity, data integration, data visualization, software development, communication, and collaboration (Wise, 2020). The best and quickest path to big data analytics success is by creating teams with widely varied skills and personalities (Wise, 2020). The combination of functional and technical skills is essential to the success of the data scientist. They should be able to perform critical technical data analysis and explain the results management and the other teams.

In summary, a data scientist is an individual employed by an organization to analyze and interpret big data information. They are responsible for developing several business decision support models used for decision making, analysis of operational risks, optimizing portfolios, to understand customer habits, and behaviors. A data scientist is responsible for developing several business decision support models for decision-making, analysis of operational risks, optimizing portfolios, and understanding customer habits, and behaviors. In any organization, there are leading and supporting roles that participate in the success or failure of the business, and the data scientist's role is highly technical. They interpret the results generated from big data tools and of their analyses to discover knowledge. A leader must understand the current state of the organization and serve as a champion to advance internal analytical capabilities. The data scientist provides support for leaders and leaders with the information they analyze and synthesize. They require a combination of skills that make independent work quicker and collaboration with others more appealing. The skill shortage in hiring data scientists can pose an issue with regards to successfully implementing big data analytics.

Cost of implementation. Challenges exist with implementing big data analytics which range from, the cost of purchasing hardware and software required for big data acquisition, the high availability storage needed to store the vast amount of data, and the hiring of resources that are already in short supply such as qualified data scientists (Sivarajah et al., 2017). One of the biggest challenges with implementing big data analytics is the high cost of infrastructure (Kottasová, 2018). Even with the introduction of cloud computing technologies and other equipment, they are still costly (Sivarajah et al., 2017). For example, 1,000 processing nodes connected over the cloud would require approximately 750 days to process one million gigabytes using this system and would cost more than six million dollars to assemble (Trelles et al., 2011). Storing and processing big data is complex, requiring large amounts of storage and processing power of structured, semistructured, and unstructured data collected. Having many different components to implement big data technology within an organization can be expensive (Braganza et al., 2017). In fact, even though most big data solutions use open source software, there are still associated costs, such as the labor expense to enable the solution like designing, developing, deploying, and maintaining the solution (Mousannif et al., 2016).

The costs to implement big data technology can also include hardware, software, resource time, support maintenance, and training for the employees within the organization (Verma & Bhattacharyya, 2017). Implementations also involve setting up a robust security architecture and a governing body to internally monitor regulatory policies and data privacy violations (Verma & Bhattacharyya, 2017). All these requirements and more can incur a high cost to the organizations that intend to implement and invest in big data analytics (Kottasová, 2018). It is also vital to note that the high costs in implementing big data could lead to a lower adoption rate of the technology, especially by organizational leaders in small businesses (Sharma et al., 2014).

However, a high implementation cost could lower the adoption of big data analytics, which poses a challenge for leaders and the organization in achieving a competitive advantage. Understanding the challenges of implementing big data analytics, particularly the strategies adopted when implementing big data successfully, including the considerable investment's cost (Matthias et al., 2017). Big data analytics can provide organizational leaders with the opportunity to outperform their competitors when adopting technology (Matthias et al., 2017). Implementing big data analytics might be time-consuming and expensive, but the advantages such as faster and better decision-making, including new products and services, could significantly outweigh the challenges or barriers over time. A survey conducted by MIT Sloan Management Review with IBM of 3,000 analysts, executives and leaders working across thirty industries in over a hundred countries, revealed that more high-performance organizations were making use of big data analytics than low-performing organizations (LaValle et al., 2011).

The benefits of big data analytics in terms of organizational performance are clear. The superiority in organization performance would be transparent within these companies. However, the investment to implement it within any company can become costly (Braganza et al., 2017). Research studies have shown that telecommunication organizations can leverage existing infrastructures when implementing big data analytics, reducing their cost (Malaka & Brown, 2015). For example, a survey conducted by Strategy Worx showed that large organizations such as telecommunication operators, banks, and retailers must have the necessary technology infrastructure to implement big data (Dekimpe, 2020). However, they do not currently use existing infrastructure in a substantial way (Malaka & Brown, 2015).

Organizational leaders would be required to purchase software, hardware, hire new resources, and introduce new processes. Regardless, the organization would be faced with having to store, manage, and extract business insights from the data collected cost-effectively. Time and cost issues also affect the implementation of big data analytics projects because they are rarely a once-off investment and tend to run long past the end date. Big data analytics projects involve multiple data sources and cross-organizational groups, involving several people within the organization without a finite project end date. However, this can present some challenges and would require senior management approval and buy-in due to the implementation cost.

Organizational cultural change. Managerial misunderstandings about big data challenges and how to tackle them can be significant for big data strategy failures (Gupta & George, 2016). Despite advances in big data analytics, it is evidence that many organizations have not incorporated their business insights into their decision-making processes effectively. Implementing big data analytics comes with organizational challenges when introducing a new system and strategy within the organization.

Organizational cultural change can be a barrier when implementing big data analytics. The term o*rganizational culture d*escribes a set of beliefs, attitudes, and values common amongst employees of an organization (Schein, 1990). The term *data-driven culture* also describes how employees, including the senior leadership team, leaders, technical and nontechnical employees, make decisions based on insights derived from big data analytics (Gupta & George, 2016).

Lacking a data-driven culture is to be one of many reasons for the high failure of big data analytics projects (Gupta & George, 2016). Leaders would sometimes need to rely on their prior experiences or intuitive ideas rather than following data-driven decisions based on evidence. If the organizational leaders do not value a data-driven decision-making culture, then their behavior can influence their employees, affecting the decision patterns throughout the organization (Tabesh et al., 2019). It is essential to know that a data-driven decision-making culture cannot thrive in an organization where the leader is the highest-paid person, and their opinion is the only decision-maker of the decision-making process (Tabesh et al., 2019). A leader that considers only his decisions is called an autocrat leader (Tabesh et al., 2019).

The best data-driven insights generated from skilled data scientists are not executable if the organizational culture does not support such a practice (Anderson & Li, 2017). Some highly paid leaders do not consider the results from the data, mainly if it differs from their preconceived opinions (Anderson & Li, 2017). The leader would not use the insights into their decision making. When the goal of implementing big data, analytics is using the data to enhance organizational decision making and attain a completive advantage.

Another challenge with organizational culture change is the difficulty leaders could face when creating a unified vision to effectively implement big data analytics and an organizational big data strategy. In an evaluation of 330 executives from public North American organizations, the results highlighted the importance of articulating a compelling vision to create organizational buy-ins, and it also showed that not every leader was embracing data-driven decision making (Dekimpe, 2020). Another survey of 108 countries' executives revealed that many decision-makers within an organization lack a shared understanding of what big data analytics is and the benefits or outcomes it can generate for their business (LaValle et al., 2011). Royal Bank of Scotland (RBS) is an example of an organization that can align its marketing staff with their big data analytics initiatives by refocusing their marketing objectives through the development of a new analytics department focused account and customer management. Marr (2016) argued that RBS no longer uses data analytics to prepare products out of the door, but it helps customers achieve the most out of what we offer.

Leaders are to remain committed to data-driven decision making and introduce structural support for big data initiatives with the organization. The organization's leadership team is to formulate strategies and provide structural and financial support throughout the implementation process as a prerequisite for the successful adoption of big data within the organization (Tabesh et al., 2019). The same principle applies when implementing big data strategies, where leaders and data scientists participate in the support to overcome any organizational change barriers related to big data (Mikalef et al., 2019). Successful leaders will provide adequate resources with bureaucratic immunity, access to data, so they can produce data-insights (Tabesh et al., 2019). These teams would consistently explore business opportunities and identify problems for which big data analytics can provide solutions (Grover et al., 2018). Some successful strategies can help leaders create a thriving data-driven culture amongst their leaders and employees.

Leadership commitment and support can lessen the cultural change barriers to big data strategies. For example, managerial commitment to big data initiatives can contribute to the formation of a data-driven culture through sharing the right information with everyone in the organization (Adrian et al., 2018). The leadership provides ample financial support for the acquisition of talented resources and data management systems to address the technological needs. The big data tools are deployed correctly in order to achieve the desired outcomes for the organization. Thus, to become successful at using big data technology, the working leaders and the organization's technical teams must become familiar with the general concepts and applications related to these techniques (Gupta & George, 2016). Leaders are responsible for defining the business goals of big data initiatives, while technical staff like data scientists is responsible for gathering the data, cleaning, transformation, and analysis to generate business insights from information.

In summary, leaders and their technical teams need to establish a common understanding of big data goals amongst themselves as it is a vital step to evaluating the possible implementation challenges that they may encounter. In other words, to mitigate big data implementation challenges, senior and middle management's general understanding of the technology is essential. Overall, having managerial analytics acumen can reduce the organizational cultural change challenges with big data implementation efforts. Organizational leaders' familiarity with the fundamentals of big data analytics leads to a better understanding of strategies for creating a data-driven culture. The technical teams would effectively transform big data into meaningful insights for decision-making to satisfy the business goals. Organizational data literacy can contribute to the technical aspects related to big data analytics processes. Leaders and fellow employees will face cultural challenges specific to developing and implementing big data strategies and organizational processes. An organizational change in the leaders and employees culturally would require some adjustments when adopting big data analytics.

Transition

In Section 1, I introduced the importance of the study, the problem statement, and provide an overview of the lack of strategies for implementing big data analytics solutions successfully. Within Section 1, I discussed components of the study, including the purpose statement, nature of the study, research question, conceptual framework, significance of the study, and literature review. Section 2 also included a detailed description of my qualitative method, the research design, population size, data collection process, sampling scheme, analysis techniques, and reliability and validity. While Section 3 includes the doctoral presentation and analysis of the study findings, implications for social change, recommendations for future study, additional future research, and the conclusion.

Section 2: The Project

In Section 2, I explain (a) the purpose statements, (b) the role of the researcher, (c) the participants, (d) the research method, and (e) the design. I restate the purpose statement and explain the researcher's role as it pertains to the data collection process. I share a detailed expansion of the research participants, method, and design used for this study. Section 2 encompasses a focus on the population, sampling, ethical research, data collection instruments, data collection techniques, data organization techniques, data analysis, and reliability and validity of the research tools used to analyze research findings.

Purpose Statement

The purpose of this qualitative multiple case study was to explore strategies that IT leaders in the telecommunications industry used to implement big data analytics successfully. The targeted population for this study was a minimum of four IT leaders in the telecommunications industry from two organizations that had successfully implemented big data analytics. The geographic area for this research was Seattle, Washington, and New York, New York. The implications for positive social change include the potential to increase the sustainability of businesses, which may lead to increased jobs, revenue, and reducing unemployment in communities. Further implications for positive social change included the potential improvement of the standard of living of the employees by providing permanent and well-paying jobs that enable employees to support their families and contribute to the community.

Role of the Researcher

In research, the researcher (a) collects and manages the data, (b) analyzes the data, (c) evaluates data, and (d) arrives at a conclusive end (McKenna, Myers, & Newman, 2017). Conducting research is a method by which researchers engage in a methodical and definite way to build awareness in a particular specialty (Alase, 2017). Researchers can be (a) goal-oriented, (b) transparent, and (c) concise when describing and articulating the data finds in any study (Malagon-Maldonado, 2014). The role of the researcher is to maintain an unbiased stance (Yin, 2018). The researcher can select the appropriate research method and design that best fits the research study. I chose to conduct a qualitative multiple case study research.

My role as a researcher was to select (a) a research method and design suitable for the study, (b) find qualified participants accountable to provide input through interviews, (c) collect and manage the data from eligible participants, (d) analyze and interpret the responses, and (e) present all the findings. My role as the researcher in this study included the collection of the data to analyze, recognize, and apply the research methodology and design. I selected the appropriate participants and inform them of the study and process. As the principal researcher, I served as the principal instrument of data gathering from the interview process. Throughout the study, my role as the researcher in collecting data required that I adhered to all data protection and privacy regulations. The researcher can gather an understanding of the participants' experience during the semistructured interview process (Kaczynski, Salmona, & Smith, 2014). First, I designed and used the interview questions (see Appendix B) that align with the research study and maintained uniformity of the questions for the interviews. Before conducting any interviews, I gained approval from Walden University's IRB body (approval number 05-14-20-0266406). I conducted interviews with the participants that passed the selection criteria. To assist with the interview process, I used a Zoom video communication, a video conference application to record the audio of all the participants' interviews. I also transcribed all participant interview responses, and last, I used a qualitative data analysis software to store and analyze all the transcribed responses. I used NVivo 12 for Mac software, which allowed me to collect, organize, analyze, and visualize semistructured data that supported transcript analysis, coding, and text explanations.

My knowledge and expertise in the research topic enabled the preparation and how I conducted this research study. I possess leadership experience in both technology and business, in the public and private sectors. I have additionally managed and participated in several successful transformational change initiatives in several organizations. As a senior IT professional, I possess business knowledge acumen and have experience with implementing different technology platforms with experience in using communication strategies to improve IT project performance and profitability. I have over 25 years in the technology space with conversant expertise in the software development life cycle (SDLC) process with delivering technology platforms globally for different industries sectors.

The Belmont report provides researchers with basic ethical standards. I complied with the ethical standards and principles, as presented in the Belmont Report protocols, throughout the study. The Belmont report contains ethical principles and guidelines that researchers will need to comply with to reduce risks by protecting participants from any potential harm from data exposure and by maintaining their privacy and confidentiality (Ross et al., 2018). I adhered to the ethical principles and guidelines standards outlined in the Belmont Report protocol during the duration of the study. No personal or professional relationship existed with any of the participants that were being interviewed. I conducted this doctoral research in the United States of America. I was respectful of the participants by obtaining their consent, observing proper conduct and behavior, and avoiding the unbiased selection of participants.

The role of a researcher would be to mitigate any personal bias. Researchers must mitigate bias that may impact how to collect, record, or analyze the information (Wadams & Park, 2018). It is essential to understand that any bias affects the integrity of the research studies because it may misinterpret information (Bengtsson, 2016). Therefore, researchers can minimize and monitor biases and beliefs by balancing the research study by using objective findings or results. I mitigated any bias through professional discretion and avoided observing collected information through a personal lens. I applied specific strategies to reduce bias by placing my opinion and beliefs aside while conducting this study. Some strategies that researchers can utilize to mitigate personal bias while collecting data include, (a) triangulation, (b) systematic planning, (c) member checking, and (e) coding (Gunawan, 2015). The researcher can consider extra steps to recognize and mitigate personal biases that may influence the research and any antecedent connection. Lastly, researchers can reduce bias to ensure the validity of the research study by cross-checking with multiple data sources (Roulston & Shelton, 2015). A researcher should comply with all the guiding principles to developing the interview questions, mitigate biases, being attentive to participants' responses, and ensure flexibility during the interview process (Roulston & Shelton, 2015).

Another role of the researcher is to establish and utilize an interview protocol to guide participants during the interview process and to ensure that the data collected is consistent and reliable (Spiers et al., 2018). A research protocol process is a tool used by the researcher to examine the correctness of the data collecting process (Yin, 2017). An interview protocol is a guiding principle to developing the interview questions, mitigate biases, being attentive to participants' responses, and ensure flexibility during the interview process (Roulston & Shelton, 2015). I interviewed each participant using the same interview questions, in the same order, in the same process, while conducting member checking and recorded all of their responses. During the interview process of this study, I adhered to Walden University's confidentiality, upheld all data confidentiality, and conformed to all participants' data security standards.

In a qualitative case study, the researcher is responsible for collecting data from various resources such as (a) interview questions, (b) the recordings, and (c) organization's documents (Yin, 2018). A researcher follows an interview protocol to establish a reliable data collection method that is objective and trustworthy, which increases the data quality (Castillo-Montoya, 2016; Kallio et al., 2016). Researchers also can develop and adhere to an interview protocol to improve the quality and consistency of research questions (Yin, 2018). Personal bias can also arise when researchers conduct a qualitative study because of possible open dialog and communication with the participants (Wadams & Park, 2018). I used an interview protocol, depicted in Appendix A, to (a) collect data uniformly, (b) maintain focus on the interview questions in Appendix B, (c) mitigate bias throughout the interview process, and (d) build a rapport with the participants.

Participants

A researcher determines participants based on specific criteria such as participant eligibility criteria, and participant selection sources (Yin, 2018). According to Yin (2018), the participants selected are required to experience the phenomenon of the qualitative study. The participant is to have familiarity and previous involvement with the research study (Vaioleti, 2016). The eligibility criteria for this study included (a) IT leaders who have successfully implemented big data analytics within an organization, (b) IT leaders in the telecommunication industry in the United States of America, (c) IT leaders with knowledge and expertise of using big data analytic strategies to achieve a competitive advantage, and (d) IT leaders with authority to provide information and participate. The participants that took part in the study had a minimum of 5 years' experience, with direct reports (subordinates). A minimum of four IT leaders participated in interviews to discuss the strategies they used to implement big data analytics.

I used some strategies such as snowball and purposeful sampling techniques to gain access to participants for a research study. I used both snowball and purposeful sampling techniques to determine my participants. Purposeful sampling is selecting participants with a wealth of knowledge and experience to contribute (Palinkas et al., 2015). In snowball sampling, participants are selected based on recommendations from other participants (Mortara & Sinisi, 2019). I used social media network tools such as LinkedIn to contact participants who fit the defined criteria for the study (Maramwidze-Merrison, 2016). Researchers can also gain access to participants through their affiliations through their associates (Maramwidze-Merrison, 2016). I obtained access to the participant's through the LinkedIn search engine to retrieve company website contact information. I used the LinkedIn message feature to make my first contact with all the participants. I sent all participants a message of invitation inviting them to participate in the study voluntarily. I also used a snowball sampling technique to locate additional participants for the study. After sending each participant a LinkedIn message, I conducted a screening process using screening questions (see Appendix C) to determine the participants that satisfied the selection criteria. The screening process was to determine which participants were qualified and experienced to participant in the study. During the first call with each participant, I was able to conduct this screening exercise.

To establish a working relationship with participants, I introduced myself in each session through the use of phone calls, video conferencing, and followed up with emails. Telephone communication is a common way to obtain participants' acceptance and develop a rapport (Darcy-Jones & Harriss, 2016). Once potential participants indicated an interest in participating in the study and had met the screening criteria, I provided them with a consent form. The consent form was sent by email to all qualified participants. The participants agreed to take part voluntarily and returned their consent form by email. All consent forms were signed, and showed evidence of the participants' approval to join in the research study. The participants reviewed the consent form before signing and were allowed to ask questions regarding the interview, the entire research process, and the study. Email requests were the most appropriate method used to schedule the interviews with each participant. Participants offered interview dates and times they were most comfortable with and available to participate in the interview. I informed the participants and got permission from them to record and document all interview sessions. I interviewed and recorded all meetings with participants, using the Zoom video conference application.

A researcher conducting a case study research will have to establish a productive relationship with all participants to ensure the implementation of the protocol (Yin, 2017). I developed trust and built a working relationship by communicating with the participants over the phone and via email, taking the opportunity to introduce the interview protocol and study. Trust between the researcher and the participant are critical components for the quality of the data and a successful Yin (2017). A researcher establishes relationships based on trust to gain to better responses from the participants (Castillo-Montoya, 2016). Building a relationship with participants can make for a safe and conducive environment for the participants to answer questions during the interview process (Dempsey et al., 2016). One obstacle to conducting a successful research was the failure to gain access to reliable participants. Trust between the researcher and participant can help obtain reliable data for first-time qualitative researchers (Dempsey et al., 2016). The researcher also appreciates the effort and time the participants contribute to the interview (Yin, 2017).

The goal of the interviews was to retrieve information from all participants without any difficulty or distress. I created a healthy rapport with participants by building consistent communication channels to mitigate any bias and establish a friendly but professional and trusting relationship. Participants may worry about data ownership and confidentiality issues, which may prevent the sharing of accurate information (Yin, 2018). To ensure confidentiality, I used letters and numbers to mask the participants' identities during coding, analysis, and reporting. Each participant understood that they had the choice to withdraw from the study without any consequences. A researcher's ability to eliminate bias in a study means correct interpretation of the phenomenon, which will validate the data quality (Fusch et al., 2018). Risks of introducing bias in qualitative research exists because of the elements such as questions, the participants, or the researcher which can accommodate biases. As the researcher, I had the responsibility to reduce any bias and to make sure that I had achieved a quality research study.

The consent form outlined the research's scope, the participant's responsibility, the participant's freedom to respond to all, some or none of the questions voluntarily, and reassurance that the information provided was confidential throughout and after the research process. The participants are to trust the researcher to maintain the confidentiality of the information shared during the meeting (Huang et al., 2016). I protected the participants' information in a secure encrypted files store on a password-protected hard drive. I would destroy all the information gathered after 5 years following the completion of the research study.

Research Method and Design

Researchers must decide between three research methods to use when assessing the problem and the purpose of a study. These three research methods are qualitative, quantitative, and mixed methods (Harry & Fenton, 2016). The research method I used was the qualitative research method. The focus of this qualitative multiple case study was to explore strategies used by IT leaders in the telecommunications industry to implement big data analytics successfully. The section included a review of the qualitative research method and why I selected it for the study. I also shared why a multiple case study design was suitable for my research study.

Research Method

The qualitative method was the most appropriate approach for this study because the purpose of this study involved exploring strategies to implement big data analytics successfully through conducting in-depth interviews rather than using statistical analysis to explain relationships. A qualitative researcher conducts an in-depth investigation of people, groups, or organizations to examine occurrences in a real-world condition (Yin, 2018). A qualitative method is suitable when researchers endeavor to understand the human motives and intentions governing the performance of the study (Harry & Fenton, 2016). The researcher can build a more in-depth understanding of the event by interviewing the participants. The qualitative researcher asks open-ended questions during the interview process to explore new ideas and understand the participants' experiences. Qualitative research methods are also suitable when researchers intend to understand the range of people who perform behaviors and investigate them with nonnumerical data (Harry & Fenton, 2016). I used the qualitative research method to understand the why, what, and how questions behind the phenomenon. I used a qualitative research method that supports communication with the participants to investigate the strategies used to implement big data analytics successfully.

By contrast, a quantitative research method requires the collection and analysis of data described in statistical patterns (Marshall & Rossman, 2016). The quantitative method involves the building of a relationship between variables (Marshall & Rossman, 2016). Researchers use the quantitative method to test a theory or a hypothesis (Marshall & Rossman, 2016; Yin, 2017). A quantitative researcher will focus on using statistical techniques to answer how much or how many questions, analyze, and measure relationships among variables, including making predictions and generalizations on the outcomes (Makrakis & Kostoulas-Makrakis, 2016). I did not intend to test any hypothesis in my study. Therefore, the quantitative method was not a consistent approach to the study.

The mixed-method approach integrates both the qualitative and quantitative methods into a single research study by combining aspects of both methods (Molina-Azorin et al., 2017). Researchers utilize mixed methods to support the exploration of solutions with qualitative methods and quantitative methods when investigating an organizational problem (Chiang-Hanisko et al., 2016). The mixed-method approach includes surveys, an in-depth analysis of the interview questions, data observations, and statistical analysis to produce a detailed assessment of responses from the participants (Alavi & Habek, 2016). Furthermore, mixed methods research can overcome any limitations of both the quantitative and qualitative methods (Sanders, 2018). Mixed methods were not appropriate for my research, as there was no need to collect numerical data or perform quantitative statistical analysis. Therefore, the qualitative approach was a more appropriate option for this study.

Research Design

The qualitative method consists of a case study, narrative, phenomenology, and ethnography research designs (Yin, 2017). A multiple case study design supports the exploration of a phenomenon (Yin, 2017). It also enables the investigation and explanation of the phenomenon within a precise context (Yin, 2018). Multiple case studies are suitable when exploring peoples' experiences to understand a phenomenon based on the perceptions of a homogeneous group (Yin, 2017). I used a multiple-case study design to explore strategies used to implement big data analytics successfully by IT leaders in the telecommunication industry. I presented a contextual and comprehensive understanding of the study's subject using multiple case studies. A case study design was most suitable because a researcher examines a phenomenon without manipulation, using multiple sources such as interviews and company documentations. A case study design is appropriate when a researcher aims to explain a multifaceted phenomenon (Yin, 2018). Researchers using a case study design can use multiple data sources such as interviews with participants, observations, and company documents to conduct an in-depth analysis of a phenomenon (Yin, 2017). A case study research design requires a flexible method for gathering multiple views from multiple sources to build an understanding of the phenomena portrayed (Wilson, 2016).

The narrative design is reminiscent of the participant experience's storytelling experience, which has led to a research challenge (Miller, 2017). The participant determines an accurate recollection of the facts while explaining the phenomenon from their perspective (Miller, 2017). Narrative researchers examine the participants' life experiences and stories (Madden et al., 2018). Therefore, a researcher conducting a narrative inquiry focuses on the participants' storytelling and life experience. The focus of this study was not on the rendition of findings from the real-world setting, or a study of experience providing a sense of being, but on exploring strategies. Therefore, the narrative design was not appropriate for this study.

A phenomenological research design supports the studying life experiences of individuals in the real world (Cibangu & Hepworth, 2016; Creswell & Poth, 2018). A researcher uses a phenomenological research design to understand people's experiences regarding a common phenomenon (Creswell & Poth, 2018). Phenomenology design focuses on understanding a person's outlook based on their living experience of the phenomenon (Vagle, 2016). Researchers use a phenomenological research design to describe participants' contextual experiences when an event occurs (Willis et al., 2016b). The design was not suitable for my study because its objective was to explore strategies from qualified and experienced participants rather than determine the participants' actual life experiences.

The researcher typically uses an ethnographic research design to explore patterns among people (Creswell & Poth, 2018). The purpose of an ethnographic research design is to study the culture of groups of people over an extended period by collecting data through observation (Fusch et al., 2018; Hyland, 2016; Molloy et al., 2017). Researchers use an ethnographic research design to obtain specific information regarding specific cultures, social groups, or communities (Creswell & Poth, 2018; Pluye et al., 2016). I did not examine a specific culture or set of lived experiences; therefore, ethnographic research designs were not appropriate for my study.

Data saturation is an indispensable component of a research study. Researchers can reach data saturation when the new data collected yields no new insights (Yin, 2017). Data saturation occurs when the data gathered is adequate to sustain the research, and any additional information collected adds no value to the research findings (Fusch et al., 2018). Data saturation means that the data is repetitive, and no additional or new data, themes, or coding is created (Lowe et al., 2018). I continued to gather and analyze data throughout the interview process until data saturation was reached. In qualitative research, a researcher does not have a set method or recipe to determine the exact sample size required to arrive at the summit of data saturation (Boddy, 2016; Nelson, 2017; Saunders et al., 2018).

Population and Sampling

In research, it is sometimes unlikely to examine every participant associated with the entire populace (Poksinska et al., 2016). It is crucial to pick a manageable sample from the population of interest (Hennink et al., 2017). Population sampling is the process of narrowing down a distinct subgroup into a smaller subset of interest representatives of an entire population (Weis & Willems, 2017). The population included a purposeful sample of four IT leaders in the telecommunications industry from two organizations, one located in Seattle, Washington, and the other in New York, New York, that have successfully implemented big data analytics. The sample size should achieve theoretical saturation, such that newly gathered data should provide no additional insights (Saunders et al., 2018).

Data saturation in qualitative research directly correlates with the size of the sample of the research used (Weis & Willems, 2017). The data saturation point was the foundation for determining whether the sample size was adequate. Data saturation occurred after the third participant, which was evident when adding new data from the fourth participant. No further value existed with the fourth participant's response. The possibility exists that when the sample size of the data collected is considerably large, then the data could become repetitive and eventually unnecessary (Dapko, 2016).

I used snowball and purposeful sampling to identify the relevant participants for the research study. Snowball sampling is a method of obtaining participants endorsed by other participants selected for the study (Mortara & Sinisi, 2019). A researcher can add participants to the sample population through the snowball sampling method (Yin, 2018). Snowball sampling helps researchers increase their population size when gathering adequate data to analyze and form results to make knowledgeable decisions (Mortara & Sinisi, 2019). A purposeful sampling includes the identification of reliable and willing participants with in-depth knowledge and experience of the relevant practice to the research (Yin, 2017). Purposeful sampling is a nonprobability method for sampling, as researchers use personal judgment to select the situation that will contain the sample (Saunders et al., 2016). Researchers need to understand that the primary purpose is to explore all the individuals so they can deliver reliability, validity, and accurate results (Fouché et al., 2016). In purposeful sampling, the researcher will identify specific characteristics that participants require to partake in the study (Poksinska et al., 2016). The extent of the participants' knowledge determined the quality of the data for the research study. Willing and qualified participants, who could communicate, were eligible to participate in the research study because of their knowledge and experience.

Ethical Research

Researchers must carefully seek to address the unique and intricate involvement of ethical, legal, social, and political issues related to research participants (Anderson & Muñoz-Proto, 2016). When addressing ethical issues, the researcher will request and receive consent from all the participants before commencing data collection (Grady, 2015). To comply with ethical standards, researchers should not place their participants in uncomfortable situations where either physical or psychological harm could befall them (Dempsey et al., 2016). Establishing an ethical framework protected participants as volunteers and kept their information confidential, which preserved the research study's integrity. Every researcher must attempt to inform potential participants of the study that they can withdraw at any time, the confidentiality of their involvement, and destroying the data 5 years after the research completion (Navab et al., 2016). The researcher is responsible for abiding to research ethics and principles described in the Belmont protocol (The Belmont Report, 1979), the research concerning human participants (Mathews & Jamal, 2014).

Yin (2017) stated that before conducting any form of research using human participants, the researchers must first gain approval. As the researcher, the IRB expects that I complied with the policies prescribed and procedures that they have instituted before commencing this research. Before conducting any research, I sought approval from the Walden University IRB before reaching out to participants for my doctoral study. The IRB was also the final administrative body to approve or deny any deviations from the original research agreement or a change in the IRB process. After I had received an approval notice from the IRB (approval number 05-14-20-0266406), I contacted the participants to determine who was eligible based on the designated criteria. I invited the participants to our first one on one meeting via video conference, to discuss the process and next steps. Once each participant confirmed their interest and met the requirements to participate, I proceeded to send an email to qualified participants only, with information such as an introductory piece of the research and a consent form for each participant to make a voluntary decision to engage with the research study.

During our first meeting, I informed each participant that protecting and safeguarding their information and their identity during and after the research was my utmost priority. A researcher can implement strategies to guarantee confidentiality, such as encoding the participants' names, password-protecting all data, and destroying all research materials 5 years after the designated retention period (Doody & Noonan, 2016). The participants' information and the data they provided were secured to ensure that ethical standards were maintained. I used alphanumeric variables such as P1 through to P4 instead of the real names of the participants and used a password to protect all electronic files for the designated retention period of 5 years. After the 5 years have elapsed, I will immediately destroy all information collected by deleting the electronic data and shred all company-related documents about the research.

Data Collection Instruments

Data collection instruments are tools to gather data, which includes interviews, organizational documents, archival records, physical artifacts, questionnaires, interviews, and observations (Yin, 2018). In this study, I incorporated two sources as data collection instruments when collecting data from the participants. First, through semistructured interviewing techniques by applying open-ended questions (see Appendix B). Second, I collected and reviewed organizational documents from participants to assess the strategies they used during the implementation of big data analytics solutions in their organization. According to Yin (2017), in multiple case studies, asking the participants' interview questions for a research study is the primary technique. The researcher uses data collection tools, including emotional intelligence and interpersonal skills, to gather information accurately. Yin (2018) recommended that researchers incorporate at least two sources as data collection instruments when conducting a study.

I used a semistructured interview approach via video conference as the data collection technique. Kallio et al. (2016) recommended that a semistructured interview method can provide researchers with the opportunity to extract the participant's experiences. As I was the primary data collection instrument, I employed the use of predetermined questions, along with having the ability or flexibility to ask other questions. Then, I used an interview protocol process (see Appendix A) to control the flow and sequence of the questions, and to establish accuracy and consistency in collecting data during the interview process. Researchers apply an interview protocol throughout the interview process to help the data collection process and the sequencing of questions (Castillo-Montoya, 2016).

I used the recording feature of Zoom, the video conference application, during the interview sessions with all the participants. The Zoom application video recording of each interview was processed and saved before the audio component of the interviews was extracted and stored on an external hard drive (USB). The audio recording captured verbatim all the responses from each participant during the interviews. During the video conference interviews with each participant, I took notes using an ECHO Livescribe pen, a smartpen. I transcribed the data stored in the smart pen to Microsoft Word documents, stored and used as another data source ingested into the NVivo 12 Mac software. The data from the smartpen and interview responses were used during the analysis to develop themes or patterns. I transcribed all audio recordings into a word document for each participant to review before ingesting it into NVivo 12 Mac software. The participant verified and validated the transcripts for accuracy. Each participant had the opportunity to provide any additional comments to the interview data for accuracy of content, correctness, and interpretation. The participants made changes to the transcript to ensure data reliability and credibility of the research study. Finally, I analyzed all the data collected using the latest NVivo 12 Mac software to compose themes and patterns.

For this multiple case study, I also collected all the documentation from the participants as physical evidence and a recording artifact of the organization for the research study. According to Saunders et al. (2016), the use of organizational documents as a secondary source of information, such as project documents and company reports, can support the authenticity of the research results. Yin (2017) described how the benefits of multiple sources of data enhance the integrity of qualitative research findings. Organizational documents improved the understanding of the participant's answers to the research questions and provided accurate information about the organization.

I enhanced the reliability and validity of the data collection instrument and process by utilizing the member checking and triangulation. Member checking is a process by which data efficacy is maintained (Marshall & Rossman, 2016). Member checking allows the participants to make changes, provide additional information, clarify, and possibly ask more clarification questions about the research (Birt et al., 2016). Researchers utilize member checking to validate the method and to ensure that participants acknowledge the findings of the researcher's construct of what the participants say and/or do during the interview sessions (Thomas, 2017). As the researcher, I ensured that all the participants evaluated the accuracy and viability of my interpretations. I also applied a member checking process with all participants and scheduled phone calls to review any inconsistencies in the transcripts and initial interpretations. Triangulation is the use of many sources to examine any variations describing the same phenomenon (Burau & Anderson, 2014). Multiple case studies produce a higher level of quality than utilizing a single source when integrating multiple sources of evidence (Yin, 2017). The value of multiple sources of data collection was essential to strengthen the triangulation of data. Therefore, I used the data triangulation technique for this multiple case study to triangulate the conducted interviews and reviewed the company documents provided by the participants.

Data Collection Technique

The data collection technique that I used consisted of the Zoom video conference application, semistructured interviews using open-ended questions, and a review of all available company documents. I collected data using multiple mechanisms such as semistructured interview questions, observation, notes, and audio recordings from video conference, as evidence for the research study. Researchers also use multiple data sources during research studies to provide the integrity of the data and the methodological rigor (Kallio et al., 2016). Researchers can utilize an interview technique to develop the validity and reliability of the results from a collection of data from multiple sources (Kallio et al., 2016). I began collecting data after I received IRB approval, followed by confirmation from the participants. When researchers conduct semistructured interviews using open-ended questions, conducting a pilot study can be optional (Yin, 2018). A researcher will conduct a pilot study to improve and test the suitability of a research instrument (Findley et al., 2016). I used semistructured interviews and member checking; therefore, a pilot study for my research study was not necessary.

Before commencing with the interviews, all possible participants received emails explaining the purpose of the study and invited them to participate. Maramwidze-Merrison (2016) stated that participants taking part in a research study should receive an information package. I provided each participant with an information packet. The information packet contained vital information such as an overview of the study, which included the expected outcomes, and the expectations of each participant. The information package included the interview questions and a consent form, which contained information instructing each participant to review their transcripts. It also included information that informed them of their right to withdraw or not to participate, should they decide not to participate.

I conducted four video conference semistructured interviews with open-ended questions with IT leaders from two telecommunication organizations with a minimum of 5 years' experience implementing big data analytics. The objective of the semistructured interviews and review of any company documentation was to answer the research question: What strategies do IT leaders in the telecommunication industry use to implement big data analytics successfully?

I confirmed the interview schedules based on availability with the participants by email. Participants have the flexibility to choose the date and setting of the interview appropriate to them (Saunders et al., 2018; Spiers et al., 2018). Yin (2018) indicated that a researcher conducts semistructured interviews to observe the participants' nonverbal and social cues during discussions and interaction. Therefore, I decided to conduct my semistructured interviews using the Zoom video conference application. Semistructured interview method can provide researchers with the opportunity to extract the participant's experiences (Kallio et al., 2016). The participant will have a chance when using open-ended questioning techniques to share and elaborate on their answers (Yin, 2017). It is also vital that during the interviews, the researcher should avoid setting any limits on the length of participants' responses to the open-ended questions to ensure uniformity when categorizing and creating themes (Kallio et al., 2016). The application of the member checking process reduced my error rate in the study.

As part of the interview process, the researcher should ask the participants for possible organizational documents related to project implementations. Organizational documents are data sources and can include materials from (a) government, (b) employee, and (c) project (Yin, 2017). I requested organizational documents from the participants, which included (a) project charters, (b) project plans, (c) meeting minutes, (d) project agendas, (e) training documentations, (f) several project emails and (g) organization communications in the form of newsletters, which I then used to validate the study. The researcher should also avoid any bias but should understand and translate the participant's responses accurately. Data triangulation will increase the efficacy of the research findings (Ang et al., 2016). Using organizational documents as part of the sources of data for the research would support combining the results from different sources, data triangulation. I used data triangulation to aid the validation of data from multiple sources. This was a powerful technique to reveal an accurate conclusion of the phenomena.

Advantages and disadvantages exists with the data collection techniques of any research study. The selection of a case study has its benefits to fully depict a participant's experience from data collection, data processing, and findings. However, it was disadvantageous by the fact that data collection could be time-consuming and time expensive to be prepared and examined. Interviews as a data collection technique are useful to obtain insight and meaning into the research study. The semistructured interview method will allow participants to describe the crucial points of concern (Gelderman et al., 2016). Furthermore, using a semistructured interview approach allows the researcher to observe participants during the interview process, and validate the answers received with follow-up questions.

Some advantages of conducting a semistructured interview are that it provides the researcher with the following: (a) insightful information, (b) the questions are tailored and focused (c) the participant and researcher get clarification on items, and (d) allows the participant to share their personal views (Yin, 2018). Nevertheless, a disadvantage of interviews is the possibility of bias from the researcher or participants, which could lead to inaccurate recordings of the discussions and findings (Yin, 2018). Another disadvantage with interviewing was maintaining a healthy balance between encouraging freedom of speech and expression with the participant when leading the interview discussions. It could be intrusive to the participants when comparing this method to other data collection techniques. Conducting online interviews with the participants over a video conference application can be advantageous to the researcher because it (a) minimizes time expenditure, (b) eliminates financial cost or burden, (c) it encourages participants transparency, and (e) removes any geographical location constraints (Seitz, 2016). Transparency is more likely to exist because of the believed anonymity of online interactions (Seitz, 2016). The disadvantage of an online interview can be the lack of intimacy between the researcher and the participant. Lack of intimacy could result in the mode of the environment which is unsuitable for discussions on sensitive matters and can independently increase the absence rate of participants compared to face-to-face interviews (Seitz, 2016).

Analyzing company documents had their strengths and weaknesses. I used company documents as a good source of background information for the research study because they can provide additional details that are often unobtrusive but useful (Basu et al., 2016). Company documents also provide readily available and accurate facts of the organizations. Disadvantages exist to having organizational documents because the information could be obsolete, irrelevant to the period, inapplicable to the research study, disorganized, or incomplete (Yin, 2018). The company information could also be inaccurate, and it may be time consuming to receive and analyze the documents properly. Observation may be preferable because the researcher could directly see what the participant was doing rather than relying on what the document or report says. However, observations are also susceptible to observer bias. Bias can also arise from how the interviewer presents the questions (Weinbaum & Onwuegbuzie, 2016). The interview protocol enabled me to alleviate any inherent risks by conducting semistructured interviews; it helped manage the discussions and secure a bond with the participants.

After IRB approval, I conducted video conference interviews using the open-end questioning approach. If used, a pilot study would test whether the process was adequate and make the necessary adjustments before commencing with the entire research study. I did not conduct a pilot study because my research study focused on a qualitative exploration of identifying the strategies IT leaders used to implement big data analytics successfully. During the interview process, I used the interview protocol (see Appendix

A) as a guide and conducted each video conference interview in a quiet location with each participant for an hour. I followed up with each participant once completing the transcripts. I also recorded each interview meeting using the Zoom application and extracted just the audio component of each meeting. I was able to convert and save the recorded interview files into audio files in an MP3 format. The MP3 files were later converted to a text Microsoft Word file using the software called Sonix. The Sonix Software is an online speech-to-text converter, and the output is a Microsoft Word document that later acted as the transcripts for the participants' responses from the interviews. The Sonix software used the latest artificial intelligence algorithms to convert any MP3 audio file to a Microsoft Word transcript. All interview transcribed responses were sent to each participant to validate before the transcripts were ingested into NVivo 12 Mac to generate themes and sub-themes. I used a smartpen such as the ECHO Livescribe pen to take notes that stand out and mitigate any personal bias during the data collection process. The data collected from the ECHO Livescribe pen acted as another data source for the study. I analyzed the collected data ingested into NVivo and generated themes after analysis, and then I triangulated the themes with the organizational documents to identify the main strategies used to implement big data within their organizations.

I used member checking to improve the credibility and reliability of the research study. Member checking allows all participants to review the findings and responses in transcript form for validation and to enhance the validity of the research study (Wild et al., 2017). Member checking can evaluate and verify feedback from the participants

(Thomas, 2017). I utilized member checking to allow all the participants to validate their responses and make the necessary changes before ingesting the converted textual transcript into NVivo 12 Mac software for analysis. I kept an audit trail of all transcribed responses before and after the participants made changes to their responses for credibility and reliability. In a qualitative case study, research ethics validates using member checking (Simpson & Quigley, 2016). Therefore, the use of member checking would improve the reliability of the qualitative research of the study.

Data Organization Technique

Data organizations can help the researcher easily retrieve and manage data collected to improve the quality of their research study (Marshall & Rossman, 2016). In a multiple case research study, the researcher uses various sources (Marshall & Rossman, 2016; Yin, 2018). The researcher can conduct a case study by creating a database to record all data collected in a systematic method (Yin, 2018). For this research study, I used a video conference semistructured interview and review all relevant documentation as part of the data collection techniques. After I had concluded the interviews with all the participants, the digital recordings remained stored in an external storage device (USB). The USB device was stored in a secured password-protected electronic vault until I began the data analysis phase. Saunders et al. (2018) stated that the researchers protect research participants through confidentiality, better preparation, and securing all the different sources of data collected.

I used the latest NVivo 12 Mac software to organize, analyze, and manage the data collected from the video conference interviews. I also used a Microsoft Word document as the format for the transcribed audio data from the interviews. The transcribed data was collected, saved, and secured on an encrypted external hard drive (USB). After all the interviews, all audio recordings were transcribed into a Microsoft Word document for each participant to review and validate. Yin (2017) stated that the transcripts of digital recordings are prepared shortly after the interview data collection process. I prepared the transcripts a few days after the last interview. I also labeled, categorized, and saved all relevant documents in a tagged file format, using identifiers. Yin (2017) stated that a need exists to label, categorize, and format artifacts from the interviews. I established individual data files and folders for each research participant identified by using a unique identifier and an alphanumeric code such as P1 through to P4 in a chronological numeric sequence for ease of reference. Each participant interviewed had a designated folder to secure their identity and the valuable data collected. The researchers' responsibility is to protect research data, which represents the participant's experience and knowledge (Barocas & Selbst, 2016). To maintain the participants' confidentiality, I secured audio and electronic data files and scanned all the journals in a password-protected electronic vault. Hardcopy documents were electronically scanned and saved to an electronic format. All the data collected for this research study was secured using password-protected and backup, stored in a locked room in my apartment. Following the Walden University IRB mandate, I will be keeping all the data collected for the expected duration of 5 years. After the required data retention period of 5 years has elapsed, I will destroy all the data collected. I will delete the electronic data files and shred or burn all hardcopy documents in my possession.

Data Analysis

The qualitative multiple case study approach consists of gathering and interpreting data from semistructured interviews and reviewing relevant documents. Data analysis is a research method that the researcher utilizes when conducting a qualitative research study (Weinbaum & Onwuegbuzie, 2016). Six data analysis steps recommended for qualitative research studies are: (a) gather all the information, (b) compile and organize the data for analysis, (c) conduct detail analysis utilizing coding scheme, (d) group the data into a sequence of groups or themes, (e) translate the themes, (f) draw conclusions from the data (Yin, 2018). Different data analysis strategies exist, and data triangulation is the most appropriate for a multiple case study (Yin, 2018).

Data triangulation is when a researcher sources multiple separate data-gathering method within a research study (Yin, 2017). In the data analysis process, data triangulation could also be an influencing factor (Yin, 2017). The triangulation process is essential to the validity of a research study (Joslin & Müller, 2016). Researchers use data triangulation strategies to improve the quality of the research with the involvement of multiple data sources. The data analysis process is a critical and integral element of each research study, to guarantee data accuracy and integrity to interpret them appropriately research findings (Austin et al., 2016). The data sources I used for this study were the participants' responses, my note transcript from the ECHO Livescribe pen, and organizational documents. Following compiling the data, I began by disassembling the data.

In disassembling data, there are interview questions presented to the participant, such as what, when, why, and how, which the researcher will conduct data analysis by examining and comparing information (Yin, 2017). I combined both the transcribed data and reviewed documents into a segment of text to identify and categorize thematic characters of the data. Reassembling data happens when a correlation of codes to specific themes is connected to the research question (Saunders et al., 2018). Coding is the method of tracking segmented data using unique identifiers or descriptive words, for natural grouping and categorization (Fugard & Potts, 2015). The coding of data was necessary for recognizing themes and similarities in qualitative data analysis. I labeled and coded all data derived from the participants' interviews. Coding and examining data using NVivo 12 Mac software could provide researchers with an in-depth analysis through recognition of patterns and themes (Roulston & Shelton, 2015). I also utilized the latest NVivo 12 Mac software to compile, organize, and analyze all the transcribed interview responses. I used the NVivo 12 Mac software to group similar responses to enable the identification of patterns or similarities.

Data interpretation and conclusion are also critical to the data analysis process. I collected the data and transcribed the recorded conversations from each participant. I conducted member checking on the participants' responses before proceeding with coding the output. Member checking elevates the quality of the transcribed data collected during the interview with the participants (Birt et al., 2016). It assures that the results from the data collected are valid and reliable (Birt et al., 2016). The member checking process provided an accurate analysis and interpretation of the data collected. The analysis, interpretation, and conclusions of the collected data are dependent on the researcher's tenacity within the research (Yin, 2017). Each participant was provided the opportunity to review and validate the content of the interpreted transcript. Member checking approach presented the participants with an opportunity to provide additional information or insight through the discussion and exploration of the integrated data (Harvey, 2015). The participants' modifications and adjustments to the transcripts were accepted to reflect an accurate encounter of the interviews. The member checking process continued until all the participants were satisfied with the desired outcome of the information. The researcher should be able to synthesize the experiences of the research participants (Sutton & Austin, 2015). Data conclusions comprise of the quotes from participants and documents reviewed following academic procedures and guidelines (Sutton & Austin, 2015). To find a conclusion is an opportunity for the researchers to provide an academic contribution with their findings of the study (Yin, 2017). I incorporated direct quotes from the research participants, supported by academic guidelines to complete the findings, using charts and tables also to represent the findings to support the conclusions of my research.

Reliability and Validity

A qualitative research method measures quality through reliability and validity (Yin, 2017). Qualitative researchers must display rigor within research findings and ensure quality by establishing reliability and validity of the research methods (Amankwaa, 2016; Morse, 2015). The principal elements of reliability and validity of a qualitative research study can include (a) confirmability, (b) credibility, (c) dependability, and (d) transferability. A qualitative research study can become credible and have integrity when the results of the research findings are reliable and valid. Transparency of the research method would guarantee the reliability and validity of the research study.

Reliability

Reliability is similar to dependability, which should commence immediately once the research study begins (Grossoehme, 2014). The reliability of a qualitative study was visible and validated by the improvement of the dependability aspect. Two dependable methods, such as the reviewed data collection instruments and member checking, improved the research study's reliability. To obtain reliability would mean that the research findings presented must be dependable, with no bias or errors (Noble & Smith, 2015). Therefore, to ensure the reliability of qualitative research, data integrity and consistency need to be used to contribute to the study (Paré et al., 2016). The research study should be reliable before the researcher begins to evaluate whether the results of the research study are valid. The researcher always needs to consider the reliability and validity of the research study (Cypress, 2017). The reliability of a research study based on consistency is evident during the analysis and conclusions (Cypress, 2017). Interview protocols, triangulation, and member checking processes, when applied can increase the reliability in qualitative research (Cronin, 2014; Hammarberg et al., 2016; Lub, 2015; Smith & McGannon, 2017). I used the member checking process and interview protocol to establish the rigor of this study and avoid inaccuracy. Member checking lends credibility to the research study (Simpson & Quigley, 2016). The member checking process is useful in validating, verifying, or evaluating the trustworthiness of qualitative outcomes (Birt et al., 2016). All participants had the same number of questions to answer in the same logical order to establish consistency, reliability, and dependability with their responses during the interview. The member checking process enables the researcher to identify any individual bias by requesting each participant's feedback on the interpretation of transcribed data (Kornbluh, 2015). Finally, to enhance the dependability of my study, I used member checking to improve accuracy, prevent researcher bias, and discuss any gaps or confusion with the participants on the interpretation of the transcribed data.

Validity

Validity in qualitative research refers to the credibility of the study (Connelly, 2016; Hammarberg et al., 2016; Munn et al., 2014). The validity of a qualitative research study could stem from the process of (a) credibility, (b) transferability, (c) confirmability, and (d) data saturation of the study. According to Amankwaa (2016), the process of validity increases the integrity and quality of the research findings. The validity of a research study designates the soundness applied to both the methodology and design to ensure that the research findings are the actual representations of the participants' experiences. Validity is also the method for validating the integrity of research results. In qualitative research, the researcher will aim to build on (a) the authenticity, (b) the credibility, (c) the transferability, and (d) the dependability of the research findings (Symon, Cassell, & Johnson, 2016).

The credibility of a research study is maintained when the researcher applies research methods that are scientifically qualified to use for qualitative research

(Bengtsson, 2016). The member checking and triangulation processes can increase the validity and credibility of results from a research study (Birt et al., 2016). Applying triangulation within qualitative research strengthens the research accuracy and validity of measurements (Yin, 2017). Triangulation enables researchers to increase credibility through the use of multiple data sources as evidence for the study. I used data triangulation to ensure credibility by interviewing IT leaders that have successfully implemented big data analytics. I reviewed relevant documentation and analyzed the findings from multiple data sources to confirm the accuracy and integrity of my methodological triangulation process.

The transferability of qualitative research is concerned with whether research conclusions can be transferred to other situations while preserving the purpose and results from the original study (Chowdhury, 2015). Transferability is synonymous with generalization, in which results from the research study are generalized and transferable to other situations (Link et al., 2016). Transferability implies reliability and consistency, which means that in the same setting and data, another researcher could derive a similar result. I ensured transferability by discussing the description of the data details, applicability, the data collection steps, accurate recording, analysis of all data, and findings pertinent to the study. The results informed future IT leaders to assess the transferability of the research study's discoveries and conclusions. This study's results could also support future big data implementations to adopt the same approach as a foundation for future research.

Confirmability defines the ability of objectivity that research findings can be replicable and consistent (Connelly, 2016). Qualitative research can be biased, inductive, subjective, and unstructured, any of which could cast doubt on the integrity of the research findings. When the researcher reduces the subjectivity of the study, it improves confirmability. Furthermore, when the researcher addresses or eliminates bias, it can improve confirmability (Yin, 2017). The researcher should always aim for neutrality and accuracy to ensure the confirmability of the data from the study (Houghton et al., 2013). I maintained a high sense of credibility and validity by following through the research process and guidelines. I also developed plans to ensure consistency in the research process and proactively achieved confirmability of the study. I utilized NVivo 12 Mac software for data analysis to generate themes and create an audit process to assist with the investigation and useful examination of the study information.

Data saturation befalls a researcher if no findings come from new data collected (Marshall & Rossman, 2016). When data redundancy occurs with no further insights exists, this is known as data saturation (Saunders et al., 2018). When the data and documents become repetitive, yielding no new information, the research study is saturated (Bredillet et al., 2017). Therefore, a failure to achieve data saturation in a research study could lead to biases and possible inaccurate findings or results from interpretations of qualitative research (Fusch et al., 2018). Consequently, at some point in the research, I reached data saturation after the third participants' response. No new themes and no new insights existed from the fourth participant after reviewing the new data collected. I conducted all participants' interviews, member checking, reviewed all the documents and continuously examined the participants' responses until no new results from the discussion or newly collected data emerged.

Transition and Summary

In Section 2, I included a review of the purpose of research, the researcher's role, the participants' research design, and method. In this section, I discussed details concerning the data collection process, instruments for data collection, the methods and techniques of collecting data, population and sampling, ethical research methods, and data analysis methods to enhance the integrity of the study. Finally, I analyzed strategies to guarantee the reliability and validity of the qualitative research study, enhancing the trustworthiness, which was significant to confirm the results of qualitative research. Section 3 includes the findings of the developed and completed a research study, and I discuss the significance of the results for professional practice. I used the research study to identify possible strategies that IT leaders of a telecommunication organization used to implement big data analytics successfully. Finally, I also present (a) recommendations for future studies, (b) the implications for social change, and (c) any point to support further study.

Section 3: Application to Professional Practice and Implications for Change

Introduction

The purpose of this qualitative multiple case study was to explore strategies that IT leaders used in the telecommunications industry to implement big data analytics successfully. Organizational leaders incorporate their primary components of the organization, namely (a) people, (b) projects, (c) structure, and (d) technology, to support effective big data analytics implementations, which leads to competitive advantage (Bellini et al., 2016). However, Warren (2016) found that there is still an unusually high failure rate for organizations attempting to implement big data analytics.

To add value to current literature, I decided to employ qualitative methodology, enhanced by the multiple case-study design. Due to imposed social distancing restrictions, the data collection process was limited to semistructured interviews via video conference calls.

The sample was composed of four IT leaders from two different organizations and states. Results from the semistructured interviews were analyzed with the assistance of NVivo 12 Mac software. This specific software program was essential in figuring out the value or perhaps the hierarchy of the present themes. Four themes emerged from the study: (a) communication, (b) training, (c) employee involvement in decisions, and (d) teamwork. These four themes that emerged from the analysis may help IT leaders benefit in developing strategies to support the implementation of big data analytics in the telecommunications industry successfully, and lead to improved competitive advantage and organizational performance.

Presentation of the Findings

The overarching research question aimed to identify possible strategies that IT leaders in the telecommunication industry used to implement big data analytics successfully. The participants were from two organizations located in the United States of America. Four IT leaders participated in a video conference call interview that lasted 60 minutes for each interview per participant. The participants in the study answered nine questions. After the interviews, the participants sent company documents through email as additional information to support the research study. I used NVivo 12 Mac software to help me analyze the research data to determine the main themes of the data. After collecting and using thematic analysis to the data, the following themes emerged: (a) communication, (b) training, (c) employee involvement in decisions, and (d) teamwork during the implementation. All participants emphasized the importance of having excellent communication, the necessary training to upskill, employee involvement in decision making, and increased teamwork pre, during and post the implementation as critical strategies. The participants also emphasized that they benefited from gaining the right training and setting the landscape or tone for communication, which enhanced employee engagement and enhanced transparency before the implementation.

I used Kotter's eight-step change and Six Sigma models as the conceptual frameworks to conduct this study. The findings from this study aligned with four of the steps of Kotter's eight-step change model and supported the peer-reviewed studies from the literature review section. The Six Sigma's model for constant improvement of business processes did not align directly with the themes and may result in further studies to better understand the conceptual framework. I followed the data protocol approved by Walden University's IRB (approval number 05-14-20-0266406). The participants responded to all the questions and provided documentation about their big data analytic projects. I had to decipher the information to identify the different themes depicted in this study. It was also vital that I knew when data saturation occurred during the research study. Saunders et al. (2017) stated that a researcher should understand that information saturation point in qualitative research since it can help manage and support the information collected.

Table 1 represents the profile and organizational demographics of the four participants. Each participant is assigned an alphanumeric value, the number of years of experience in big data analytics, the number of years as an IT leader and each of the two organizations represented as an alphanumeric value.

Table 1

Profile and Demographic Information of the IT Leaders

	Participants			
Parameters	#1	#2	#3	#4
Participant Code	P1	P2	P3	P4
BDA Experience	13 years	11years	14 years	10 years
Year as a Leader	20 years	18 years	25 years	22 years
Location	L1	L1	L2	L2

I assigned identification codes to denote the combination of organization and participant such as L1P1, L1P2, L2P3, and L2P4, and to ensure the confidentiality of the participants' name and organization information was kept. The alphabetic letter L and the numeric values 1, 2, denoted the two organizations, while the letter P and the numeric values 1, 2, 3, 4, denoted the four participants taking part in the research study. The combination of the two denoted the organization and participant.

Theme 1: Communication

The first theme that emerged from the analysis of the participants' responses to the questions and the review of the supporting organizational documents was communication. The analysis of the participants' responses revealed that communication from both sides of the aisle, leaders, and employees throughout the organization was a crucial strategy required to implement big data analytics successfully. The communication theme emanated from all participants' responses and had the highest frequency from the data analysis processed. All participants expressed the significance of communicating during the implementation. They also discussed the importance of communicating extensively and how it was a vital strategy required during the implementation process of big data analytics in their different organizations.

The participants implied that limitless open communication involving all employees affected facilitated a suitable and steady implementation of the planned change. Clear and continuous communication from organizational leaders of their expectations and goals is another aspect of communication that determines the successful implementation of a change initiative (Lewis et al., 2015). Participant L1P1 stated the following:

> It was essential that the leaders frequently communicated with the employees on changes and big data projects within the organization. It was also crucial for employees to communicate with each other in ways that brought about awareness

of the change at hand. Information communication flowed in two-ways, both vertical and horizontal directions.

Floyd (2018) described the direction of communication flows as being either horizontal or vertical. Horizontal communication happens between individuals of the same hierarchical level, communicating back and forth (Floyd, 2018). In contrast, vertical communication happens between individuals of different hierarchical levels and can be downward, upward, or both (Floyd, 2018). Communication during the implementation of the projects was continuous between management and employees with several meetings and shared information with workers in a timely manner. Some examples of downward communication from leaders to employees are through memos, meetings, newsletters, and company emails (Floyd, 2018).

Most IT project failures result from poor communication between leaders and employees in the project network (Gupta et al., 2019). Study participants talked about communication flow. After reviewing their organizational documents, it was apparent from the many company-wide newsletters and project status updates, that communication within their organizations was maintained. Communication is among the most vital elements of any change initiative (Lewis et al., 2015).

Participant L2P3 stated the following:

> I am part of our senior management team in my organization, and I take part in all business and IT-related projects. Over the years, I have developed the trust of the executive management, my peers, and the other teams we work with to maintain communication by informing them of what is coming ahead. The horizon view of

> things can be foggy in the beginning, but it is essential to communicate still what is coming down the line to all teams vertically or horizontally. Perhaps a little too much, I have in the past communicated in person to groups or via email to the different teams. This is to make sure that everyone involved is aware of the project. I have a direct line to the project management office team, who are responsible for communicating project initiatives to the wider audience in our organization.

Participant L2P3 also stated, “Communication was key to our success.” Participant L2P4 stated, “The role of the project management office team was to communicate to the organizational community about the project pipelines categorized into (a) prospect projects, (b) pre-gating projects, (c) approved project, (d) active projects, (e) canceled projects, and (f) completed projects.” In the case of big data-related projects, much emphasis is made on communicating because of the business value, it brings to the organization (Grover et al., 2018). Participant L1P1 explained that “The communication reached everyone who was involved with the project. Employees were on board with what was about to be achieved.” Participant L1P2 stated “Different steps exist in our internal organizational process before a project commences; transparency is always present in our project management office process before any project begins. Therefore, if anyone found any issues, they can raise their concerns and it gets addressed.”

The participant L1P1 also stated “Communication means that we do not work in a vacuum within our company.” The lack of effective communication can result in inadequate or failed communication between senior management and employees within an organization (Kearns, 2014). One of the many critical success factors of change is for leaders to have an effective communication plan (Lewis et al., 2015). Communicating change initiatives ensured that the required project information was shared with all levels and individuals promptly. The participant L1P1stated, “Communication was additionally noticeable throughout the project implementation cycle.” Participant L2P3 stated, “The organizational leaders focused on communicating new changes and defining the what, how, and why to everyone and any individual impacted from the onset was informed perhaps to contribute or learn.”

Organizational leaders should develop communication abilities to successfully implement change (Johansson et al., 2014). All the participants repeatedly expressed that leadership teams needed to initiate communication in their organizations, meaning communication was vertical and top-down from management to the employees. Participant L1P1 stated, “Great communication between brought about inclusiveness and motivated commitment.” Participant L1P2 also stated the following:

> Effective communication existed in the organization because it is part of their project cadence and employee orientation to new change initiatives.
>
> Communicating with the individuals in my group or other business users was the most important strategy used. It also supports the need for open feedback.

The participant indicated that a lot of information sharing was necessary amongst technical teams during projects. Participant L2P3 stated that “communication in our organization is like a four by one hundred meters race, where you have to pass the baton and with that in mind, information needs to be shared with the working community, me and amongst others from technical teams." During the project implementation the flow of information amongst the different teams was managed and controlled through communication. Participant L2P3 expressed that, "All forms of available technology was used, but regular meetings and meeting minutes are key sources to communicate project statuses. It is our organizational culture to over-communicate if that is even a word."

Research findings have shown that communication improves employee support and success rates because of transparency in implementing change initiatives (Fuioaga & Rusu, 2018). Probably the most critical success factor of implementing change was communication. Employees get to see the progress and success of their big data analytics implementation during regular follow-ups, meetings, and project communication. Participant L1P1 stated, "communication also increased employees' confidence, team bounds, and morale pre and post-implementation of all our big data projects. The employee community took part in the change process, from the beginning to the end, so less resistance to the change." The participants confirmed that the procedure of adopting and applying effective communication took several years to complete. The communication strategy produced the necessary goals and received the stakeholders' buy-in to implement big data analytics as a company-wide initiative.

Communicating successfully within the organization promoted the pros and cons of the big data analytics implementation. Organizational communication also helped prepare the strategic alignment of the scope and provided all with transparency for the change. Participant L2P4 stated the following:

> My team and I communicated using emails, the Microsoft Teams application message feature, during the team meeting, or through one on one ad-hoc conversations. In our company, we utilized the Microsoft Teams application to minimize excess paperwork and maximize inclusivity through the use of project notice boards, which is also a feature of Microsoft Teams Application.

Participant L2P3 expressed, "Our paper footprint has reduced using the Microsoft Teams application, library, and messenger services to help us keep track of all the communication. The Microsoft Teams Application was used for training and sharing your discovery."

The participants' interview responses and supporting business documents demonstrated that downward and upward, vertical, and horizontal communication existed during the implementation of big data analytics within both organizations. Data triangulation established the alignment of the participants' responses and company documents which included emails and project materials such as (a) project agendas, (b) newsletters, (c) meeting minutes, (d) project mandate documents, (e) project team structure, (f) project charter, and (g) project plan details. Based on the dimensions of the big data analytics initiatives within each organization, the findings indicated that leaders' horizontal or vertical communication was essential for their project success. The level of commitment to implementing big data analytics could only occur with effective communication throughout the organization. All four participants in the study believed the leadership team must encourage the other stakeholders on the results and concerns about any change during project implementations.

The findings indicated that communicating within an organization improved transparency amongst the leadership and employees, and these findings are consistent with prior literature from Fuioaga and Rusu (2018). These findings are consistent with prior literature showing that communication increased success rates and employee support for organizational leaders to implement change initiatives (Fuioaga & Rusu, 2018). IT leadership assertion provides a positive work environment that leads to employees maximizing their involvement in systems or process change and projects (Daddi et al., 2018).

The findings to the conceptual framework are in alignment with Kotter’s change model. The participants found that a communication strategy was a vital component for the implementation of big data analytics. The participants believed that applying a communication strategy led to a successful outcome of projects, complete leadership, and employee buy-in. The project charter, meeting minutes, and newsletters documentations provided by the participants showed the alignment with the communication theme. It was evidence that the change initiative was communicated within the organization. The findings indicated that a communication strategy could play an important step in accomplishing each level of the Six Sigma model. A communication strategy would apply to all the five principles of DMADV when planning, during and post-implementation, and the sustainment phases of a change. Other literature studies concluded that organization leaders who applied communication strategy would improve the project's change implementation (Johansson et al., 2014). Effective communication was essentially the most critical success factor in change management.

In this study, the IT leaders' strategy seemed to align with Kotter's eight-steps conceptual framework as a foundational change approach to communicate the organizational vision of any change initiative to be implemented within the organization. The communication theme that emerged aligned with Kotter’s change model by supporting the communication of the leaders' vision and benefits of change, eliminating roadblocks, earning employee support and participation. Communication represented a working strategy to be used when implementing big data analytics to sustain and transition to the next phase of the change initiative. Six Sigma theory also helps generate a strategic vision, incorporating data in powerful analytical tools derived from the statistical process control. The findings to the five principles of DMADV (Six Sigma model) with the communication theme had no direct alignment. It was important to note that before using Kotter's change or Six Sigma's models, there needs to be an iterative process to recognize and investigate the change initiative characteristics before implementing the change. Therefore, leaders and employees need to be involved and participate in implementing the change initiative transition from start to finish of the project.

Table 2 represents the frequency with which participants mentioned the word communication during the interview. It also shows the percentages of interview questions answered were the participants mentioned the word involvement as a strategy for implementing change initiatives. Participant L1P1 mentioned the word communication in five of the nine interview questions, including 69% of the collected responses. Participants L2P4 and L2P3 mentioned the word communication in four of the nine interview responses, which was 62% and 61% of the responses received. Participant L1P2 had the least mention of the word communication in only three interview questions and had 60% in the responses.

Table 2

Frequency of Communication

Question where participants response includes the word Communication	Times Discussed	Percentage Value
Participant L1P1, Interview question 1, 3, 4, 5, 9	16	69%
Participant L1P2, Interview question 1, 3, 5	10	60%
Participant L2P3, Interview question 1, 3, 5, 9	12	61%
Participant L2P4, Interview question 1, 3, 4, 5,	13	62%

Theme 2: Training

The second emergent theme was training. The IT leaders indicated that training was a crucial strategy that led to their successful outcome with the implementation of big data analytics. When developing an implementation strategy for a change initiative, educating employees was critical for success. All participants emphasized the value of training employees whose role changed due to the implementation. The participants also disclosed that training or upskilling had a positive influence during and after implementing the change initiative. By offering training opportunities and new or extended knowledge, leaders can build the confidence of their employees, who are vital contributors to successfully implementing change initiatives (Al-Haddad & Kotnour, 2015). Training staff members and leaders in change management procedures has proven to boost employee's self-confidence and trust (Park & Kim, 2015). In order to derive the highest benefit from the strategy, IT leaders offered training and delegated distinct roles to employees assigned to the project members. As indicated by Porter et al. (2015), various kinds of training exist for employees in an organization before, during, and after implementation, such as peer tutorials, mandatory participation in training, improvement of reference sheets, and manuals.

Participant L1P1 stated the following:

> Training was a continuous and fluid step within the organization because we had very few people with the knowledge and expertise in house. We needed to understand the technology and what it could deliver to our business community. Initially, there was a high dependency to acquire knowledge from the vendor of the software to help with the implementation. This dependency diminished over time due to the training we received from the vendor.

Participant L2P3 stated, “external consultants were used for the initial knowledge transfer and expertise of the software. Different teams were assigned to execute and deliver particular activities.” Participant L2P4 expressed that “my team and other group’s responsibilities lay with having the intellectual knowledge of the business. Participant L2P3 stated, “Vendors and external consultants conducted the initial training for the employees that took part in the implementation of big data analytics and the aspects included: (a) workshop training for frontline employees, (b) training backup resources, (c) on the job training, (d) train the trainer, (e) skills and knowledge propagation.”

The importance of training organizational leaders is often underestimated, but without adequate training, the change initiative may be hindered (Al-Haddad & Kotnour, 2015). Participant L1P1 stated, “On the job training had some setbacks because the employees still had their regular duties, which they had to focus on in conjunction with the introduction of this new technology. So, we changed the training delivery method for short training workshops." Training improved the knowledge and understanding of technology, encouraging people to understand the importance of the change. Training enhances performance at levels that are different (Turab & Casimir, 2015). To derive the highest benefit from the strategy, IT leaders offered training and delegated distinct IT functions to employees assigned to the project.

Participant L1P2 mentioned, "I reviewed the vendor's training documentation before the workshops were set up for the managers and technical individuals to evaluate the scope of the training to be delivered to the community. I had to promote and show support for the training phase, considering that inadequate project sponsorship from IT leadership can contribute to project failure, which was supported by Hughes, Dwivedi, Simintiras, and Rana (2016) research study." Participant L2P4 stated, "Training was delivered to first the employees who had a direct or similar role to big data analytics. For example, all our data analysts were trained first because of the prerequisites of data-driven techniques to aid decision-making in gaining and sustaining competitive advantage. Data analysts collect and process data in real-time and have faster access to data within an organization. So, they were the best candidates to be trained by the vendor before the project commenced." This training exercise increased the satisfaction level of the employees and made the change process more continuous. Training ensures that individuals have the tools to help other employees, which may reduce resistance and improve morale. Participant L2P3 echoed a similar response and added that offering training to the employees helped increase employees' confidence and comfort a level with the technology during the implementation process. Training enables our employees to gather external knowledge and use that knowledge to help improve project success (Chen & Hung, 2016).

Participant L2P3 stated, "IT leaders of a change process must continuously measure the implementation process to determine whether additional training for the management and employees is mandatory." It is vital for us IT leaders to get some training in executing essential components of change that should incorporate into daily organizational practices. Participant L2P3 noted, "It is essential that my team and other members of the working community receive the necessary training before, throughout, and after implementation of big data. I cannot direct my team to success without training and having the right resources." Participant L2P3 stated the following:

> We brought in the key experts from within the organization to meetings with the various vendor meetings. My IT team was always responsible for involving business members, subject matter experts to meetings for technical elaboration and depth. We brought about the relationship with our internal business stakeholders and software vendors to participate with the software selection. The software selection process required a vendor presentation of their solutions, after which we internally decide on a product. The IT leadership team identified what resources were needed, what training, who gets trained, and how we would be able to use the tool. We identified and created all of these processes bringing all these experts together and the implementation transition smoothly."

During the follow-up questions, I asked participants to explain further whether they thought their employees benefited from the training workshops that occurred before, during and after implementation of their big data project. Participant L2P3 stated, "The importance of training is that the enablers of the solution had to have an in-depth knowledge of the statistical modeling needed big data analytics.” Other participants also indicated that additional training in statistical models contributed to their achievements and that it was necessary because they lacked the experience and preparation for the introduction of the new processes and change initiative. Their employees were prepared for further tasks and skills after training took place.

Participants L1P1 and L1P2 both expressed that their teams looked forward to the new training, which provided him with an ample and well-planned foundation to tackle and address the changes ahead of the new skills needed to implement big data analytics.” Participant L2P4 said, “I think that training in the statistical model gave the team a lot more pride to participate in the big data analytics project. I think the added knowledge gave them some satisfaction that the organization had invested in them." Participant L2P4 alluded, that the employees felt a greater sense of ownership in the project and believed they were part of the decision-making process. Participant L1P1 used similar strategies and acknowledged his team for taking the responsibility and ownership to drive success.

The company documents supported the participants' responses that they invested much time with training the team extensively to realize the benefits and contribute to future project success. Training workshops for different project groups and employees were organized, such as one-on-one targeted training for subject matter experts and technical leads of the project team. Chen and Hung (2016) stated, that it is best for organizational leaders to seek and gather external knowledge, then implement that expertise to help improve the incidence of project success. After triangulating the responses and documents, there was a positive correlation to the training theme being a key component for successful change implementation.

This theme aligned with a recent literature review. Scholars showed that implementing processes and resources during the change was an essential strategy for successfully completing the change implementation phase (Ahmad & Cheng, 2018). Organizational leaders invest in training and the necessary tools to improve the implementation of a change initiative and enable project participants to provide their feedback and make the required adjustments for success (Bejinaru & Baesu, 2017). The literature study revealed how organizational leaders improved employees' performance through training and established an excellent working environment and teamwork (AbuAlRub et al., 2016).

The findings confirmed the importance of training before, during, and after the implementation of big data analytics to ensure a stable transition. It also indicated that training for leaders and employees was a key strategy when implementing change within an organization. The documentation provided by the participants showed alignment with the theme. The results from the study were consistent with prior literature and suggest that leaders and employees who received training were driven, engaged, and dedicated to the change (Lawrence et al., 2014). Therefore, leaders and employees need the training to be successful when implementing changes (Lawrence et al., 2014). Porter et al. (2015)

indicated that ongoing training conducted within the organization relates directly to the sustainability of change.

The findings of the conceptual framework, the fifth step of Kotter's change model of empowering employees, was aligned with the participants' broad understanding of how their employees felt after receiving training. Participants thought training was an essential strategy for successful implementation methods. The findings did not support the Six Sigma model directly, but a training strategy was vital throughout the entire change process to stimulate and educate the employees to a higher level of performance and commitment to their organization. Two participants shared training documents such as training manuals, training plans, training schedules, and training attendance documents, including the courses that were on offer to the different levels of management and employees that participated with the implementation.

Table 3 includes the frequency with which participants discussed training employees and IT leaders throughout the interview process and the percentage of interview questions answered concerning training as a strategy for implementing big data analytics change initiatives. Participant L2P3 discussed training in four of the nine interview questions, inclusive of 62% of the responses collected. It was the highest response obtained. Participants L1P1 and L2P4 also discussed training in four of the nine interview questions, which was 61% and 60% of participants' responses. Participant L1P2 referenced training in three of nine interview questions, which was the lowest participants' responses of 48%.

Table 3

Frequency of Training

Question where participants response includes the word Training	Times Discussed	Percentage Value
Participant L1P1, Interview question 1, 3, 7, 8	12	61%
Participant L1P2, Interview question 1, 3, 8	8	48%
Participant L2P3, Interview question 1, 3, 5, 8	13	62%
Participant L2P4, Interview question 1, 3, 5, 8	10	60%

Theme 3: Employee Involvement in Decisions

The third theme was employee involvement throughout project implementation. For all four participants, the essential strategy used when dealing with the employee was practicing active communication and close interactions. Employee participation and involvement may constitute teamwork and collaboration to accomplish a common goal (Baruah & Ward, 2015). Teamwork, as well as cooperation, are essential to implement change initiatives as changes in a single product might impact other teams (Longenecker & Longenecker, 2014). Employee participation builds teamwork. The IT leaders in my study all indicated that early engagement and feedback from their employees about the change was vital to improving and implementing the change initiative. Some, however, aired caution because IT leaders must coordinate with other business stakeholders when deciding when to roll out the desired big data analytics change. Project success hinges on the project responsibility and accountability on effective employee interaction (Burga & Rezania, 2017). All participants acknowledged that the implementation of big data analytics has a higher chance of success if IT and business leaders collaborate and engage the appropriate and skilled employees of the change process. The involvement of the skilled employees participating in the implementation process for the planned change was essential.

> Participant L1P1 indicated the following: Obtaining employee feedback from all employees impacted negatively by the change is vital before commencing an implementation to avoid low performers in the team. I say this because the project may not succeed if caution is not taken to review and understand the feedback to ensure the right individuals take part in the project. It is my responsibility as an IT leader to ensure that the project begins well and to educate employees on how the implementation change will benefit them, and not only the organization. It is still important to note that we did not involve the employees in the decisions to determine whether big data analytics was necessary for the organization.

Participant L1P2 echoed the same point but added that "during the initial or presales engagement with the vendor for vendor and tool selection, a small number of employees were involved in that phase of the project cycle." The participants indicated that it was not very easy at the early stages in decision-making to include everyone in the vendor and tool selection. They ensured that only the same key people involved throughout the process are consistently engaged and involved with the change process. Teamwork incorporates groups of individuals involved to accomplish a common goal (Baruah & Ward, 2015). Interestingly, Swanson et al. (2012) revealed that employee involvement in the decision-making process, can benefit employees in learning the value of the change. Participant L2P3 and L3P4 mentioned the following:

> It is essential to involve the various teams at different stages during the implementation process of any project. Every individual that participated had an appointed role or function to perform during the implementation. Several groups of teams were involved with the implementation, such as business analysts, project managers, data analysts, technical architects, and data scientists.

Participant L1P2 explained, "We did not want to burden the employees with the pressure of knowing all the multitude changes that lay ahead until we the management team were certain on understanding the what, why, when and how of the implementation. Participant L1P2 used an analogy "Having too many cooks in the kitchen does not always deliver a positive outcome. We did not think that it was be productive to have too many decision-makers during this phase of the project." The management team, along with some key employees, contributed to deciding what the solution would be, after which a company-wide communication with all employees informed them of the change initiative and implementation. After I reviewed some of the documentation provided, some of the emails requested employees with the expertise to participate and support the change voluntarily. L1P2 stated, "These sessions are designed not to burden employees nor put pressure on a play for pay incentive. Nevertheless, transparency of the change initiative maintained a pleasant working environment." Employees contributed to the project's decision-making process of the implementation of big data analytics and were able to voice their opinions through the organizational notice board and project forums. Participants L2P3 and L2P4 voiced similar responses to having a smaller team of individuals to manage the initial phases of the project, such as vendor presentations and the tool selection process, and this response resulted in data saturation to this study.

The methodical triangulation used organizational documentation for the employee engagement activities conducted during the big data analytics project. All participants provided these documents, which demonstrated that employee involvement was a primary strategy to establish early for big data projects. Several meeting agendas and workshops are organized with the vendors and stakeholders before the start of any project. The documents provided by L1P1 were emails or notices supplied to attend meetings, with the agenda and then minutes from the meetings with information on a planned change initiative. The participants expressed that the employee involvement in the decision-making was necessary to determine the actors before each project commenced. The participant comments aligned with the literature on employee involvement during the change initiative. Through team collaboration and ongoing dialogue, employee involvement could help the organization keep abreast of issues (Stanciu et al., 2016). The findings confirmed how understanding the project's value could increase employees' involvement and lower the employees' resistance to the change. The findings provided IT leaders and employees with a better understanding of the project mandate, resources required, and skills. The documentation provided by the participants showed alignment with the theme. The participants explained that the strategy to involve individual employees earlier in the process boosted the success of the big data analytics project.

Employee involvement aligned with the conceptual framework of the second stage of Kotter's change model to build a powerful coalition necessary to direct the project's change endeavors. The team participating in the change transformation includes senior leadership, managers, and employees committed to improving the performance and financial stability of the organization (Kotter, 1996). The goal of building a powerful coalition was to collaborate to create the necessity and force to participant in the change. However, for a project to succeed, the team would have the experience, commitment, credibility, knowledge, and skills to influence and mobilize change within the organization. The Six Sigma theory did not align directly with employee involvement, but the theory supports the quality process improvement in a project. These individuals become experts and lead the organization through business process improvements. The documentation showed that building a powerful coalition within the organization began after deciding for change.

As shown in Table 4, the frequency with which participants mentioned the phrase employee involvement during the interview. It also shows the percentages of interview questions answered were the participants mentioned the word involvement as a strategy for implementing change initiatives. Participant L1P2 discussed employee involvement in four of the nine interview questions, inclusive of 61% of the responses collected. Participant L2P4 discussed employee involvement in three of the nine interview responses, which was 49% of the responses received. Participant L1P1 and L2P3 referenced employee involvement three of nine interview responses, which was 47% of the responses, which constituted the lowest responses collected.

Table 4

Frequency of Employee Involvement

Question where participants response includes the word Employee Involvement	Times Discussed	Percentage Value
Participant L1P1, Interview question 1, 3, 5,	8	47%
Participant L1P2, Interview question 1, 3, 5, 9	12	61%
Participant L2P3, Interview question 1, 3, 5,	8	47%
Participant L2P4, Interview question 1, 3, 5,	9	49%

Theme 4: Teamwork

Teamwork was another theme to emerge from the analysis from NVivo 12 Mac software. The definition of teamwork included joint participation in decision making and forming a bond to support each other. Teamwork is another critical factor to success in implementing a change initiative (Barrett et al., 2019). Organizational management and employee participation and involvement are crucial to accomplishing a shared purpose when implementing a change initiative (Baruah & Ward, 2015). All organizations practiced some form of team building during the implementation of the big data analytics project.

The participants from my study spoke of how teamwork helped them identify a common strategy with which to implement the change initiative and sustain it through to the business operational stage. Teamwork assists in identifying processes and strategies during a change initiative to create organizational goals, methodology, or engagement and key performance indicators to help measure the team's progress. L1P1 said, "To have teamwork within the team, we as IT leaders will need to create a successful project team within the organization. The project team comprises staff members experienced with subject matter expertise, technical leadership skills, and the development teams." Management and employees have a responsibility to collaborate and work together for a common purpose (Pardo-del-Val et al., 2015). For an organization to achieve teamwork, a project team should be comprised of many different groups within the organization.

A project team is a group of employees of an organization carrying out tasks associated with the project. Project teams can include senior leadership, managers, leads, subject matter experts, non-managers, external parties, and business stakeholders. The groups of people made up the team that would work together to accomplish the common goal. The study participants indicated the need for management and employees to participate as members of the project team and take responsibility for the successful implementation of big data projects.

The project team also takes the lead in implementing change initiatives (Georgalis et al., 2015). Participant L1P1 stated the following:

> Every beginning of the week the project team, which included senior management and other employees, held meetings to discuss what is working and what is not; they also discussed ways of tackling issues and agreed on how to proceed. All meetings had an agenda and meeting minutes for everyone to know their action plan or next steps and who had the ball in their court.

Participant L1P2 response aligned with that of participant L1P1 since they both attended similar meetings. Participant L1P2 added that “during these meetings, teamwork was visible when decision making and individual of the project team negotiated with each other in the group on the way forward. The meetings helped map out the approach or methodology to which the different groups within the project team would operate." Participant L1P2 stated that "I have my style of working and so do several other individuals. Still, we now have to come together to define a useful approach that gets us to the summit of our goal by instituting teamwork."

Participant L2P3 indicated that "the project team must be moving along through partnership and collaboration. As a leader, through teamwork, I developed harmony, dedication, and openness amongst the different groups. We were like a rock band: one sound, one band." Participant L2P4 added that "during project meetings, the management team tends to deal with any challenges the project team members bring to the forefront to discuss. The team could be requesting more funding or approvals for more resources. At these meetings, I had to attend to make decisions or take the information to the executive leadership for approval. Furthermore, I can make a decisive decision at our weekly meetings, which would not slow down our momentum in delivering the project on time. I am part of the project team as a participator and to help foster togetherness and familiarity with the other employees in the team. Less of a hierarchical cadence existed during these project meetings, and everyone knew their roles and responsibilities. It does work when everyone in the team feels like equals."

I observed that both organizations had a significant focus on teamwork, team building, and they supported each other to achieve the desired outcome. Different leadership styles can contribute to various aspects of team effectiveness (Choi et al., 2017). The change to implement big data analytics in both organizations was inevitable, so management used an effective engagement strategy to develop all the functions in their organization. Organizational leaders should try to form prolific relations with their employees and again their loyalty and trust, to reduce their employees' resistance to change (Stephan et al., 2016). Employees within an organization can evolve through teamwork. Organizational leaders have the responsibility to find innovative ways to optimize employee performance and output (Caniëls et al., 2018).

Participants L2L3 stated, "We spend a larger percentage of our life working, so the environment should be conducive." Participant L1L1 asserted that "it is our responsibilities as IT leaders not to create an atmosphere of distrust and conflict for the project to be successful." Teamwork also helps to create a sense of urgency because all projects have a finite timeline. Project success begins with teamwork, which starts by taking small steps. Teamwork brings the different parts of the project implementation, together with a common goal and objective that unifies everyone.

Specifying the tasks to the project team can reduce confusion and improve judgment. Rewarding the project team establishes an excellent example for employees to demonstrate a sense of urgency. Therefore, there was a tendency to take short-term wins to boost the morale of the project team and present progress to the stakeholders and sponsors of the change. Participant L1P1 and L2P3 indicated that "projects could be naturally stressful to the project team because of different project cycles to accomplish and the sometimes very tight timeline we find ourselves in. However, it was crucial to have a stable group, with excellent teamwork culture, working in tandem, and unison with each other."

The findings confirmed how teamwork has a positive effect on employee involvement. Teamwork is also directly linked to implementation success and reduces employee resistance. These findings are consistent with previous literature, which showed that effective teamwork produces improved success rates in implementations of change initiatives (AbuAlRub et al., 2016). The findings were consistent with previous academic literature. Vos and Rupert (2018) found that teamwork improved the success rate of change implementation, and the results of their further study revealed that the partnership also enhanced employee engagement and collaboration. The findings also confirmed that Kotter's change model aligned with teamwork as a strategy to navigate through a change successfully. Teamwork successfully stimulated and encouraged the project team to a higher level of responsibility and achievement for the business.

Kotter’s model first, fourth, fifth, sixth, and seventh steps; sense of urgency, communicate vision, empower employee, short-term wins, and consolidation of improvements, all aligned with the theme of teamwork. Teamwork was essential to Kotter's model, which lists building a guiding coalition as its second step. The project team embodied teamwork, which directly aligned with Kotter's model steps, eliminating barriers, empowered to make decisions, communicated effectively with a single vision, and had the same resources and experienced employees working together to sustain the change initiative. Kotter (1996) suggested that the guiding principle would be to work in tandem as a team. Kotter suggested not to include individuals with self-ego and argumentative tendencies because it does not facilitate a conducive environment for teamwork. The Six Sigma model was used to develop a brand new product or to redesign a current service or process. The proper use of DMADV methodology yields substantial advantages to an organization. The participant's comments and organizational documents provided did not align directly with the Six Sigma model, but teamwork was required to implement the approach successfully. When organizational leaders adopt the Six Sigma model, they experience improvement in product re-engineering and product redesign.

As shown in Table 5, participant L1P1 had the highest level of frequency of teamwork, with 68% of the data collected including a reference to the theme teamwork. This was followed by participant L2P3 with 64% and both participant L1P2 and L2P4 with 60%, the lowest frequency.

Table 5

Frequency of Teamwork

Question where participants response includes the word Teamwork	Times Discussed	Percentage Value
Participant L1P1, Interview question 1, 2, 3, 4, 9	15	68
Participant L1P2, Interview question 1, 3, 5, 9	11	60
Participant L2P3, Interview question 1, 3, 5, 9	14	64
Participant L2P4, Interview question 1, 3, 4, 5,	11	60

In summary, based on the research findings, participants identified four strategies they or other IT leaders would use to implement big data analytics within an organization successfully. The data were collected via semistructured interviews through video conferencing and analyzed using NVivo 12 Mac software. The data collection analysis showed that the participants achieved the successful implementation of big data analytic with the strategies identified in the themes and Kotter's eight-step model. The implementation of big data analytics brought about the use of communication, training, employee involvement, and teamwork, as shown in Tables 2, 3, 4, and 5. Kotter (1996) emphasized that 50% of change implementations are doomed to fail because the leaders have not prepared the employees for the change. The failure in implementing change was an issue with which most organizational leaders are grappling.

Leaders and employees have concerns before implementing any change initiative (Monauni, 2017). Kotter's literature revealed that when organizational leaders are able and prepared for change, there was a higher chance that the workers invested more time and effort, displaying confidence and motivation during the implementation of the change. Also, employees may continue to be loyal to their leaders if they are part of a team that contributes to the decision-making process (Jernigan et al., 2016). Therefore, IT leaders' strategies must lead the entire organization to the desired outcome of success. In this study, a direct and indirect alignment existed between the themes with the conceptual framework, which previous literature also supported.

Kotter's eight-step change model has specific strategies that business leaders apply when building team stability, employee involvement, continuous progress within a company (Calegari et al., 2015). According to Trinidad (2016), some organizational leaders have successfully implemented change through efficient teamwork and communication, adequate training, and employee involvement strategies during change initiatives. As for the Six Sigma theory, it strengthened the principles of change, leadership, and project management (Wiler et al., 2017). These strategies do not directly align with the themes of the study, though the conceptual framework was consistent with the type of specific improvement projects of business processes that would be needed when following the standard DMADV five-phase pattern. Overall, to have a successful implementation of big data analytics with the organization, IT leaders would need to prepare for the change by (a) communicating the change vision effectively (b) having training to upskill the workforce, (c) involving employees, and (d) building strong teams. Leaders must prepare their employees for any change and help them to cope while implementing the change successfully (Kotter, 1996). From this study, all four participants revealed the importance of the four themes mentioned in the study and how the themes contributed to understanding the strategies used to implement big data analytics.

Applications to Professional Practice

The applicability of the findings concerning the professional practice of business detailed what IT leaders consider to be essential strategies to successfully implement a change initiative such as big data analytics within the telecommunication industry. Dynamic change strategies are necessary for organizational leaders to adopt to lead their organizations to remain viable in a competitive environment (Yi et al., 2016). This study may be useful to other organizational leaders who attempt to implement a change initiative successfully within their organization. Based on Kotter (2012), the basic need for organizational leaders is to remain competitive and survive over time. Leaders would now have to understand the tools for implementing change in order to succeed and keep their competitive advantage in a highly volatile environment (Jeong & Shin, 2019). By identifying what strategies make some leaders successful, other organizational leaders can acquire the necessary skills and knowledge and create their strategy or plan for their respective industry and business. The findings of this study may have a positive influence on identifying these strategies.

Overall, the qualitative results are of relevance to IT leaders because they provide a more profound understanding of the essential elements linked to implementing big data analytics successfully. By analyzing the IT leaders' expectations and experiences, we could see crucial strategies used for the design and implementation of a successful big data analytics project from using a multiple case study design. The study participants were skilled and experienced IT leaders with a tenure of over 10 years of big data analytics experience. The findings also indicated that the strategies were critical to the organization's project team adoption and delivery of big data projects successfully within their respective organizations. The participants emphasized the significance of being proactive, having open and continuous communication, providing adequate training and workshops, defining clear roles and responsibilities for the project team, having a top-down, bottom-up approach with employee involvement, and creating a thriving teamwork culture to truly successful change implementations. The participants also insisted on the importance of having a working process model and documenting the entire processes across the different functional areas and reusing the same successful model again and again for future implementations. IT leaders in telecommunication must understand how to successfully implement big data analytics because of the benefits it brings to the organization to remain competitive. The significance of this study would help determine the best strategies and techniques for IT leaders to use during the implementation of big data analytics.

Theoretically, it appears simple to note the critical success indicators for implementing big data analytics projects, but reality showed that there was still a high project failure rate. More complicated sets of problems or serious project implications could influence the project failure rate, but that will need further investigation. This study highlighted the relationship between management and employees and some tangible strategies used during the implementation process. These strategies serve as a foundation for a standardized change initiative process for IT leaders to use to reduce high failure rates. The findings of this study could also serve as a foundation to increase productivity and minimize financial losses. IT leaders who successfully implement change initiatives can increase productivity, reduce financial losses, and become more competitive. All four themes that emerged from the study, aligned with Kotter's eight-step change model but only partially aligned with the Six Sigma methodology DMADV.

The four themes of (a) communication, (b) training, (c) employee involvement in decisions and (e) teamwork correlated and aligned with several of Kotter's model steps, such as (a) establish a sense of urgency regarding the need for change, (b) build a powerful coalition, (c) create a vision and strategy, (d) communicate the vision, (e) empower employees to act on the change vision, (f) plan and create for short-term wins, are essential and necessary to ensure a successful implementation of a change initiative. DMADV methodology develops the ideal business model destined to satisfy the customers' needs. The method is associated with the creation of new services and products. The crucial thing to note is that the product or service did not exist. It is also essential to know that the DMADV methodology could be used for new and existing processes to improve performance and technology, but it sometimes provides unfortunate outcomes. This study focused on introducing a new technology into the organization.

Nevertheless, the DMADV methodology supports identifying areas for improvement when developing a new product or process. The study's result focused on identifying strategies for successfully implementing big data analytics and not on identifying areas for improvement. The DMADV methodology does not show a direct correlation to the themes identified in the study. It was also important to note that none of the participants had mentioned they used any conceptual framework or theories during the implementation of big data analytics projects.

Kotter’s eight-step change, and Six Sigma change models provided the conceptual framework for this research. The four themes were found to be directly aligned to Kotter’s change models and partially to Six Sigma. The data analysis revealed that IT leaders used strategies communication, training, and involvement of employees and teamwork to implement big data analytics in their respective organizations successfully. According to Babbie (2015), IT leaders could become successful by recognizing strategies that other IT leaders have used to implement big data analytics successfully. Though the participants had a limited perspective of the conceptual framework, they achieved success when implementing big data analytics.

Implications for Social Change

The study’s implications for positive social change include the potential to increase the sustainability and competitive advantage of businesses, which could lead to an increase in jobs, revenues, and possible reductions in unemployment. Business leaders who implement change initiatives effectively can bring down costs and be more competitive (Van den Heuvel et al., 2016). Improved organizational performance using big data analytics can lead to an increase in employee wages, revenue, and financial performance (Grover et al., 2018). Thus, this study could positively impact social change by creating higher wages and creating a collaborative working environment for employees. Organizational success might also provide business leaders with the opportunity to invest more money into the communities.

Furthermore, an organization with exceptional financial standing as a direct result of a change initiative can attract more investors and improve stakeholders' confidence in the organization. When businesses thrive, their employees may gain better work compensation through bonus schemes and overtime. The implications of this study might drive steady employment and help to reduce the cycle of poverty. Furthermore, when organizational leaders are successful in implementing change, employees become loyal and committed, having a more positive outlook, which creates a healthier working environment. Therefore, IT leaders who successfully implement change initiatives can increase productivity, reduce financial losses, and become more competitive.

Recommendations for Action

Four recommendations emerged and correlated with the purpose and research question of the study. IT leaders wanting to implement change initiatives need to select effective strategies. These findings from this study would aid them in successfully implementing a change initiative within their organizations to gain competitive advantage and increase profitability. The outcomes of this study indicated four effective strategies to drive a triumphant change process success. Based on the results, these strategies are (a) effective communication, (b) training, (c) employee involvement in decisions, and (d) teamwork.

The first recommendation of this study is that IT leaders communicate continuously, openly, and regularly with the project team members, vendors, external contractors, stakeholders, and other organization employees. During any change initiative, the leaders should communicate the following vision, objectives, implementation plan, and project process at the appropriate time of the project life cycle. The management and employees must communicate both vertically, downward, and upward, and horizontally. According to Saruhan (2014) indicated communication flows can either be horizontally or vertically, and the response can flow both downward and upward, this depends on the initiator. The participants mentioned that better success was achieved when they used both of those communication variations throughout the pre-implementation, during implementation, and post-implementation to sustain each phase. The participants in the study also observed the most significant success with communication was that everyone in the organization was informed, prepared, understood their roles, and knew when the change would take place. It also helped employees better understand the reasons and benefits of the implementation of big data analytics or the change. Great teamwork is also a by-product of effective and continuous team communication. Communication can help employees become engaged, help them feel empowered to be dedicated, and indulge in the big data project success.

The second recommendation from this research is to develop and conduct practical employee training throughout the organization. The training schedule and training audience identification are critical milestones that need to be reached before the implementation begins. Training is essential to ensure that employees understand the expectations and have the necessary skill to support the delivery of the big data analytic project. Training in statistics for employees who had no prior knowledge of statistical modeling was vital to implementing big data analytics. Training done during the implementation phase conveys as well as creates the expertise, abilities, and strategies required for the change. Training post-implementation reinforces and supports the evaluation of the big data project's implementation to ensure the sustainability of change. Training provides the employees with new skills required for the change. The results from the study and the participants highlighted the importance of IT leaders obtaining the necessary training related to the implementation of change initiatives.

The third recommendation is to make sure employees are involved before the implementation of the change. The benefits of early employee involvement are that the employees are retained, motivated, and talented employees are attracted, nurturing a learning environment, and they care more about accomplishing the goal. More importantly, employee involvement results in effective teams, better communication, enhanced morale, significantly less anxiety, a good relationship among coworkers, innovative thinking, higher efficiency, and greater success with the change. It leads to an early evaluation of what is needed to implement the change successfully, which may mitigate the risk and reduce the change or project failure rate. In every business, employee engagement has continuously been the top priority for remaining relevant and competitive. The IT leaders interviewed indicated that employee involvement means employee engagement, and it was an essential strategy to have when implementing big data analytics. The participants also recognized that motivated employees meant better performance and tenure during the project's life cycle and within the organization.

The fourth recommendation is to encourage teamwork when implementing a change initiative. Teamwork provides employees with the ability to interact with each other effectively and efficiently to accomplish a shared goal. The value of teamwork and team building through effective communication is vital because both management and employees can influence the implementation of the changes. The participants revealed that teamwork fostered creativity, learning, and increased efficiency. The participants also indicated the importance of teamwork when implementing a change because it builds trust, promotes a sense of ownership, and blends complementary strengths to help reduce risk and improve the effectiveness of implementing big data analytics successfully.

IT leaders in a telecommunication organization may be able to use these recommendations to implement big data analytics successfully. Applying these recommendations can also help IT leaders to minimize the failures to implement big data analytics. I plan to convert this study into an academic paper suitable for publication and to share these findings with IT professionals and organizations, as well as distribution outlets such as (a) academic research journals, (b) business journals, and (c) science journals. I intend to publish this study in Walden’s ScholarWorks database, ProQuest so that fellow students and researchers can access the information. The findings from this study may be shared with IT leaders in other telecommunication companies, as well as IT leaders from different industries, through presentations at conferences and consulting training to provide them with a broader perception of strategies to use when implementing big data analytics successfully. I also intend to approach leading business-consulting firms and forums to expand my knowledge on other strategies that could influence the implementation of big data analytics. I would be readily available to answer any questions about my study.

Recommendations for Further Research

The purpose of this qualitative multiple case study was to identify strategies that IT leaders in the telecommunication industry can use to implement big data analytics successfully. The limitation identified was the sample population size of 4 participants from two different organizations. The sample size was representative of the study period but was also a standard limitation of qualitative multiple case studies. The limitation in the sample population size limits the transferability of the research results to different telecommunication organizations. The researchers should have a broad range of participants than a small population for analysis (Marshall & Rossman, 2016). Therefore, conducting further research on a more extensive organization sample population may provide additional insights into different strategies for implementing big data analytics. The future researcher could support views from a broader spectrum of participants, including business leaders, to identify the strategies that make implementing big data analytics successfully. After performing the study, the findings aligned to some steps of Kotter’s eight-step change model results, while with the Six Sigma model, it did not directly align. I recommend further qualitative research on the effectiveness of the suggested strategies (a) communication, (b) training, (c) employee involvement, and (d) teamwork, in other telecommunication organizations. Recommendations for future studies would include conducting quantitative analysis to assess the findings of the recommended strategies to implement big data analytics. Quantitative research provides the measurement of the recurrence of the strategy recommended (Fugard & Potts, 2015). For example, a quantitative study measures the frequency of the suggested strategies such as the number and types of training courses on offer and attended during the implementation of the change initiative, which could extend and provide new insight on the results on training.

Reflections

The doctoral program at Walden University provided me with the opportunity to conduct this research to identify strategies that IT leaders use to implement big data analytics successfully. During the doctoral program, the Walden University provided me with the essential tools and knowledge to become an independent scholar to be able to conduct research. The entire experience was enriching but also very challenging, having to work and study at the same time. I began my doctoral program to bridge the gap between the world of practitioners and academic scholars by getting graduate students to perform research in real organizations and on real business problems. The decision to select the industry, the research question, and participants were informed by articles I had read which led me to want to understand why big data implementations had a considerable failure rate. My interest was in big data analytics, as I would like to explore the use of the solution as the next step in my career.

I encountered several challenges in completing my doctoral study. Still, I was able to leverage the materials and tools Walden University provided. My excellent chair, my daughter, niece, and classmates also offered support through the completion of my prospectus and proposal, final study, and the oral defense presentation for conducting my research. The continuous effort and perseverance have resulted in preparing this research study on a topic of interest, which is rewarding and has provided me with additional knowledge on how to conduct a research study and leadership skills for implementing big data analytics.

My perception changed during the study, as the IT leaders provided insight into how they were successful with their implementations. I also realized that even though the failure rate was considerable, some IT leaders would continue to succeed. During the data collection stage, the participants were very engaged and showed much interest in my research. I am very privileged to have had participants who were open-minded and contributed immensely to this research. It does raise the idea of why there are not many consultancy capstones, where graduate students research an organization's actual business problem.

As an IT professional, I am satisfied with my educational progress, achievement, and gratitude for Walden University, which would allow me to become a scholar. The doctoral study comes from my own goal I set for myself after completing my MBA. I believe that the experience and knowledge I have gathered during this period would serve the community and me well when I conduct further research studies in the future.

Conclusion

The purpose of this qualitative multiple case study was to identify strategies that IT leaders use to implement big data analytics successfully. Although a considerable number of big data analytics implementation trials fail, the results of the study may provide IT leaders with some strategies with which to implement big data analytics successfully. Change remains inevitable, as organizations try to survive in the ever-changing economy. Therefore, implementing change initiatives was crucial to organizational success. The identified strategies in this study could be the starting point for understanding how to implement big data analytics successfully. A total of 22 themes emerged from the analysis using NVivo 12 Mac software, but only four themes were significant strategies. All four participants attained success in their projects and suggested the necessity of effective communication between management and employees, training and workshop sessions to all involved, employee involvement earlier in the change process, and efficient and effective teamwork with the project teams.

In the study, I tried to learn from IT leader experiences and the strategies used to reduce the instances of big data analytics project failures. The results from this study showed that although the failure to implement big data analytics was considerable, using the suggested strategies identified could increase the success of implementing this change initiative. Therefore, I would recommend that the results from the research provide IT leaders in the telecommunication industry with valuable insight on how to use strategies when implementing a change initiative or to implement big data analytics successfully in the future.

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Appendix A: Interview Protocol

Interview Protocol	
What you will do	**What you will say—script**
Introduce the interview and set the stage—often over a meal or coffee	Hello. My name is Delton Aneato, and I am a doctoral student in the Doctorate of Business Administration program at Walden University. I want to thank you for participating in this research study "To identify strategies that would support the successful implementation of Big data analytics." Please, I would also like to inform you that this interview session will be recorded, and confidentiality will be maintained.
• Watch for non-verbal queues • Paraphrase as needed • Ask follow-up probing questions to get more in depth	1. What, if any, strategies have you used to implement big data analytics in your organization successfully? 2. What role did you play in the implementation of the big data analytics system? 3. How do you evaluate the effectiveness of your big data analytics implementation strategies? 4. Based upon your experience, what are some of the specific organizational improvements and outcomes realized since the implementation of big data analytics in your organization? 5. What, if any, strategies have you used to address employee concerns before the implementation of big data analytics? 6. What key obstacles have you encountered with the implementation process and how did you resolve them? 7. In retrospect, what, if anything, would you have done differently during the implementation process? 8. What type(s) of training did you and your team receive before implementing a big data analytics system? 9. What additional information would you like to add to the current organization, and its strategy in implementing big data analytics?

Wrap up interview thanking participant	I would like to thank you for taking the time to participate in the study.
Schedule follow-up member checking interview	I will also like to inform you that I will be reviewing the recording from the interview. I will be transcribing your answers to the questions I asked during the interview. In the following days, once I have finished transcribing your answers, I will contact you via e-mail. I will provide you with a summary of my transcript of your answers for each question. You will also be requested to verify and confirm by e-mail if the information is accurate and correct. You will be able to change any information or add additional details if missing.
Follow–up Member Checking Interview.	
Introduce follow-up interview and set the stage	After reviewing the recording of interview, I summarized your answers and transcribed them for easy reading. I have included a summary of the recorded transcript of the meeting.
Member checking will be conducted by sending all participants an e-mail with their transcribed responses.	Please kindly review each question and response confirming by e-mail of your satisfaction for each answer. Below is a summary of my comprehension of your answers. Please inform me of anything that could be missing or inaccurately worded in the transcript. You are also welcome to correct or modify any of the responses. But please notify me in your e-mail response of which statements were changed or where you may have added additional information
	1. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed
	2. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed

	3. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed
	4. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed
	5. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed
	6. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed
	7. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed
	8. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed
	9. Question and succinct synthesis of the interpretation—perhaps one paragraph or as needed

Appendix B: Interview Questions

Interview Questions

1. What, if any, strategies have you used to implement big data analytics in your organization successfully?
2. What role did you play in the implementation of the big data analytics system?
3. How do you evaluate the effectiveness of your big data analytics implementation strategies?
4. Based upon your experience, what are some of the specific organizational improvements and outcomes realized since the implementation of big data analytics in your organization?
5. What, if any, strategies have you used to address employee concerns before the implementation of big data analytics?
6. What key obstacles have you encountered with the implementation process and how did you resolve them?
7. In retrospect, what, if anything, would you have done differently during the implementation process?
8. What type(s) of training did you and your team receive before implementing a big data analytics system?

What additional information would you like to add to the current organization, and its strategy in implementing big data analytics?

Appendix C: Screening Questions

Screening Questions

1. How many years have you been working in a Technology Department (IT)?
2. How many years of experience do you have with big data analytics?
3. Have you been involved with implementing big data analytics? (Yes/No)
4. Was the implementation of big data analytics successful or unsuccessful?