6-4-2024

Effective Leadership for Supply Chain Management in the Big Data Era

Tianshu Wu
Walden University

Walden University

College of Management and Human Potential

This is to certify that the doctoral dissertation by

Tianshu Wu

has been found to be complete and satisfactory in all respects,
and that any and all revisions required by
the review committee have been made.

Review Committee
Dr. Richard Dool, Committee Chairperson, Management Faculty
Dr. Patricia Polastri, Committee Member, Management Faculty

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

Walden University
2024

Abstract

Effective Leadership for Supply Chain Management in the Big Data Era

by

Tianshu Wu

MA, University of Central Oklahoma, 2004

BA, Guangdong University of Foreign Studies, 1983

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

Walden University

May 2024

Abstract

The diffusion of big data technology undergirds a fast and far-reaching digitalization process that has posed challenges for many supply chain organizations. Big data refers to large volumes of data from various sources in real time. Although the literature indicates the benefits and challenges of deploying big data within supply chain operations, there is a lack of research on the problem of lag-behind and the impact of digital disruption. The purpose of this study was to examine the impact of big data and leadership strategy on supply chain management. The research questions focused on the current perceptions of big data by modeling the concepts of assimilation. A qualitative Delphi method was used to gather multiple sources of information through three rounds of questionnaire to derive consensus. A purposive sampling procedure was used to select at least 30 participants to form the expert panel in this study, the overall 78 expertise were involved in the process. The Delphi findings contribute to the extant knowledge by identifying opportunities, challenges, barriers, and strategies linked to the emerging 5Vs (volume, velocity, veracity, variety, and value) digital transformation trend from the perspective of supply chain experts. The research addresses a gap in the existing knowledge on the desirability, feasibilities, and challenges of big data related to digital transformation strategy. It further presents a framework for the role of leadership in digital transformation within supply chains. The study may effect positive social change by providing knowledge that supply chain leaders can use to transform siloed operations to an ecosystem, which may result in the burgeoning of supply chain infrastructure oriented toward meeting customers' needs.

Effective Leadership for Supply Chain Management in the Big Data Era

by

Tianshu Wu

MA, University of Central Oklahoma, 2004

BA, Guangdong University of Foreign Studies, 1983

Dissertation Submitted in Partial Fulfillment

of the Requirements for the Degree of

Doctor of Philosophy

Management

Walden University

May 2024

Dedication

This dissertation is dedicated to my deceased parents, who gave me their love and encouragement to achieve my dreams. To my wife, Jana Chen, my daughter, Christina Wu, for filling my life with love, joy, and happiness. To my sister, Yihong Wu, and brother, Tianhao Wu, for their understanding and to my well-wisher schoolmate Hong Zhang and middle school teachers, Jiaxin Li, and Hong Lin.

Acknowledgments

Working on this dissertation was a tough journey. There were times when it seemed hard to get through it due to various reasons and circumstances. However, with persistence and a keen focus, I finally completed it. There are many people who provided help and support, without which this dissertation would never have been finished. Hence, my special thanks and appreciation shall go to the following:

To Dr. Kenneth Sherman for his guidance in developing initial proposal for my research topic,

To Dr. Richard Dool for his guidance and advice on paper content during my entire dissertation journey.

To Dr. Patricia Polastri for her guidance in reviewing and evaluating research design and method for my dissertation.

To Dr. Tara Kachgal for her guidance on Forms and Styles to meet manuscript for publication requirement.

And very much grateful to URR, IRB, Writing Center, and the Center for Research of Walden University and my cohorts for providing invaluable feedbacks at various points in the dissertation process.

Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction to the Study

The proliferation of data is a key characteristic of contemporary society. According to the International Data Corporation (2019), the amount of digital data will be as high as 40 trillion gigabytes by 2020 as compared to approximately 2.8 trillion gigabytes in 2012. The International Data Corporation predicted that the big data technology and service market would grow at a compound annual growth rate of 34%, reaching a scale of 274,000,000,000 U.S. dollars by 2022. Big data is not only characterized by its structured, semi-structured, or unstructured format, but it is voluminous (Vijayarani & Sharmila, 2016). The 5V (volume, velocity, veracity, variety, and value) feature of big data illustrates the limitations of traditional information processing. Simply acquiring these data is not enough; business leaders need to have the capability of strategically maneuvering these data to obtain competitive edge.

In recent years, business researchers have found that big data analytics (BDA) has a positive influence on supply chain operations (Gunasekaran et al. 2017; Wamba et al. 2017). The supply chains adopting the BDA are referred to as “big data-driven supply chains” (Kamble & Gunasekaran, 2020). Forty-five percent of the supply chain operations from retailers like Wal-Mart and Amazon are driven by big data (Sanders, 2016). According to an October 2013 report by the Industry Market Research and Analysis Company, service providers, manufacturers, and retailers are the main industries that most often use big data in supply chain management (SCM). Gawankar et al. (2020) conducted a study on investments in the big data-driven supply chain in Indian retail 4.0 context and found a positive relationship between BDA and supply chain performance measurement because big data-driven decision-making contributes to improvements in supply chain processes, logistics, inventory control, and cost reduction.

The advent of big data has made it possible to integrate management concepts and information technology (IT) with supply chain operations, which has allowed for the innovation of supply chain models and improvements in supply chain services and management. Now, there are many BDA tools being used in SCM. For example, IBM, HP, Oracle, SAP, Dell EMC, Amazon, and other vendors have launched many big data software suites that are highly integrated with existing enterprise resource planning (ERP), SAP, and other manufacturing execution systems. How to take advantage of these tools and how to adapt to the Big Data era strategically through digital transformation have been hot topics among supply chain scholar–practitioners because only 17% of supply chain managers had adopted BDA techniques (Siddique et al., 2021). It is necessary to investigate why there is a low uptake in digital transformation in SCM. Moreover, low adoption of BDA in SCM has overshadowed profit-making capability and competency of any organizations (Wamba et al., 2017). Compared with other industries such as banking, healthcare, life science, and energy management (Siddique et al., 2021), these sectors have succeeded in BDA application when dealing with huge amount of data. If this study can assist supply chain managers in optimizing organizational performance with increased profit-making and competency in meeting customer demand, it will change conventional data handling system (such as siloed system in SCM) to analyze the complex data structure of today’s business organization (Siddique et al., 2021).

Background

Addo-Tenkorang and Helo (2016) conducted a literature review across all sectors and found that big data has not only grown at an incredibly fast speed but has also impacted industrial enterprises as well as governmental institutions. However, a clear understanding of big data across industrial operations and supply chain network does not seem adequate. A definition of big data is overdue because there has been a lack of consistent efficiency and effectiveness across the supply chain network. Therefore, practitioners in the supply chain network have called for SCM stakeholders to work together to enhance efficiency and effectiveness in information and communication processes to obtain competitive advantage (Gunasekaran & Ngai, 2004).

Velocity and veracity of big data necessitates the need for SCM to monitor product life cycle, product planning, warehousing, and inventory management. These activities generate a huge amount of data that requires big data technology to store, manage, process, interpret, and visualize these data into valuable information. At the 13th International Conference of Computer Systems and Applications in 2016, scholars emphasized the importance of supply chain process through supply chain operational reference modeling that called for transformation of the way supply chain is currently designed and managed since the opportunity and challenges would derive from these data sources (Abla et al., 2016).

Huang and Handfield (2015) conducted research on the impact of ERP on SCM maturity models across different companies. Their study findings indicated that the ERP improved company return on investment and helped businesses in strategic sourcing from customer demand all the way through suppliers' relationship management. However, the ERP system is inadequate for assessing supply chain performance across different company environments (Huang & Handfield, 2015). Therefore, the existing ERP system needs to be enabled to allow for the analysis of big data to strategically advance SCM.

Klein's report emphasized the importance of the big data in aiding performance measurement in SCM. The storage, acquisition, and processing of these data for the best practice of SCM depends on the quantity and quality of the data. The application of the big data not only enables SCM to be more effective and efficient, but also challenges the organizational capability of BDA. It is likely that smart utilization of the data will separate tomorrow's winners and losers in the SCM arena (Klein, 2017).

Lamba and Singh (2017) conducted a literature review to look for the gaps in research. They searched literature published between 2012 to 2016 and found that the utilization of big data in SCM remains nascent when checking business activities from procurement, manufacturing, and logistics. They stated that the low uptake of big data for use in making SCM decisions deserves attention. The main reason behind this low acceptance of big data is due to less theoretical research focused on SCM model that can be adopted from, let alone a huge upfront investment is required for building business analytic capability (Büyüközkan & Göçer, 2018). Lamba and Singh outlined several key aspects in operation and SCM with a low-adopted usage percentage in the big data application across different countries and regions. In sum, the application of the big data in making SCM decision is not seen to gain performance improvement and competitive edge.

Tiwari et al. (2018) conducted literature review on the development of BDA applications in SCM. They used systematic literature reviews through key word searching for articles from 2010 to 2016 and found that BDA applications were an important trend and tool to extract useful information and wisdom for decision-making. The quick development of the 5Vs features of big data changed the way in which business leaders made decisions. The extracting technique for big data mining challenged the reliance on the existing information processing tool because of the large amount of data flow in the form of speed and coverage. Big data refers not only to the volume, but also to its veracity and value. Their study provides an overview of the evolution of big data from a factor affecting a single sector in one industry to an encompassing feature that covers every sector of business decision-making.

Kazim (2019) conducted a case study on the impact of leadership style on digital transformation initiatives in France. Kazim noted that the critical role of any individual leader, regardless of level, is to execute and implement the initiative through adequate communications, and vision sharing with followers in the process of digital transformation. The study findings indicated that building up the leadership communicative capability in digital technology is the prerequisite for a successful digital transformation regardless of leadership styles in medium and large-sized organizations. Therefore, leaders' knowledge of IT in the digital era may positively change the nature of work, training, moving, and other dimensions of organizations—for instance, the use of technology, change in value creation, structural change, new market opportunity, financial performance, and new models of business operations (Matt et al., 2015).

The advent of big data has changed the way many businesses operate. Many companies have transformed decision-making process from conventional wisdom to digitalized analytics based on multiple data sources or big data (Sanders, 2016). Research articles on SCM in the existing ERP, SAP, IBM, and Oracle systems has indicated both the impact of big data on business performance and the rethinking of leadership effectiveness in SCM (Gunasekaran & Ngai, 2004). There might involve in changes in business operational model, leadership style, management strategy, organizational culture, and decision-making mechanism. Application of the BDA involves the prediction, forecasting, assessment, planning, implementation, and evaluation of organizational performance (Gunasekaran et al. 2017; Lamba & Singh, 2017; Sanders, 2016; Wamba et al. 2017; Tiwari et al. 2018). However, none of these researchers addressed the relationship between leadership commitment and business analytics capability building in measuring leadership effectiveness. This gap in the research exists even though business leaders know that the assimilation process is an important part of data acquisition, storage, and IT. The extent to which assimilation of big data technology is an importance measurement of leadership effectiveness in supply chain operation is not known, which has resulted in inconsistent criteria for measuring leadership effectiveness for SCM practitioners.

Problem Statement

The fast and far-reaching operational digitalization process has posed challenges for many organizations and has resulted in them falling behind in this decision-making transformation (Heavin & Power, 2018). Every day, 2.5 quintillion bytes of data are created, and 90% of the data today were created within the past 2 years, according to research published in 2018 (Shields, 2018). It is expected that the data size will reach up to 44 zettabytes or 44 trillion gigabytes by 2020 and that it will be approximately 163 zettabytes in 2025, per a report published in *Economic Times* (Gupta et al., 2020). The distinctive characteristics of big data as represented by the 5V (volume, velocity, veracity, variety, and value) concept presents many technical, operational, and social challenges for business analytics. The general problem was that business leaders are lagging in the systematic adoption of digital technologies, which may make their organization's performance less than optimal. The 5V characteristics of big data are challenging organizational assimilation because only 17% of enterprises had implemented BDA in one or more supply chain functions in 2017 (Nguyen et al., 2018). The process of collecting, organizing, and analyzing large sets of data to discover patterns and other useful information has not been widely deployed. According to a report from the International Data Corporation (2011), the overall created and copied data volume in the world was 1.8 zettabytes, which had increased by nearly 9 times within 5 years (V. Ahmed et al., 2017). It is expected that this figure will soon double at least every other 2 years (Yin & Kaynak, 2015). Given the growth in data as well as the emergence of emerging tools, a direct connection between BDA and SCM seems likely (Waller & Fawcett, 2013).

The specific management problem was that the diffusion of digital technology is outpacing the ability of leadership to adopt and execute digital transformation strategies since traditional business models and IT in supply chain operations have been separate and siloed in many firms (Sibanda & Ramrathan, 2017). Many supply chain leaders are awash in big data yet are engaged in fragmented implementations rather than a systematic and coordinated effort (Sanders, 2016). Therefore, there was a gap between leadership commitment and digital transformation in supply chain operations.

Purpose of the Study

The purpose of this qualitative classical Delphi study was to determine how a panel of at least 30 subject matter experts, all of whom were SCM professionals in the United States, viewed the desirability, feasibility, and importance of successful digital transformation of SCM through use of the big data. In line with the problem statement and research questions (RQs), I sought to establish criteria to evaluate what constitutes a successful digital transformation for SCM in the Big Data era. A successful digital transformation contains a series of elements that builds up a maturity model for organizations. This maturity level can be viewed as a comprehensive indicator that reflects an organizational success level in digital transformation. Therefore, as a subjective and qualitative method, the Delphi method can be used not only in the field of forecasting, but also in the construction of various evaluation index systems and the process of determining specific indicators (Daniel & White, 2005; Ju & Jin, 2013). To assess a successful digital transformation, it is necessary to evaluate its desirable and feasible elements.

Research Questions

In line with the problem statement indicates, I sought to answer two RQs, which were:

RQ1. What are the challenges and or barriers that result in SCM being lag in digital transformation?

RQ2. How is the desirability, feasibility, and importance of digital transformation of SCM impacted by use of the big data?

Theoretical Foundation

Several theories offer both a deductive and inductive explanation of big data in SCM. Given the forward-looking view of digital transformation in supply chain operations, I chose to apply the dynamic capability theory (DCT) in the study. I did so because the dynamic capabilities' framework is an entrepreneurial approach that emphasizes the importance of business processes, both inside the firm and in linking the firm to external partners (Wamba & Akter, 2019). DCT also focuses on the importance of critical resources and good strategy that could well address how a process of assimilation could be achieved for a successful digital transformation in supply chain operation as part of a larger ecosystem in applying the BDA (Chen et al., 2015).

DCT differs from resource-based theory that emphases digging into a firm's existing advantage. It emphasizes a firm's agility to shift the environment toward favoring the firm's routine operations. In the era of big data, companies that excel have demonstrated their ability to leverage data for internal innovation and creativity. This has translated into rapid product and service innovation to meet customer demand (Hajli et al., 2020). The leaders of these firms know how to turn their existing internal competence by integrating external sources into their sustainable competitive edge. Therefore, DCT emphasizes the key role of strategic management in appropriately adapting, integrating, and reconfiguring internal and external organizational skills, resources, and functional competences toward changing environment (Teece & Pisano, 1994).

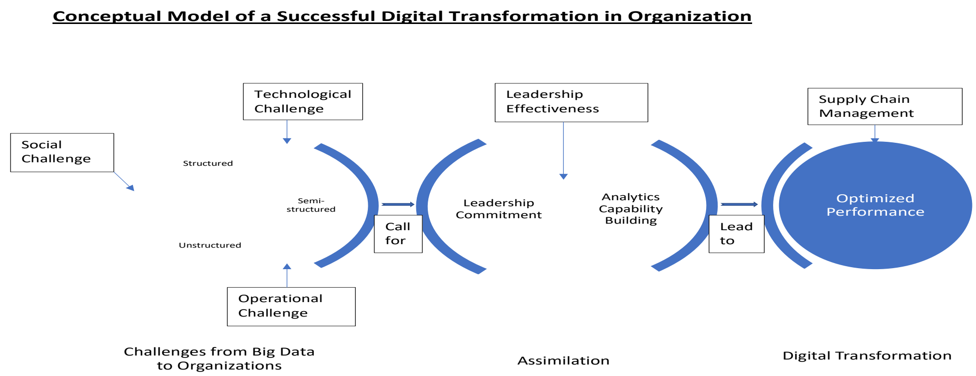
Teece and Pisano (1994) argued that the new product and or service would have to be derived from the firm's agility capability to meet market demand through digital capability building and leadership commitment to BDA. Hence, the DCT offers dynamic capabilities as an emerging paradigm of the modern business firm that draws on multiple disciplines and advances with the help of industry studies in the United States and elsewhere (Teece & Pisano, 1994). Given these factors, the DCT was a good fit for me to address the study's RQs.

Conceptual Framework

The challenge of big data for organizations is two-fold. First, technically, big data would impact the existing organizational infrastructure of information processing capability. Second, externally, the presence of big data has changed the way in which stakeholders perceive, demand, and expect the service level offered by organizations. Alternatively, how well organizations as a part of a larger ecosystem adapt themselves to this changing environment challenges SCM leaders' agility to respond to big data and commitment on building the analytic capability for their organizations. It is a process of mechanizing the decision-making using BDA. The extent of assimilation determines the level of a successful digital transformation. The conceptual framework for this research is presented in Figure 1.

Figure 1

Conceptual Framework



Nature of the Study

How to define a leadership effectiveness has long been associated with task-oriented performance and financial outcome. Recently, due to the digital revolution, researchers have begun to link leadership effectiveness with information application (Gartzia & Baniandrés,2016). In general, the leadership performance and effectiveness measurement have not been differentiated conceptually in the age of the big data, but in fact, evaluation of a leadership effectiveness has surpassed conventional wisdom (Marshall et al., 2015; Spil et al., 2017). In the information era, SCM leadership effectiveness has been implicitly viewed based on how leaders could successfully apply BDA in SCM. However, there is no consensus on the criteria for gauging leadership performance in SCM arena due to low uptake of BDA across industries and sectors

(Siddique et al., 2021). This phenomenon dominates SCM, which impedes the creation of a unanimous criterion for measuring leadership effectiveness.

A Delphi consensus study with leaders in SCM development and academic research was conducted. Some background information about information techniques is discussed and how they are used in the supply chain. Also, previous attempts to measure leadership with criteria was reviewed, the benefits and uses of information techniques in operational settings were introduced. How these measures apply to the SCM context, and how to evaluate key performance indicators in general were illustrated. There is more information given about the study definition, and the gaps in the literature are outlined. The overall goal of this research was to contribute to the development of a transparent and reproducible process to evaluate the leadership effectiveness that will be used across different SCM networks.

Ever since the initial application of the Delphi method by Rand Corporation for the U.S. air force project in 1950s, the Delphi method has been widely used in both academic and practitioner research across different disciplines. The Delphi method has been applied in the fields of education, business, and health care, in addition to engineering, environment, and social science (Dimitrijević et al., 2012). In addition, the Delphi approach, unlike other research methodologies, has been commonly used in forecasting; estimates based on the subjective judgment of a panel of experts can be helpful in areas where no empirical data are available (Farell & Scherer, 1978; Linston & Turoff, 1975). The Delphi study method was consistent with my desire to build a consensus on leadership effectiveness criteria for SCM. I sought to do so through three rounds of questionnaires to derive at least 51% agreement on the leadership effectiveness measurement criteria (see Loughlin & Moore, 1979). My findings may aid SCM practitioners in evaluating leadership performance.

Many studies in the literature have indicated that results of the first round of any Delphi investigation are characterized by diversified opinion (Linstone & Turoff, 1975). However, after several iterations, there is a tendency for subjects to achieve consensus. Dalkey and Helmer (1963) considered this as almost inevitable. An important issue among researchers who use the Delphi technique is to understand what is referred by the meaning of consensus. Loughlin and Moore (1979) suggested that there should be at least equal to 51% agreement among respondents.

The nature of this study consisted of a qualitative classical Delphi approach to build consensus regarding a forward-looking strategy deemed desirable and feasible for the use of big data in SCM. By using this qualitative approach, I was able to obtain consensus to answering my RQs. Focusing on the application of BDA to aid decision-making process was also consistent with the continuous improvement objective of SCM leaders. To avoid the subjectivity issue in each round, I applied quantitative analysis to determine the most common value or variables so that each round of questionnaire was empirically observed and set. In this way, I could make the Delphi study as objective as possible. The steps for conducting this Delphi study were as follows:

1. Identify no fewer than 30 respondents (panel of experts from the supply chain management professionals in the United States).
2. Define the problem (factors, challenges and or elements).

3. Round 1 brainstorming question with an open-end format on challenges, factors, and barriers from SCM professionals in the trend of digitalization.
4. Round 2 questions based on the answers to the first-round questions will be delved deeper into the topic to clarify specific issues (narrow-down).
5. Round 3 questions are aimed to rank essential challenges, factors and or barriers for a successful digital transformation in terms of desirability and feasibility for SCM, and hone-in on the elements of agreement like "What is it the experts are all agreed upon?" A consensus will be generated based on the most agreed challenges, factors and or barriers.
6. Present the findings.

To minimize the subjective issue in the Delphi method, I quantified the rounds of question statements to seek consensus. Specifically, this three-round Delphi approach required at least 30 participants to verify their level of agreement regarding the challenges, factors, and/or barriers; participants wrote comments on each if they considered it necessary and ranked the items for importance. Each item was analyzed quantitatively using the percentage of agreement ratings, importance rankings, and the number of comments made for each item. Then I qualitatively examined the findings by performing thematic analysis. The interquartile range (IQR) is a statistical metric that represents the spread of data around the median. It encompasses the middle 50% of the observations. Therefore, if the IQR is smaller than 1, it indicates that over 50% of all opinions are concentrated inside a 1-point range on the scale (De Vet et al., 2005). The

Delphi method is commonly employed in studies and is well recognized as an unbiased and rigorous approach for establishing consensus (von der Gracht, 2012).

Definitions

Assimilation: The extent to which technology diffuses across organizational processes as part of a three-stage post diffusion process (i.e., acceptance, routinization, and assimilation; Hazen et al., 2012; Saga & Zmud, 1994). Gunasekaran et al. (2017) paraphrased the term *assimilation in detail* to denote these three stages with details. Therefore, assimilation is referred to as the three components with each emphasizing perception, governance, and diffusion of big data across the entire organization (Gunasekaran et al., 2017).

Big data: Huge volumes of data captured from a variety of sources in real or near-real time (Lamba & Singh, 2016).

Big data analytics (BDA): The use of data, analytical tools, computer algorithms, and techniques to derive meaningful insights and identify patterns (Jeble et al. 2018; LaValle et al. 2011).

Big data ecosystem: An environment of interconnected systems, platforms, and databases. The data ecosystems are sociotechnical complex networks in which actors interact and collaborate with one another to find, archive, publish, consume, or reuse data as well as to foster innovation, create value, and support new businesses (Oliveira et al., 2019. P. 589).

Data characteristics: The nature of data features such as structured, semi-structured versus unstructured, and so forth.

Data technology: Technologies that enable the collection, storage, processing, and distribution of data.

Digital transformation: A term that originated from Andal-Ancion et al.'s (2003) article "The Digital Transformation of Traditional Businesses," in which the authors introduced the concept of new IT (NIT). NIT encompasses the harnessing of opportunities to create new business models. NIT are driven by information intensity, electronic deliverability, customizability, aggregation effects, search costs, real-time interface, contracting risk, network effects, standardization benefits, and missing competencies (Andal-Ancion et al., 2003). With marketplace digitalization, businesses rethink of what customers value most and creating operating models that take advantage of what's newly possible for competitive differentiation (Berman, 2012). Therefore, the digital transformation is commonly referred to as the need to use new technologies to stay competitive in the internet age, where services and products are delivered both online and offline (Mergel et al., 2019).

Ecosystem: A set of actors with varying degrees of multilateral, nongenetic complementarities that are not fully hierarchically controlled (Jacobides et al., 2018).

Leadership effectiveness: A term that has various definitions depending on leadership styles, behaviors, focus, and strategy. From Quinn's framework of complex leadership in 1984 to integrated competing value framework by Vilkinas and Cartan (2001), there is no consensus of what makes an effective leader (Tricia Vilkinas et al., 2019). The emergence of big data has challenged notions of conventional leadership and led to a rethinking of leadership effectiveness. In this study, I used an integrated definition of leadership effectiveness. This included a leadership focus on big data, talent and technology management for big data, and culture development, as managerial and organizational practices suited to influence big data decision-making capabilities (Shamim et al., 2018).

Management commitment: Constant support for big data initiatives and the creation of strategic and action plans for successfully executing them; management commitment inculcates a data-driven mindset across the entire operations and SCM (Lamba & Singh, 2018).

Supply chain management (SCM): In this study, a series of integrated activities that deliver value on a consistent basis to customers and consumers through the alignment, linkage and coordination of people, processes, information, knowledge, and strategies across the supply chain to facilitate the efficient and effective flows of material, money, information, and knowledge in response to customer needs (Stevens & Johnson, 2016. p. 19-37). The term "supply chain management" varies in practice and across disciplines (Durach et al., 2017). Regardless of the variation in its definition, the core element in any SCM is business processes (Brinch, 2018).

Assumptions

SCM is a broad topic that covers a large range of aspects starting from market demand all the way through suppliers' and buyers' relationship management. When people talk about supply chain, it is generally meant for logistic activities in supply and demand. It could be referred to as the whole stream along the supply chain network, it could also be related to part of the whole stream, even it could only mean logistics.

Therefore, the concept of the SCM varies with the underlying activities along the chain. Further, the practice on industrial standard in the SCM vary with countries and regions due to different level of economic development. In this study, the SCM, in general, is referred to as the whole stream starting from front door of a manufacturer all the way through the end user, i.e, from customer order management to the suppliers' relationship, which processes cover procurement of raw material, manufacturing, distribution, logistics, retail, and individual users along the chain stream.

This research result is based on the survey from a panel of 30 experts in SCM in the United States. The findings cannot be applied universally since the extent of digital transformation initiative varies with country and region. Situation in one region or country might not be applicable in another place due to difference in country policy, technological status, demographics, economic scale, and customer experiences. Nevertheless, the findings could serve as a reference across industries of the other countries in terms of digital transformation effort.

Scope and Delimitations

The purpose of this research is to determine a consensus among a panel of 30 experts from a SCM professional association through a controlled brainstorming process to addressing the RQs. In the field of SCM, there is no consensus on the evaluation of a leadership effectiveness in the Big Data era because the existing information processing technology and system are separate and siloed, which renders the measurement of the leadership effectiveness inconsistently in the United States. It is vital that a broadly accepted measurement criteria for gauging the leadership effectiveness for the supply chain practitioners. The current criteria for measuring the leadership effectiveness in the SCM still remain unchanged even though the big data concept is overdue. Moreover, the low uptake of the BDA technique has far lag behind the pace of digital transformation. The reason for being lag behind and low acceptance of the BDA capability building is closely related to the leadership commitment (Silahtaroğlu & Alayoglu, 2016; Migliore & Chinta, 2017; Merendino et al., 2018; Yadegaridehkordi et al. 2018; Raut et al., 2019). Also, the implementation of the digital transformation and building of the organizational capability to undertake such a transformation has been costly. To be practical, the organizations involved will be limit to an annual gross sale of 1,000,000 USD and above with at least an in-house IT team with data accessibility.

The empirical studies from literature review emphasized heavily on the critical role of leadership for various organizations in leading the digital transformation initiatives regardless the leadership styles in practice. However, conventional leadership performance measurement missed IT assimilation that a leader shall be agile on. The commitment on the IT learning and building becomes an integral part of their leadership effectiveness, which embodies in their decision-making process. Given this call, this study is limited to the extent of the assimilation of IT for their organizational decision-making mechanism as an objective performance. To make advantageous use of IT is now a prerequisite for business analytics capability building. For this reason, the leadership effectiveness under the Big Data era has been integrated with a new layer of performance on IT. So is the digital transformation.

Limitations

It is well known that the Delphi study is good for forecasting, estimating, and areas where there have been no empirical data available. In addition, the Delphi approach is a controlled process of brainstorming that is used for gaining consensus on a policy, strategy, and tactics from a group of experts (Linstone & Turoff, 2002). It is inevitable that the subjectivity will be remained regardless how well to remove bias in the process of conducting the research. However, a lot of cautious instrument and approach will be applied during the process to minimize the effect of bias. To this end, the quantified result will be aggregated by running statistical analysis for each round of questionnaire to derive ranking of the issues. Another issue in this study will be from limited data source because the data collection comes from professional association that might limit the opportunity of the input from other sources, which could be a biased representation. Finally, the cost-effective way of conducting this research has rendered our sample size being limited although 30 participants could satisfy a sample size requirement statistically.

Significance

To address the problem of lag-behind in digital transformation, impact of digital disruption on leadership, and management effectiveness as well as organizational performance (Kumar, 2015; Kane et al., 2016), many companies are setting up corporate venture capital funds to tap into the digital ecosystem (Sibanda & Ramrathan, 2017).The ecosystem, according to Jacobides et al. (2018), can be categorized into stream of business, innovation, and platform with each stream focusing on a unique interactive dimension. The platform ecosystem takes a “hub and spoke” form to allow firms to be connected to a central platform via shared or open-source technologies (Jacobides et al., 2018). By connecting to the platform, firms can not only generate innovation, but also gain access to the platform’ marketplaces where the platform participants foster entrepreneurial action under coordination (Jacobides et al., 2018). To address the issue of leveraging the emerging technologies and the leaders’ capability to apply BDA for sound decision-making is of a significance in transforming siloed system to the digital ecosystem (Vera-Baquero et al., 2015; Sanders, 2016; Sibanda & Ramrathan, 2017). If the supply chain operation leaders are still unaware of the emerging digital disruption (Bughin, 2017; Skog et al., 2018), they will likely encounter a restrained uptake of digital technology and obstructed formulation of effective strategies in the supply chain operations (R. Ahmed et al., 2014).

A review of the literature on this topic showed a paucity of research on approaches to leaders’ effectiveness in strategically aligning with digital ecosystem in SCM amidst digital transformation (Andal-Ancion et al., 2003; Berman, 2012; Sibanda & Ramrathan, 2017; Mergel et al., 2019; Oliveira et al., 2019). Through addressing this gap, the study will contribute to the strategical alignment of organizational leadership (Migliore & Chinta, 2017) with SCM effectiveness by prompting a digital transformation initiative in response to the digital ecosystem (Sibanda & Ramrathan, 2017).

Significance to Practice

The study will create a threshold for building a consensus on leadership effectiveness criteria for the SCM through three rounds of questionnaires to derive at least 51% agreement on the leadership effectiveness measurement criteria based on digital transformation initiative (Loughlin & Moore, 1979), which findings will help SCM practitioners in evaluating overall leadership performance.

Significance to Theory

The study will contribute new knowledge to the academic research with an implication of theoretical guidance for the leadership effectiveness in the Big Data era.

Significance to Social Change

This study could generate greater understanding of how the product end-users envision leadership effectiveness in context of shifting supply chain network from transforming customer experience, operational process all the way through business model innovation. The research could bring changes in consumer society by complementing end-users with a group of suppliers through ecosystem-based value creating stream instead of a single, combined offerings under a traditional buyer-supplier arrangement.

Summary

There is an ample discussion on the big data phenomenon, impact of the overall business society, current situation, and challenges in SCM and operations in this chapter, each of which has been integrated into the presentation of the problem statement, together with our conceptual model for a successful digital transformation. Background of the study through literature review across disciplines has reflected a need for more academic research to provide empirically based guideline for practitioners, especially called for thorough study on the big data that could generate competitive edge for businesses to gain advantage. The fact that the low acceptance of the big data usage and fragmented development of the existing IT system in SCM continues has gone far against the trend. New management research has shown that about 47% of the total number of indicators of organizational performance are related to nonfinancial management (Dossi & Patelli, 2010). However, mere financial performance measurement for the leadership effectiveness has always been a focal criterion for the SCM performance, which renders SCM far behind the pace of digital transformation initiative. What hinders the development of the digital transformation, how the digital transformation effort shall be, and what solutions or suggestions could be made for the SCM practitioners become the purpose of this research. The rationale for taking the Delphi approach has also been elaborated based on the nature of this research.

Through the classic Delphi study, it is anticipated that the research findings would aid SCM practitioners in theorizing leadership effectiveness measurement from the empirical data observed from a panel of at least 30 experts in SCM as a forward-looking view, deemed desirable, feasible, and the important use of the big data. Hence, I examined how big data affects the digital transformation of SCM. This dissertation will be proceeded with the following order. Chapter 1 is the introduction, Chapter 2 will be for the literature review, Chapter 3 will be on methodological presentation, Chapter 4 on result, and Chapter 5 for discussion, conclusions, and recommendations.

Chapter 2: Literature Review

The fast and far-reaching operational digitalization process has posed challenges for many organizations that fall behind a decision-making mechanism transformation (Heavin & Power, 2018). The general problem is that business leaders are lagging in the systematic adoption of digital technologies, which may make their organization's performance less than optimal (Ross, 2015). The 5Vs' characteristics of the big data are challenging the capacity of the organizational assimilation because only 17% of the manufacturing have implemented BDA for enhancing distribution performance in one or more supply chain functions (Nguyen et al., 2018). The specific management problem is that the diffusion of digital technology is outpacing the ability of leadership to adopt and execute digital transformation strategies since traditional business models and IT in supply chain operations have been separate and siloed in many firms (Sibanda & Ramrathan, 2017). Many supply chain leaders are awash in the big data yet are engaged in fragmented implementations rather than a systematic and coordinated effort (Sanders, 2016).

A review of the literature on this topic showed a paucity of research on leaders' commitment on strategically aligning with digital ecosystem in SCM amidst digital transformation. Therefore, there is a gap between leadership commitment at senior level and digital transformation in supply chain operations. Through addressing this gap, the study will assist in shaping the emergence of the platform-based ecosystem (Jacobides et al., 2018), and will contribute to the strategical alignment of effective leadership in SCM through a series of digital transformation initiatives in response to digital ecosystem

(Sibanda & Ramrathan, 2017). The purpose of this qualitative classical Delphi study is to determine how a panel of 30 subject matter experts from ISM in the United States views the desirability, feasibility, and importance of successful digital transformation of SCM through use of the big data.

Literature Search Strategy

The purpose of the literature review is to obtain as much evidence as possible to address our RQs. Our search would be conducted in two stages. To begin with, we need to identify a series of data concepts like the origin of big data, types of data sets, analytics skills, techniques, capabilities, leadership commitment, effectiveness, and their relationship between leaders' capability and the BDA. These constructs and relationships have been drawing scholarly attention in the context of SCM.

The Business and Management database comprised of many different disciplinaries in scholarship from Walden Library was used to search for the concepts and evidence of the big data, analytics techniques used in the SCM of various business sectors, the relationship among leadership commitment, leadership effectiveness, and supply chain performance. For example, the use of the Boolean operator "AND" with two terms, *big data analytics* and *supply chain management*", yielded 325 peer-reviewed articles from various disciplines that were published between 2013 and 2020. These research are mainly reflected in the following aspects: (a) big data, (b) BDA and decision-making support, (c) operation and SCM, (d) business processes, (e) logistics performance, (f) value creation and competitive edge, and (g) business model and sustainability. In sum, BDA is defined as the best SCM practices in keeping the organizational performance stay at its optimal level. When the question "when is the big data analytics initially used in supply chain management?" was entered into the Google Scholar, it yielded 20,200 works on the topic for any time frame. When narrowing the search to works published from 2016 onwards, we still have 18,500 papers, it seems that the topic on the big data and SCM still prevails in scholarship. For inclusion criteria, we will only include the peer-reviewed literature published since 2016 to reflect academic influence on the practice.

The keywords and phrases used for the relationship search between BDA and leadership commitment were singled out from the concepts and constructs obtained in the previous concept search. The search strings for the keywords and phrases were set by way of term or phrase combination. Also, the Boolean, truncating, and asterisk search filtering skills were applied when the search strings were entered into each database for each round of Search. The search strings were (a) *BDA and leadership commitment*, (b) *BDA and leadership effectiveness,* (c) *BDA capability and leadership effectiveness,* (d) *BDA and supply chain management,* I *BDA and logistics*, (f) *leadership or management style and organizational performance*, and (g) *BDA and organizational performance*. The central database sources selected were Business Source Complete that includes ABI/INFORM Collection, Emerald Insight, SAGE Journals, ScienceDirect, and EBSCOhost through the Walden library. Google Scholar was also used as alternative source in this literature review Search.

With the previous Search experience, we were exposed to a broad coverage of the subject on BDA and SCM. We decided to apply for a complete search string that included all the concepts and constructs in the search string by using two databases: Business and Management of the Walden Library, and Google Scholar. The search string *(Big Data Analytics AND (supply chain OR supply chain management OR supply chain operations) AND (leadership commitment OR leadership effectiveness OR leadership capability)* served as the keywords in this Search. We were provided with 17,000 articles from Google Scholar. For example, when this search string was entered into ABI/INFORM Collection database, we got 590 peer-reviewed articles. Detailed search processes and filters used in the selected database search are indicated in Appendix A for PRISMA.

To narrow down the articles to those with related keywords, terms, and phrases, I applied the inclusive and exclusive criteria, per the specific rules were outlined in Table 1. For example, I limited search results within the business and social science by removing the articles from other content providers, which generated 450 articles. Second, I removed articles without keywords, terms, and/or phrases by title screening; doing so, I was able to remove an additional 230 articles, narrowing down the results to 220 articles. To be included, the articles had to be peer reviewed and relevant to the relationship between BDA and the leadership commitment, leadership effectiveness, and/or leadership capabilities in SCM; with this restriction, I was able to reduce the number of results to 190 articles from the Walden Library Business Source Complete Search database. I initially got 17,000 articles when using the same search string in the Google Scholar search engine with the same Boolean phrases. Applying the same criteria and article selection process under the PRISMA model, I was able to narrow down the results to 10 articles from Google Scholar after removing duplicates and all doctoral dissertations through citation checks. In total, 200 articles were selected and included in this literature review. Appendix A includes more details on the general search and PRISMA scheme.

Table 1

Inclusion and Exclusion Criteria for Article Selection

Category	Criterion
Inclusion	Published between 2016 and 2020
	Written in English
	Abstracts that contain keywords, terms, or phrases of the search strings
	Studies that refer to the involvement of big data analytics and supply chain management in any context
	Articles that discuss the relationship between big data analytics and leadership commitment or leadership effectiveness, or leadership capabilities or decision-making
Exclusion	Articles that were not found in business and management databases
	Article that was not peer reviewed
	Articles that were not from academic journals
	Doctoral dissertations from Google Scholar search results
	Full text not available
	Keyword listing not related to the search string keywords, terms, and phrases in combination

Note. There is no filter setting in the Google Scholar search engine. Therefore, inclusion and exclusion criteria were manually applied by performing citation checks and scanning search results.

Theoretical Foundation

There are several theories used in the academic research with both deductive and inductive explanation of the big data in SCM. Given the view of forward-looking in digital transformation in the supply chain industry, the DCT proposed by Teece et al.

(1997) will be applied to the study as the dynamic capabilities framework is an entrepreneurial approach that emphasizes the importance of business processes, both inside the firm and in linking the firm to external partners (Wamba & Akter, 2019). DCT also focuses on the importance of critical resources and good strategy that could well address how a process of assimilation could be achieved for a successful digital transformation in supply chain operation as part of a larger ecosystem in applying BDA (Chen et al., 2015). The reason for DCT application assumes that the dynamic capabilities approach as an extension of the resource-based view of the firm (Barney, 1986, 1991), which intends to explain the conditions under which firms may achieve a sustained competitive advantage based on their bundles of resources and capabilities (Barreto, 2010).

The phrase "dynamic capabilities" was first introduced in 1997 by Teece et al. in their paper of *Dynamic Capabilities and Strategic Management*. The dynamic capabilities were viewed as organizational ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments (Teece et al., 1997). The idea of dynamic capabilities, to some extent, resembles the concept of operational capabilities that relate to the current operations of an organization, and these capabilities pertain to an organization's capacity to change these operations and develop its resources efficiently and adaptively (Helfat et al., 2009).

The main assumption of the DCT is that an organization's basic competencies should be used to create short-term competitive positions that can be further developed into longer-term competitive advantage. For instance, in the Big Data era, supply chain managers can continue to utilize the existing network as their basic competency that can be further turned into their competitive advantage through digital transformation. Nelson and Winter (1982) linked the concept of dynamic capabilities to the resource-based view of the firm and the concept of routines in evolutionary theories of organization in their book of *An Evolutionary Theory of Economic Change*. Douma and Scheuder described DCT as a bridge between the economics-based strategy literature and evolutionary approaches to organizations (Douma et al., 2002).

The resource-based view of the firm emphasizes sustainable competitive advantage while the dynamic capabilities view focuses more on the issue of competitive survival in response to rapidly changing business conditions. The difference between these two perspectives lies in how the process is to be defined. Hence, the strategy scholars Gregory Ludwig and Jon Pemberton (2011) had once called for clarification of the specific processes of dynamic capability build-up in different industries to make the concept more useful to senior managers in some of their empirical studies (Ludwig et al., 2011).

DCT concerns the development of strategies for senior managers of successful companies to adapt to radical disrupt change, while maintaining minimum capability standards to ensure competitive survival. Before digitalization, organizations that have traditionally maintained an industry-specific decision-making mechanism are always unable to change this process responsively when a new technology is launched. Often, managers need to take time to adapt their routines to the most of their existing resources while planning for new process changes as the resources depreciate (Ludwig et al., 2011).

Similarly, the kind of changes that the theory is emphasizing are the internal capabilities rather than only looking into the external business forces (Alojairi et al., 2019). Given the view of DCT and its theorizing coverage, it would lay a firm ground for any organizations that need to tap into their basic or core competencies while responsively taking steps or measures to adapt to rapid changing environment through assimilating both internal and external forces to derive a higher level of leadership effectiveness.

Conceptual Framework

The challenge of the big data to organizations is in two major forms; technically the big data would impact the organizational existing infrastructure of information processing capability, and externally, the presence of the big data has changed the way in which stakeholders perceive, demand, and expect the service level that the organizations have to offer. How well could the organizations as a part of a larger ecosystem adapt themselves to this changing environment challenges the SCM leaders 'agility to respond to the big data and commitment on building the analytic capability for the organizations. It is a process of mechanizing the decision-making using BDA, i.e, the extent of assimilation determines the level of a successful digital transformation. This framework just fits in the DCT that Douma et al (2002) and Ludwig et al (2011) advocated, they insisted that the senior managers should be able to turn their existing resources into a long-term competitive advantage while taking steps to new "routines" in the changing environment. It is more of a process redefining rather than simply investing in new technology. It calls for leadership commitment to responsively interact with both internal and external forces to drive digital transformation. Only in this way, could their leadership become effective.

To take advantage of leveraging the emerging technologies and the leaders' capability to apply BDA for sound decision-making is of a significance in transforming siloed system to the digital ecosystem (Vera-Baquero et al., 2015; Sanders, 2016; Sibanda & Ramrathan, 2017). A review of the literature on this topic showed a paucity of research on approaches to leaders' effectiveness in strategically aligning with digital ecosystem in SCM amidst digital transformation (Andal-Ancion et al., 2003; Berman, 2012; Mergel et al., 2019; Oliveira et al., 2019; Sibanda & Ramrathan, 2017). Through addressing this gap, the study will contribute to the strategical alignment of organizational leadership (Migliore & Chinta, 2017) with SCM effectiveness by prompting a digital transformation initiative in response to the digital ecosystem (Sibanda & Ramrathan, 2017). The study will create a threshold for building a consensus on leadership effectiveness measure for the SCM, which findings will help SCM practitioners in redefining the concept of leadership performance. The study will also contribute new knowledge to the academic research with an implication of theoretical guidance for the leadership effectiveness in the Big Data era (Arun et al., 2020).

Literature Review Related to Key Variables and/or Concepts

Literature review have enabled us to be more knowledgeable about the role of big data and its impact on business practices. From evolution of the big data all the way through digital transformation across entire world, the big data has brought in upside down changes in every aspect. Patterns of change and emerging themes could be found in every sector of industries as drawn from these literatures. Given our literature review coverage, we can categorize the evolution of big data into the following patterns and themes.

Evolving Definitions of Big Data

Andrea De Mauro et al (2016) and Lee (2017) both conducted research on the big data evolution, its development and definition, they used different research methodologies in their research, but found the similar result. Andrea De Mauro et al (2016) studied 1,581 literature sources and found that there were four prevalent themes on the concept of big data. Big data has its root in the following aspects. They are from information, technology, method, and impact. These four areas are aggregated into big data that has brought in many data-related activities, events, programs, paradigms. Models, and social changes (Andrea De Mauro et al., 2016). Several versions of big data definition in the past, each of which addressed the big data not to the full feature of it. Hence these definitions are not complete. However, after thorough review, they have been able to come up with the most complete definition for the big data so far, which findings increased the need for advanced technology that could transform these data into value. Lee (2017) used descriptive study on the big data development from early stage all the way through current situation and found that each evolutionary stage was characterized with a major theme from the Big Data 1.0 to the Big Data 4.0, during each growth period, the big data was accompanied with a focused application from simplicity to complexity. As such, BDA becomes both a benefit and challenge in business operation, marketing, customer service, and privacy, each of which needs a lot of further addressing.

Impact of Big Data on Organizational Change and Performance Management

Changes in communication have taken places in all walks of life along with the development of digital platforms and phenomena like the internet, media, and the Internet of Things (IoT), which have created a huge amount of text-based data. These data contain patterns, trend and meaning. Rob (2014) explored the evolution of big data from its initial emergence all the way through its impact on current way of knowing things and found that previously science-driven knowledge was replaced by data-driven science since many paradigms of current days arise from BDA, and this analytics could accurately predict result such as customers' buying behavior, sales demand forecast, transportation scheduling and more, they are all generated from historical data. Now the knowledge production shifts from science-driven to data-driven.

Bail (2014) conducted how the big data even shifted social scientist in their research, and the digital development has resulted in digital humanities in cultural sociology. However, computer scientists lacked theoretical frame to guide generation of test-based analysis for cultural sociologists, whereas the cultural sociologists did not have methodology to retrieve these large amounts of data, so he called for the big data scientists and cultural sociologists to complement one another since the computer scientists lacked theoretical frame to guide generation of test-based analysis for cultural sociologists, whereas the cultural sociologists did not have methodology to retrieve these large amount of data. Kuoppakangas et al. (2019) and Pugna et al. (2019) conducted qualitative research on organizational change and performance management respectively, they both used thematic analysis in their case studies and found that the awareness, understanding, and perception of the big data were the key to organizational transformational change in digital culture. Their studies implied that the big data application though in trend in organizational change, it is not the only force that drives organizational change, the change effort depends on the readiness of the organizational agents (Kuoppakangas et al. 2019); Pugna et al. 2019).

The research on the big data application in the process of organizational change and performance management highlight the need of executive commitment for the digital transformation. In customer relationship management CRM), the big data is the critical success factors in CRM that has been underpinned by big data-enabled CRM. Zerbino et al. (2018) explored how the big data-enabled strategical CRM, they found that CRM planning, infrastructure, insight from data management, CRM project and organization were important factors that were big data-enabled. They addressed the importance of bid data-enabling factor in successful CRM performance. Furthermore, the feeling about a brand can be generated through social media that impacts company image. The brand image is affected first from the reflection on a single product, then spreading onto the entire branding because brand sentiment characterized with four dimensions (need to get back to the article to check what are four dimensions are) bring about both positive and negative impact on the brand itself depending on how the social media convey messages through tweeter (Shirdastian et al., 2019). Influence has also stretched into human resource management. Pera (2019) compared result out of several reports on HR management via BDA and found that the organizational performance was 50% higher than those who did not use BDA (Pera, 2019).

Big Data as a Driver of Business Innovation

Many business leaders feel hard to initiate the big data technology investment, and this situation is often found within supply chain operation as supply chain practitioners are reluctant to change due to ambiguity in recognizing potential benefit (Arunachalam et al., 2018). However, science-driven knowledge has been replaced with data-driven information that has empowered many emerging businesses from launch to thriving, and this trend continues to give birth to new business models (Rob, 2014). Evidence has shown that the success of emerging industries is largely due to constant innovational ideas generated from BDA. Ettlie and Sanders (2017) studied why innovation theory was ungeneralizable and discussed the relationship between big data and innovation. They thought disconnection between innovation and practice was due to many interdisciplinary approaches to science and problem-solving has been in its current, vague form, and called for innovation process and "big idea" shall be initiated from industry, not from academia (Ettlie & Sanders, 2017).

Moreover, Erevelles et al (2016) approached innovation idea through digging into what were unknown, they applied ignorance-based view for driving innovative ideas. Business shall not only build up an organizational culture that facilitates the process of extracting, storing, organizing, collecting, and analyzing the big data, but the organizations shall also understand what they do not know (ignorance). With a view of ignorance-based perspective to explore what would be the driver for innovation, Erevelles et al. (2016) found that ignorance-based view was the prerequisite for innovation, creativity, and performance. What this research indicated has informed practitioners to look for what is not known, a starting point to initiate innovative process. However, in real world, the established businesses seem to have known everything, leaving no room for innovation.

To find out how the big data would promote organizations for innovation and why there were large difference between leading organizations and that lag behind, Marshall et al. (2015) conducted research with a survey from 341 respondents on questionnaire concerning usage of big data, analytics tools, and measurement metrics used, there appeared three distinct groups in terms of the big data application, and innovation. These groups are categorized as leaders, strivers, and strugglers (Marshall et al., 2015). The report indicated that there was a big difference in those who could take advantage of the big data application. Study by Marshall et al. (2015) highlights the importance of organizational commitment on big data application through investing in employee training, building organizational culture based on innovation metrics measurement, and facilitating innovation idea across the board.

The source of innovation comes from the big data and business analytics. Empirical study in this respect can be found in many literatures. To enable manufacturers' agility that would generate competitive advantage through the big data and business analytics, Gunasekaran et al. (2018) surveyed four manufacturing companies in UK in their explorative case study and found that agility of a company reflected in the four aspects: system design, supply chain, manufacturing technology and organizational empowerment.

Also, the big data is considered as a driving force for innovation. As the conventional way of intelligence still prevails, but gradually and surely it will be replaced with an increasing demand in embracing data sharing for innovation across industries. Witjas-Paalberends et al. (2018) used a quantitative questionnaire to rank challenges in the order of number of frequency that challenge appeared from a panel of expert in the health care industry, then formed a focus group from eight key opinion leaders, four of them completed questionnaire, and the other four were not asked in the questionnaire so that they had different interview background. The study indicates the effect of big data on the innovation initiative in the health care sector, which shed light on the big data and innovation.

Literature review has shown more studies on the relationship between the big data and innovation, the major theme has been centered on how the big data prompted innovative ideas in different sectors of businesses. Goldsby and Zinn (2016) informed several representative technological advancements in SCM. The disruptive technologies not only change traditional operational pattern, but also changes the way in which organizational structure, culture, and management and or leadership had been built (Goldsby & Zinn, 2016). The disruptive technologies have changed SCM in a fast than expected model and it needs our attention to be paid closely since these technologies not only impact SCM, but also, they show up quick and newer tech replaces the old quickly as well, which phenomenon renders scholars hard to observe, and explain (Goldsby &

Zinn, 2016; Krittika et al., 2017; Len Tiu et al., 2019). Drawing upon these studies, we can conclude that the characteristics of big data drive innovation between product/services and customer demand.

Big Data and Business Intelligence

Digitalization has brought in many changes in business world. Online marketing, shopping online, internet transaction, social media, and Zoom meeting, just name a few, have been of prevalence in our daily life. In the past, many statisticians had to dig into various historical data to predict future action in decision-making. However, this entire situation has been changed by big data. Increasing data continues to stream online, and many businesses have relied on BDA to generate business intelligence, CRM, ERP, and other important business systems. How to make the best use of these various data varies with industrial preferences.

Some scholars studied how to turn big data into marketing mix intelligence through data source identification, method, and application (Fan et al., 2015). Khan and Vorley, (2017) researched literature of 196 articles from 2013-2014 through categorization, visualization and interpretation and found that analysis of text messages was a very valuable way to generate new knowledge to gain competitive advantage for the institution and better knowledge management. To find out how social media plays an increasingly important role, Ram et al. (2016) administered a questionnaire, together with interviews from across-industrial sectors to see the impact of social media on business performance and found that the social media development and its widespread usage created a new stream of data source that further aided the business decision through business intelligence effort. The characteristics of structured and unstructured data set from social media necessitates the business to have BDA to aid business intelligence in a more and more rapid speed (Ram et al., 2016).

In sum, the prevalence of internet thing has made businesses to take advantage of BDA through a good number of sources to generate business intelligence in decision-making process, which enables organizations to gain competitive edge in many respects. However, there was once a confusion in knowledge management because people cannot tell if knowledge management (KM) is part of big data or the big data is part of KM. Pauleen and Wang (2017) clarified the difference between these two constructs as they considered that the big data, though creates knowledge, is subject to context within which the knowledge is based on.

Big Data Analytics and Supply Chain Management

Literature review enables us to catch up research advancement of big data and SCM. Many well-known scholars and practitioners have presented numerous observations in application of the BDA techniques for SCM decisions. Most of the research have been focused on how the big data thing aided SCM logistic operations, transportations, after-sales service, how to take advantage of the BDA to gain innovation, and how investment on IT technology renewal shall be necessary, but few were engaged in studying the relationship between leaders' commitment in building organization-wide capability and BDA culture fostering.

Our literature review, however, will be weighed more on the empirical study of why leaders' commitment is critical in building up organization-wide BDA capability to outperform conventional wisdom. Arunachalam et al. (2018) conducted a literature review to seek out pattern of SCM capability maturity model and found that large volume of data generated in the process of prior stages made the data become so magnitude that traditional way of dealing was not able to handle it thereby causing the SCM short of advanced IT technology. Big data is characterized with 5Vs (volume, variety, velocity, veracity, verification) that prompts the need of computationally analytics, but many supply chain organizations were technically limited to handle these data, which was the main reason making the SCM under maturity.

Since prior research were all about theoretical application, very little had been related the use of big data empirically, Brinch et al. (2018) conducted research to seek out empirical evidence of what big data application could do for SCM and found that the big data application has brought in benefit for SCM in several specific area (planning, marketing, and customer service.). Wamba et al. (2017) studied the relationship between big data analytics capabilities and firm performance focusing on the mediating effect of firm dynamic capability. They identified a causal relationship between the variables. Big data analytics capabilities were comprised of three capabilities: infrastructure, management, and personal expertise. This research finding addressed the gap between IT capability and firm performance in terms of BDA capability. Another reason of being lag in SCM comes from different buy-in among supply chain managers. Robert Glenn Richey et al. (2016) studied the influence of big data on supply chain, they interviewed at three respondents from each country, and collect data from interviews, then coding each answer to the interview by category to see if there were any consensus in the way in which the big data was understood among supply chain managers from different countries. However, they found that the understanding of big data varied with their expertise perspectives in the industry.

Moreover, Frederico et al. (2019) argued that the supply chain 4.0 shall be part of the framework in the evolution of industrial 4.0, they thought that at least BDA as part of industry 4.0 shall be considered in the evolution of supply chain 4.0. However, supply chain 4.0 has not been evolved at the same pace, the current evolution of supply chain 4.0 still at its growth period compared to industry 4.0 (Frederico et al., 2019). Again, Wamba et al. (2019) argued that big data-driven supply chain required firm to quickly take advantage of organizational existing competence through analysis of big data, Bradlow et al. (2017) studied the role of big data and predictive analysis in retailing industry, Shamout (2019) tested the relationship between supply chain analytic, innovation and robustness capability in SCM in his quantitative study, and concluded that the supply chain analytics from the big data brought about supply chain innovation, and innovation brought about robustness capability.

There were a series of organization theories being used and developed during the Big Data era. To explore how and to what extent the organization theories have been used and developed, De Camargo Fiorini et al. (2018) found that 19 theories that have been the major framework in discussing about the big data and organizational performance, other theories were also found with evidence, but with little impact. Their research findings have both provided us with a system view of theories used in addressing the big data and organizational performance, and it especially tells us how the big data has impacted the

SCM through the lens of organizational theory series. More studies in this regard from other scholars and practitioners echoed similarly in calling for the big data application in routine supply chain operation and decision-making process, and at the same time, these scholars weighed leadership commitment heavily in roll-out organizational digital transformation effort.

Our literature review has revealed some patterns in terms of methodologies used, theories applied, and resulting themes. Among the twenty-two articles on this topic, more than half of the research were done in quantitative studies, Delphi method was commonly used for building up consensus from expert opinions from various industries to seek common ground in both theory and empirical observations. BDA has been most helpful in the areas of logistics, services, planning, uncertainty reduction, and the promotion of sustainable SCM, each of which requires a reduction of information processing requirements and an increase in information processing capability (Brinch et al., 2018; Kache & Seuring, 2017; Roßmann et al., 2017; Tseng et al., 2015; Vidgen et al., 2017). Building of organization-wide capability in application of BDA is vital for the SCM performance because there were 43 kinds of opportunities and challenges confronted by the supply chain industry (Kache & Seuring, 2017). Another theme lies in theories applied in this research. Resource-based view, knowledge-based theory and DCT are frequently taken to frame the research for the relationship between the big data and SCM performance in addition to other theoretical models. Systematic review is the major pattern of research, making the study very empirical to some extent.

Data-Driven Supply Chain Operations and Performance

BDA has been considered as an analytical tool through computer algorithms and techniques to derive meanings, insights, patterns from the collected large data sets (Jeble et al. 2018; LaValle et al. 2011). Application of the BDA is increasingly turned out to prevail in the SCM in terms of delivering value, improved business performance and competitive advantage (Wamba et al. 2017). Manyika et al. (2011) mentioned that BDA might lead to a new movement of productive growth by transforming economies. In fact, BDA has enabled new ways of organizing and analyzing supply chain processes to enhance performance (Hazen et al. 2016; Waller & Fawcett 2013), build up manufacturing capabilities and improve customer satisfaction (Anwar et al., 2018). Studies have also been found that the BDA has a positive influence on the firm performance (Gunasekaran et al. 2017; Wamba et al. 2017), sustaining competitive advantage (Chen et al., 2015) through cost reduction, improved decisions, and improvements in products and services (Matthias et al. 2017).

These are all the facts that the supply chain operation is driven by BDA, hence the term “data-driven supply chains.” Yu et al. (n.d) tested the existence of relationship between data-driven supply chains and financial performance using Likert 7-point scale pattern and collected data from manufacturing sector located in five regions in China, through two hypotheses, quantitative method under the resource-based view framework, and found that coordination and responsiveness are significantly related to financial performance, whereas activity integration and information exchange are not positively associated with financial performance. The findings from this study are consistent with the fundamental principles of the resource-based view theory that the relationship between data-driven supply chains and financial performance exists.

Gupta and George (n.d) conducted two studies, one as pilot study to see if there exist any validity of the testing from the data collected from data managers. The second study based on the result of the pilot sample, they further test the relationship between tangle, human and intangible aspects that build up company's comprehensive capability in lens of RBT view, and concluded that how big data could build up a firm competitive advantage not only through investment, but also through the organizational capability of learning, availability of big data –specific technical and managerial skills, and culture where insights extracted from data are valued and acted upon. The research by Gupta and George (n.d) sheds light on how to build up BDA capability in organization. Corte-Real et al. (2017) found strong relationship between BDA application and organizational agility as they studied relationship between big data value and organizational performance in terms of sustaining competitive advantage.

To find solution for improving organizational performance, Vera-Baquero et al. (2015) used an empirical data set through a cloud-based information sharing system across diversified organizations to show the power of making use of big data, and how important business organization shall accommodate to growing demand for big data-based business analytics. Studies by Mandal (2018), Sundram et al. (2018), and Gawankar et al. (2020) are each focused on relationship between the big data-driven analytics and supply chain performance with different emphasis. The central issue seems to be the capability of information management in the organization. In other words, many supply chain organizations have invested heavily on IT technology, infrastructure buy-in, and hiring data expert, but the research findings show up a different result.

A close look at the issue, we find that acceptance of the big data thing at executive level is turned out to be a decision for front line managers in making the use of BDA, which resulted in many investments underperformed in supply chain operations. The research findings indicated that organizations simply invest in BDA would not influence performance alone (Mandal, 2018), which study sheds light on the impact of the big data management capability on supply chain performance. Therefore, the big data management capability in supply chain activities means entire organizational capability in making use of BDA.

Big Data Analytics and Leadership

The ability to communicate technical insights to team fellows is one of the vital leadership skills that comes with an understanding of data analytics. Empirical studies have otherwise showed a different story. Silahtaroğlu and Alayoglu (2016) conducted study on the popularity of information system (IS) application at company executive level through interview and literature review. The fact is that only two out of ten companies have taken advantage of BDA to make strategic and tactical decision on a partial application of information system in Turkey. Most of the executives who made strategical and tactical plan or decision do not based their strategy on BDA. The main reason is that most of executives still do not place full trust on the big data due to lots of reasons like data being not cleaned or needs purification process, even few executives still believe in their own experience when making decisions. The study reveals how and what still hinders the digital transformation in practice. Also, study on the relationship between the big data and strategic leadership within the theoretical lens of data as currency reported that the level of IT understanding perceived by the C-level executives determined the degree of their decision-making (Migliore & Chinta, 2017).

However, Raut et al. (2019) presented us with a different view on the use of BDA on how to become greener, sustainable SCM at executive level. The research was in quantitative study on the relationship between BDA and sustainable operation in supply chain, using state, central governmental policy, management, and leadership as variables with BDA as moderator. Seven out of nine factors are contributing to sustainable operation with moderating BDA, and they found that sustainable operation depended on how BDA was utilized in sustainability effort. This empirical study provided us with a detailed explanation of how to implement greener effort in management and leadership in SCM. Dong and Yang (2020) found market performance from synergy between big data and firm resources in terms of complementarity when they studied it through social media diversity and BDA combined. The interaction of combining social media and BDA existed, and such effect turned out to be large in small- and medium-sized enterprises than that of large firms (Dong & Yang, 2020), which means that value creation in digital time needs managers to pay more attention to social media diversity rather than simply a broad concept of the big data.

The effect on leadership can be further observed in the literature. Merendino et al. (2018) studied the impact of big data on board decision-making; they invited 20 senior managers to participate in the interview process thereby to generate theme in the RQs.

Different interviewers conducted the interviews, one at a time with the same interview questions. From the response by the respondents, they were able to generate three categories with each representing an area of concern in big data applications. Through theme analysis, they were able to figure out three core categories for trigger the dynamic and adaptive capabilities that support strategic decision-making, which fills the gap in the literature for big data's impact on senior level decision-making factor change. BDA adoption at executive level has never been an easy agenda since many organizational decision-making is still a final say from the top executives, which creates a curiosity.

To find out what the factors are and how they are important in the order of the organizational decision-making processes, Yadegaridehkordi et al. (2018) conducted quantitative study, using DEMATEL-ANFIS framework. Their questionnaire was categorized in three subjects on technological, organizational, and environmental factors, then they analyzed the data with the aid from DEMATL-ANFIS technique. data collected from the managers of various manufacturing companies across Malaysia through survey and ranked factors in the order of importance in the organizational decision-making process. They found that the technology was ranked the top for considering big data adoption compared to organizational, and environmental reasons, which provided us with a concept of factorial impact on the adoption of BDA.

Another quantitative study by Verma et al. (2018) on the relationship between attitude toward BDA and intention of BDA usage within technology acceptance model TAM, they used survey questionnaire and distributed it to managers, IT leaders across industries in India to test their assumption. They set up nine hypotheses, with six independent variables that drive the dependent variable (intention of BDA usage) and found that six independent variables that drive the dependent variable (intention of BDA usage). They concluded that intention of BDA application was driven by the belief in BDA benefit and user's attitude, which findings provide practitioners with the clue of how to drive big data usage by fostering user's belief in the benefit of the big data and assurance of external information quality. Examples of how BDA was used in SCM in Brazilian industry was also reported by Francisco et al. (2019) when they recalled the development of the big data and proposed a series of challenges facing further explorative use of the big data. This report is of a good source for big data in its trending usage, and complex concern that needs further address.

The Role of Big Data Analytics in Industry 4.0

BDA uses advanced computing technologies on large volume of various data sets to uncover valuable correlations, patterns, trends, and preferences for companies to make better decisions. Historically, we have experienced three waves of industrial revolution from the first one all the way through the fourth industrial revolution, which is now referred to as industry 4.0 (Hermann et al., 2016). Recalling the prior three industry revolutions, it is all about speed efficiency advancement. The fourth one is both advancement of speed efficiency and intelligence. Industry 4.0 is referred to as the connection of machines, systems, assets, and organizations to create smart grids along the value chain to control the production processes autonomously. Within the Industry 4.0 framework, organizations will have the capacity and autonomy to schedule maintenance, predict failures and adapt themselves to new requirements and unplanned changes in the production processes (Jazdi, 2014).

Industry 4.0 requires the adoption of proper big data technologies that be integrated to fulfil the data collection, storage, processing, and analysis needs (Santos et al., 2017). As the supply chain heads toward digitalized SCM in industry 4.0 (Hofmann et al., 2019), BDA still plays irreplaceable role in areas of smart factories, where sensor data from production machinery is analyzed to collaborate between machine and human beings for operations. Tjahjono et al. (2017) conducted a preliminary analysis of the impact of Industry 4.0 on SCM, aiming to provide a thought towards Supply Chain 4.0 through literature review of all sources. Analysis of the theoretical review was limited on procurement, warehousing, transportation, and order fulfillment, they come up with many potential opportunities and threats facing the factories of future in Industry 4.0 environment. Of these four areas, most affected are the order fulfilment and transport logistics with 53.84% of the impact of the technology being opportunities, while the reminders being opportunities or threats (Tjahjono et al., 2017). Transport logistics has 61.54% of the impact can be identified as opportunities, 7.69% being threats and the rest being opportunities or threats (Tjahjono et al., 2017). Concerning warehouse, 66.6% can be opportunities and 33.3% can be opportunities or threats (Tjahjono et al., 2017). Finally, within the procurement function, Industry 4.0 shows 71.43% of opportunities, the remainder being opportunities or threats (Tjahjono et al., 2017). The implication of these findings give rise of alert for SCM executives since almost the other half are the threats that have been either overlooked or ignored, which raises the question of why SCM is lag behind in the big data utilization.

To explore the impact of industry 4.0 on SCM to fill the gap in the existing SCM theory, Hofmann et al. (2019) reviewed 26 articles on the impact of Industry 4.0 on SCM and came up with the four themes identified. They are digitally dominant paradigm in SCM, changed procurement landscaping, real-time data processing in SCM, and manual labor replaced by automated robot (Hofmann et al., 2019). Each of these four themes proposes challenges for SCM executives due to increasing automation, transparency, communications and decreasing manual labor in products and services that were traditionally handled at different levels of operations. How supply chain executives are going to spot gaps between them, monitor the efficiency of production, and to plan future action from descriptive-based reporting to predictive analysis remains challenging. The development of the IoT would eventually bring about the industrial IoT (IIoT) where a series of changes would take place from a simple internet thing to a complex networking. Within this network, the integration of BDA process into IIoT would be value creation that maximize profitability. ur Rehman et al. (2019) studied on the trend of BDA under IIoT environment, and concluded that the integration of BDA into IIoT, there involves eight steps, with each sub-system aggregated becomes a technological ecosystem (Hofmann et al., 2019).

Within this ecosystem, opportunities, research challenges, and future technologies emerge and complement each other in IIoT environment, which predicts the future IT development and where value creation could be arising from. How Industry 4.0 would work in a data-oriented operational system, Santos et al. (2017) presented a big data system that implements and validates a specific set of components of this architecture, using the ongoing work on a multinational organization (Bosch Car Multimedia – Braga) as a case study to show the big data model system. Big data architecture is comprised of several layers, each with specifically proposed architecture, and specific components for those layers, they were then integrated into a data workflow from data collection to data analysis and visualization (Santos et al., 2017). The case study on Bosch demonstrated how each component in the big data architecture complement one another to assist decision-making from data collection all the way through data analytics and visualization, serving a comprehensive goal of decision-making.

There has been more literature on the trending of Industry 4.0 study, all of which are centered on the impact of businesses, and opportunities and threats facing the factories of future including supply chain operation. we just listed a few for acknowledgement. In the context of Industry 4.0, leaders and managers including top executives need to adapt their skills to the needs of the Factories of the Future. The manual labor will be replaced by automated robots, raising new challenges to SCM decision-makers, in an environment of huge technological variety and challenges (Hermann et al., 2016). In sum, when operating under the industry 4.0 environment, what SCM practitioners should think about is not new technology, but of how to organize, and schedule operations in a smart way given three levels of integration; the cyber-physical objects level; the big data infrastructure and models of machine learning and human intervention; and the services based on the available big data (Drath & Horch, 2014).

Nowadays various sources of data structured, semi-structured and or unstructured continue to stream both online and offline. With advanced technologies, these data are either turned or integrated into existing business intelligence, CRM, ERP, and other important business systems, which gives rise to BDA for every industry and business. With Industry 4.0, and further digitalization that makes automation connected with human intervention possible, this brings disruptive innovation of the SCM into concern. Even though the impact has not been felt by most supply chain operations and SCM leaders and managers, some companies are striving to see how that impact can come to play soon.

We have reviewed most recent studies on SCM and big data. The presence of big data from its initiation to a fast evolution has been so disruptive in every step of the way leaving the businesses far behind, especially in supply chain operation. Empirical observations have also showed that many organizations that quickly adopted changing strategy have been able to outperform by applying BDA, building data analytic skills, and investing on new IT thereby gaining competitive advantage, becoming more intelligent, and being an industrial leader. However, none of the observations has been paid attention on the leadership commitment. Therefore, there is a gap between the digital capability building and leadership commitment. The aim of this research paper is to identify the challenges, factors and or elements that result in being lag behind in digital transformation in SCM through addressing the digital capability building and the organizational leadership commitment in terms of desirability and feasibility under the

Big Data era. Our research findings will fill this gap and contribute to the knowledge of BDA and leadership effectiveness for SCM.

Summary and Conclusions

Literature review, though inadequate from exhaustive coverage, has enabled us to see the progression of academic development within the SCM research arena, and informed us of the theories applied, commonly used research methods, research findings and results that have improved the SCM performance and enhanced practitioners' ability to innovate, create new business processes and models, and initiate social changes. To synthesize, the studies from 2014 to 2020 demonstrated following strengths and attributes. Most of the research is conducted using literature review with meta-analysis. Deductive approach in quantitative analysis is found to be a main theme in research method. Resource-based view, knowledge-based view, DCT, systems theory, and sustainability are the most frequently applied framework. Delphi studies are a commonly applied research method in addressing RQs about consensus, recognition, and awareness of a new technology and or solutions to the problem in question. Case studies and hypotheses are used to show examples in testing authors' theories for the relationship between what was observed and empirically found. In addition, the literature during these periods is found to address more on the impact of the big data on supply chain operation, SCM, and frontline managers and fellow workers, very rare or little attention is paid onto the top executive commitment when addressing the need to build organizational capability in using BDA.

The BDA seems to be a tool only for mid-level leaders, frontline managers, and fellow workers, leaving the top executive commitment behind the BDA capability building. Therefore, organization-wide, it is hard to foster a data-driven culture in SCM platform. Finally, much research is conducted in a regional effort, and most of the research are found to have a low response rate when questionnaire and survey were administered, all of which have rendered this research with limited generalization. The aim of this research is to explore challenges that cause the pace of SCM lag in the use of BDA so that we could fill the gap between BDA capability building and leadership commitment for the measurement of effective leadership. The chapters that follow will be organized as methodology, research result and findings, discussions, limitations, and conclusions.

Chapter 3: Research Method

The purpose of this qualitative classical Delphi study is to determine how a panel of 30 subject matter experts from SCM professionals in the United States views the desirability, feasibility, and importance of successful digital transformation of SCM through use of big data. In Chapter 1, we have introduced the development and impact of big data that have changed peoples' life, market condition, and social environment (Barkham et al., 2022), these changes force organizational leaders rethink business processes to make right decisions. Adaptation, digitalization, transformation, agility, assimilation, big data, and ecosystem are common terms in organizational change agenda. Therefore, the problem statement, RQ formation, aim of study, theoretical framework application, and significance and limitation of the study are each discussed in association with the challenge facing the current SCM status quo given the 5Vs of the big data proliferation that forces businesses adapt to this changing environment.

Research Design and Rationale

The research question for this study was "How does a panel of at least 30 subject matter experts from supply chain management professionals in the United States views the desirability, feasibility, and importance of successful digital transformation of SCM through use of the big data?" The central constructs in this research question are desirability, feasibility, and digital transformation under the Big Data era. To understand these constructs, we need to see what these constructs mean in the context of SCM. Alternatively, what does it mean by desirability, feasibility in a successful digital transformation? There have always been new findings and implications from empirical research in literatures that inform businesses across industries on how to adapt to the changing situations. Old patterns are often replaced with new models, products and services that were once impossible can now be easily accessible through digitalization, and digital revolution has brought many impossibilities to possibilities.

All these developments are due to innovations and creativity in the Big Data era (Del Vecchio et al., 2018), which drives business leaders to rethink of the business models. The definition of digital transformation has been so far inconsistent from academic and practical view (Morakanyane et al., 2017), its meaning varies with organizational digitalization agenda. How shall experts from SCM view, perceive, and interpret a success of digital transformation would provide us with insight of digitalization in SCM arena. Since this research is grounded on forward-looking perspective on how digital transformation in the Big Data era would impact performance of supply chain operation, we choose Delphi design to answer our RQs. The rationale of taking Delphi method to conduct this research is based on the nature of the Delphi method that it is used to forecast, predict, evaluate result from decision-making process (Linston & Turoff, 2002).

The Delphi method was developed by RAND Corporation during the 1950-1960s (Rescher, 1998). The name Delphi originated from the ancient Greek myth about the Sun of God Apollo who had the ability to predict the future. In 1946, RAND used this method for the first time to make predictions, and later this method was soon recognized widely (Ju & Jin, 2013). The Delphi method is also known as a structured communication technique using a systematic, interactive forecasting method that relies on a panel of experts. It is a method of presenting a particular issue to a group of experts who are asked to offer their opinions through back-to-back communicational loop for problem-solving, then these experts' opinions are collected and summarized, and sorted out in an aggregated way. The aggregated opinions and predictive questions are fed back to the experts anonymously for further opinions. The experts revise their original ideas based on the aggregated opinions, then correct their early answers. This iterative process last two to three rounds, then the response would gradually become a more converged idea thereby we can derive consensus.

The Delphi method is based on a systematic procedure of communication within a panel of experts by anonymously expressing their opinions (Yousuf, 2007). For our dissertation study, the selected experts do not discuss face to face with each other, instead, they can only communicate with the facilitators or researchers who are their contact windows. Through multiple rounds of surveys, the experts' opinions on the questions raised in the questionnaire are summarized, revised, and sorted out to look for consensus pattern. Hence, the Delphi method is purposefully chosen and considered reliable for our study.

To check how many research on SCM were applied with Delphi study, we have conducted a thorough search from the Business Source Complete database by using Search term "Delphi" as method in the first line, the second line, we entered "supply chain management or SCM", we were provided with over 90 literatures in SCM topic that were applied with Delphi method to predict, forecast the performance in SCM. Then, we limited our search result to peer-reviewed, language in English and year range from

2000 to 2021, we got 77 research articles on the topic. We have categorized these papers into five main purposes, they are identification, forecasting, investigation, framework development, evaluation, exploration and understanding. Table 2 shows a list of literature on SCM with Delphi methodology.

Table 2

Delphi Studies on Supply Chain Management

Statistics on 77 Delphi Studies in Supply Chain Management from Business Source Complete Database (2000-2021) as of March 31, 2021								
Publication Date			**Main Subjects Involved**			**Main Purpose of Study**		
Years	Frequency	%	Topics	Frequency	%	Purpose	Frequency	%
2000s	15	19.48	Sustainable SC	16	20.78	Identification	27	35.06
2010s	50	64.94	IT Technology	3	3.9	Evaluation	12	15.58
2020s	12	15.58	Management and Performance	22	28.57	Investigation and framework development	18	23.38
			Big data application and processing	4	5.19	Forecasting	7	9.09
			Transportation and logistics	4	5.19	Exploration and understanding	6	7.79
			Decision-making	5	6.49	Others	7	9.09
			Others	23	29.87			
Percentage		100%			100%			100%

Another reason why Delphi method is chosen to conduct this research is due to the uniqueness of the Delphi used for the research topic with little or even without existing empirical evidence or observation (Powell, 2003). Also, there is no secondary data source accessible. The RQs in our study were grounded in forward-looking perspective to forecast desirability and feasibility for a successful digital transformation in SCM under the Big Data era. Literature review has been so far found mostly in the relationship between the big data impact and organizational performance, very few studies are found on the topic of how a successful digital transformation shall be viewed for SCM in terms of a sweeping changes in customer experience, business model, and organizational structure. Therefore, a Delphi approach is the best to answer this RQ since an aggregated view collected from panelist groups could enable us to forecast future pattern although with a subjective inference (Daniel & White, 2005). Finally, literature review has exposed us to many studies in SCM with Delphi method, and these studies by scholar-practitioners have brought in significant impact on the advancement of both academic research and practical implications. For example, the research by Kache and Seuring (2017) and Brinch et al. (2018) were not only furnished with answers to the RQs, gap filling, but also significantly impacted the organizational performance. Through addressing the intersections between SCM and BDA, the scholar practitioners can provide solutions to real world problem, which reflects a practical utility of the Delphi methodology.

Given the RQs, we need to establish criteria to evaluate what constitutes a successful digital transformation for SCM in the Big Data era. A successful digital transformation contains a series of elements that makes up a maturity level for an organization in digitalization process. This maturity level can be viewed as a comprehensive indicator that reflects an organizational success level in digitalization transformation. Therefore, as a subjective and qualitative method, the Delphi method can be used not only in the field of forecasting, but also in the construction of various evaluation index systems and the process of determining specific indicators (Daniel & White, 2005; Ju & Jin, 2013). For this research, when we consider the importance of a successful digital transformation, we need to evaluate the desirable and feasible elements that are contained in the process of a successful digital transformation.

A general search engine in Google for what elements is contained in a successful digital transformation, we were provided with several versions of it. Some researchers listed five elements, some listed three, even some listed twelve. Among these listed elements, we found that they were overlap or cross reference one another. And these elements are industry-oriented, meaning organizations vary with the importance of digital transformation given their differing agenda in digitalization initiatives. To determine what elements are considered desirable and feasible in digital transformation, we prefer to take nine elements in digital transformation proposed by Westerman, Bonnet, and McAfee (2014) from MIT Center for Digital Business who categorized these nine elements into three patterns related to transforming customer experience, operational processes, and business models (Westerman et al., 2014). As the advancement in digitalization, and increasing emphasis on data analytics for innovation and creativity and proliferation of AI use and IoT, Westerman and Bonnet revisited their original 2014 version and updated these elements through further interviews, teaching and surveys with hundreds of company executives, the updated framework for the elements reflected two shifting dimensions that emphasize on digital capability and leadership capability in organizational digital transformation (Bonnet & Westerman, 2021). Given evidence-based management view, we will list these relevant elements in Table 3 and Figure 2.

Table 3

Nine Elements of Digital Transformation (2014)

Transforming Customer Experience	**Transforming Operational Process**	**Transforming Business Models**
Customer Understanding	Process Digitization	Digitally Modified Businesses
Top-line Growth	Worker Enablement	New Digital Businesses
Customer Touch Point	Performance Management	Digital Globalization

Adapted from Westerman, G., Bonnet, D., & McAfee, A. (2014). The nine elements of digital transformation. *MIT Sloan Management Review*, *55*(3), 1-6.

Figure 2

The New Elements of Digital Capability (2021)

Business Model		
Digital Enhancements		
Information-based service extensions		
Multisided platform businesses		
Customer Experience	**Operations**	**Employee Experience**
Experience design	Core process automation	Augmentation
Customer intelligence	Connected and dynamic operations	Future-readying
Emotional engagement	Data-driven decision-making	Flex forcing
Digital Platform		
Core		
Externally facing		
Data		

Adapted from Bonnet, D., & Westerman, G. (2020). The new elements of digital transformation. *MIT Sloan Management Review*, *62*(2)., p. 85.

This comprehensive indicator viewed by the experts is equal to the weighted sum of the elements. The importance of each element in composing a successful digital transformation is the weight and the score of the element needs to be determined by the subjective judgment of the expert panel.

Role of the Researcher

Given the nature of a classic Delphi design, researchers have two roles (i.e., to plan and to facilitate the entire structured communications among a panel of experts through anonymity; Avella, 2016). In planning stage, researchers need to identify the discipline, creates number of groups and content design, and establish the method and procedures of communication. For this study, we will work out a list of experts from different disciplines and selection criteria for qualified experts such as number of years of working experience in SCM, educational background, management tenure status or age groups, and professional technical experience. Based on experts' qualification and background, we will decide number of panels and number of experts in each panel. Detailed grouping is presented in Table 4.

Table 4

Panelist Grouping Criteria

Disciplines	Organizations	ISM Member	Non-ISM Membership	Each Panel
Practitioners	Manufacturing, Retailing, Distributing, Transportation and Logistics, Wholesales and Trade	5	5	10
Academics	Universities,	5	5	10

	Research Institute, Consulting Firms			
Government Agent	Federal, State, County, City	5	5	10
Total Participants		15	15	30

Next step for the researchers is to work out procedures and processes to facilitate anonymous communications for each round of questionnaire, and based on the feedback from each round, the researcher consolidates, organizes, and categorizes all inputs from prior round for further inquiries from the experts to obtain answers to the questionnaire through iterative involvement in the questionnaire intersperse until consensus is reached (Linstone & Turoff, 2002).

I solicited answers to the questionnaire items from experts of ISM. Like any other Delphi studies, there are four types of biases inherently residing in the process of Delphi approach, each of which might unavoidably take effect on resulting judgement by the expert panel since these experts might have been preconceived with cognitive bias, perseverance in belief bias, anchoring, framing, bandwagon, and desirability biases (Hallowell, 2009; Winkler & Moser, 2016). To bring these types of biases to its minimum, for example, we will deliberately apply for group heterogeneity in forming each panel to minimize framing and anchoring effect as the group judgement is shown to be significantly better or worse depending on the extent to which group member diversity is achieved (Belsky & Gilovich, 2010; Yaniv, 2011). Other biases such as desirability, believe perseverance, and bandwagon effect will also be brought under control by using heterogeneity in terms of participants' educational background, professional tenure, divergent industrial experience and geographic disperse.

Participants in our study will be randomly selected from a pool of SCM professionals associates based on our predefined selection criteria. These participants have no prior direct contacts with the researcher since these SCM professionals are from all walks of life across the United States. Some may be from academic disciplines such as university teachers, social scientists from research institutes, some are from business and industrial sectors like CEOs, COOs and frontline managers and logistics planners, and even some are from government departments such as purchasing directors, buyers, and planners whose role is in sourcing, purchasing and logistics. There is not any power relationship between our dissertation committee and computer-assisted randomly chosen participants. To counter against bias, a third-party platform will distribute questionnaire and collect answers to the questionnaire so that the researcher will have no direct connection to any of the participants during this entire Delphi study. All these measures are in place to make the dissertation research as objective as it is supposed to be. Finally, in view of ethical concern, this research will be completely conducted outside the researcher's current workplace, there are no issues regarding power relationship between the researcher and researcher's organization or management in terms of financial support and authoritative dominance, meaning the research result will be in no way either favoring or bringing harm to the organization where the researcher works.

Methodology

Implementation of the Delphi method involves a careful and deliberate execution of several stages. For our dissertation research, we will follow the procedures and steps outlined by Okoli and Pawlowski (2004) as the format in which my research is to be undertaken.

Participant Selection Logic

To begin with, we will predefine a rigorous participant selection criterion to obtain qualified experts. In this research design, we plan to create three panelist groups with each representing a different sector in the supply industry since there is a need to obtain perspectives from heterogeneous sources (Linston & Turoff, 2002). In this way, we could bring biases down to the minimum. The three panelist groups are categorized as academics, practitioners, and government sector. Following the empirical Delphi studies in literature, there will be 10 experts in each categorized panel, and each panel shall have at least over half of the experts who are associate members of ISM. This design can obtain enough perspectives from ISM membership so that we could compare perspectives and figure out differences for analysis from both inside and outside respondents. The goal for this type of design structure is to set up a transparent platform from which we can obtain a reasonable degree of consensus while heterogeneity is maintained to reduce biases. Next, we will work out a list of panelists following the Delphi methodology guideline by Delbecq et al. (1975), identification of expert participants will be made through the following five steps as shown in Table 5.

Table 5

Steps for Identifying and Recruiting Panelists

Step	Action
Prepare ISM membership directory of Dallas chapter.	Identify relevant disciplines: academics, practitioners, government officials. Identify relevant organizations. Identify relevant academic and research institutions.
Populate ISM membership names of Dallas chapter.	Write in names of individuals in relevant disciplines. Write in names of individuals in relevant organizations. Write in names of individuals from academic and research institutions.
Nominate additional experts.	Contact experts listed in ISM membership directory of Dallas chapter. Ask contacts to nominate other experts.
Rank experts.	Create three sublists, one for each discipline. Categorize experts according to the appropriate list. Rank experts within each list based on their qualifications.
Invite experts.	Invite experts for each panel, with the panels corresponding to each discipline. Invite experts in the order of their ranking within their discipline sublist. Target size is eight to 10 experts. Stop soliciting experts when each panel size is reached.

Note. The procedure for selecting experts was adopted from Okoli and Pawlowski (2004).

The specific actions taken in each step were as follows:

1. Identify classes of experts through ISM membership directory to create a nomination worksheet (Delbecq et al., 1975). The purpose of creating this worksheet is to group expert by category before identifying them. Therefore, we will invite a person in charge of ISM membership service who is familiar with membership mapping and workplace concerning organizational change to fill in the worksheet so that we could identify the most appropriate disciplines, and organizations.

2. Enter the worksheet with names. After the worksheet is completed, we will enter each category with actual names of potential experts in table 5 for each corresponding discipline, each discipline in the table represents a different approach of identifying experts. There might be overlapping in entering the expert names between and within each heading since some experts are known for cross-disciplinaries.
3. Start initial contact in worksheet and request for referrals from the identified experts. Given the name list in the worksheet, we can contact the identified experts and ask them to refer any other experts that they know well to include them in the selection pool. The biographical information of these experts will enable us to understand which expert is qualified for which panelist group.
4. Qualify experts by ranking. Based on the obtained biographical information about each expert and their disciplinaries, we will be able to categorize each expert into three different groups, and within each group, then to create a sub-list nomination for each category because some experts are known for multiple roles. To place all the experts into their appropriate panelist group, we will manually rank them given the bios and qualifications that each expert possesses to derive a top 10 experts who will be assigned for the three different panelist groups before invitation.
5. Invite identified experts for the research. Given the ranking derived from aggregating the three different ranking lists, the top 10 experts in each category for panelist building will be invited. Due to certain unforeseeable

reason such as one or two experts drop-out, more experts than we need for each panel will be invited so that we could have back-up list. During the invitation process, we will expressly state the purpose of our Delphi research, and the reason why they are identified and needed for the duration of our study. we will contact these experts through email to begin with, then followed by a phone call to make sure if the contacted experts have received our invitation and check to see if they are able to participate in the survey. For those who are interested in the survey, we will send an invitation letter to each contacted expert who would then reply for their interest to participate by a return email so that we could be assured of their participation. In addition, the interested experts will also be informed of the requirement on response time, communication channel, and procedures for feedback loop. For this study, we will use Google Form to be sent via email for receiving and returning questionnaire.

For each panel group, there will have maximum 10 experts in each panel, at least half of the experts shall be from ISM associate members who are knowledgeable for the digitalization progression in SCM of the United States, these experts are from various organizations that include manufacturing, retailing, wholesale, government agencies, research, and consulting firms. The reason for this design is that the perspectives from these experts represent mainstream of the digital capability building, and we could compare the resulting view of the ISM members with the element benchmark stated by MIT center for digital business so that we could understand better the reason of being lag-behind and challenges facing the SCM of the United States in digital transformation under the Big Data era.

Instrumentation

Data collection in Delphi design is mainly through each round of survey questionnaire. I administered the Delphi questionnaires by emailing via the platform of Institute for Supply Management (ISM) or ISM professional local chapter. The selected experts will be free to choose whichever questionnaire to answer or not to answer. Delbecq et al. (1975) estimated that the average Delphi study could take 45 days to 5 months. However, in this study, we have all the selected participants within the United States, this would enable us to have a shorter turn-around time. We assume that a panelist from ISM membership would fill out and return a questionnaire within a few days after the receipt of each round questionnaire. Surely it would not take long for us to conduct analysis between each round before the next one could be sent out. Finally, we will follow the Delphi questionnaire administrative guideline to conduct survey in this electronic world (Dillman et al., 2014, p. 1), which process would end up with the same validity as that by conventional mail-in answers.

Questionnaire Design

Questionnaire compilation is another important issue in the Delphi study. To effectively work out a set of workable questionnaires, we are going to adopt the questionnaire design by Kache and Seuring (2017) with some minor modifications tailored to fit our research context and purpose. The questionnaire includes two main levels (organizational and management) of questions, with each level followed by three sub-questionnaires that tap into desirability, feasibility, and challenges involved in digital transformation. In this way, a pilot study will not be needed in terms of saving time and cost. Table 6 shows the modified questions that will be administered in this research.

Table 6

Questionnaire Items

Question	Subquestion
1. What are the potential implications of an effective leadership in digital transformation through the use of the big data on the supply chain organizational level?	1. What is the potential desirability in a forward-looking perspective? 2. What are potential feasibilities in a forward-looking perspective? 3. What are potential barriers?
2. What are the potential implications of an effective leadership in digital transformation through the use of the big data on the supply chain management level?	1. What is the potential desirability in a forward-looking perspective? 2. What are potential feasibilities in a forward-looking perspective? 3. What are potential barriers?

Adapted from Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations & Production Management, 37*(1), 10–36.

There are times when questionnaire is administered, low response rate or non-response from the participants results in. There are many reasons why less than expected response rate appears, one of the issues, according to Dillman et al. (2014), is that researchers fall prey on one of the four types error (coverage, sampling, non-response, and measurement) in the survey design. To avoid these shortcomings, and motivate selected participants to respond, we are going to apply customized survey questionnaire based on the knowledge about big data, data application and analytic capability, and the IT infrastructure available in SCM. Next, the content of survey questionnaire will be compiled based on the daily work relevant to digital transformation processes where their organizations have undergone. For example, we may raise a question like "How digitally capable is your organization compared with other organizations that you know of?”. “What steps or measures do you think critical for organizations to consider when going from conventional to digital model?”,

Procedures for Recruitment, Participation, and Data Collection

Questionnaire administration will follow the ranking-type procedure in which three rounds of data collection are normally taken. There are three stages involved in the process: brainstorming, narrowing, and ranking (Schmidt, 1997). Each stage will be divided into two phases with the first phase serving as initial data collection and second phase as validation of the responses obtained after the categorization. we will use Okali and Paolowski’s diagram (2004) to depict these three rounds as shown in Table 7.

Table 7

Phases of Data Collection

Phase	Action
1. Brainstorming	For this phase only, treat experts as individuals, not panels. Questionnaire 1: Ask experts to list relevant challenges, factors and/or elements (not in any order) for digital transformation in terms of desirability and feasibility. Consolidate these two lists from all experts, regardless of panel. Remove exact duplicates and unify terminology. Questionnaire 2: Send consolidated lists to experts for validation. Refine final version of consolidated lists.
2. Narrowing Down	Thereafter treat experts as three distinct panels. Questionnaire 3: Send desirability and feasibility items (factors, challenges, and elements) list to each expert. Each expert selects (not ranks) at least ten items on each list. For each distinct panel, retain items selected by over 50% of experts.

3.	Ranking	Questionnaire 4: Ask experts to rank items on each of their panel's pared-down lists. Calculate mean rank for each item. Assess consensus from the list using Inter-Quartile Rater (IQR). Share feedback with each panelist and ask them to re-rank each list. Reiterate until panelists reach consensus or consensus plateaus. Result is six ranked lists, two for each panel.

Note. *The Delphi study process used in this study was adopted from Okali and Pawlowski (2004, p. 24).*

In the Brainstorming Phase 1 stage, I used an open-ended questionnaire survey to brainstorm three types of survey questions, i.e, challenges that result in SCM lag behind, milestone that indicates the success of a digital transformation, and relationship between building organizational business analytics capability from the big data and leadership commitment. Given these question categories, we will ask each group to identify any barriers or factors that result in the SCM lag behind in digital transformation within their organizations, to list any milestone progress that they could think to indicate the success of digital transformation in their industries in terms of desirability and feasibility, and to comment on the rationale of business analytic capability building and leadership commitment. The experts will be asked for giving a brief description to explain the reason for each question answered in the category so that we could better understand their meanings.

In the Brainstorming Phase 2 stage, I consolidated a list of responses by the experts from the initial questionnaire and categorize these responses into patterns and themes. To validate our understanding of the experts' responses, we will send back what we sorted it out, together with the responses that individual expert made in the first phase so that they could review against their response to make sure that we have correctly understand and interpret their answers. Therefore, in this phase two, we will ask experts; 1) to verify that we have correctly interpreted their responses and entered them in an appropriate category; 2) verify and refine their answers. Without these steps, there is no basis to claim that a valid, consolidated list has been produced (Schmidt, 1997). Often at this moment, the experts can come up with additional items that they probably ignored initially. After this validation process, we can be assured of the consolidations and refinement.

The aim of the Narrowing Phase 1 stage was to understand important opinions that different stakeholder groups indicate on the three categorized solicitations. To narrow down, we need to ask the experts to cluster each of their responses into major constructs/themes and rank these themes in terms of relative importance. Since some groups of experts might view these categorized issues in SCM somewhat differently, and some feedbacks might have overlapped cross one another, or there are potential implications for government policy and managerial action. Therefore, our strategy is to have groups with similar opinions reconcile among themselves which responses are the most essential, rather than trying to elaborate different perspectives individually. By so doing, we would be not only able to identify the reasons why they furnish me with their answers to each category, but also generate insight into how they view the challenges and factors more critical than that of others (Keil et al., 1998). In this specific research, their answers to the questionnaire indicate what essential actions would have to be taken in terms of a success of digital transformation in SCM under the big Data era.

In the Narrowing Phase 2 stage, I focused on listing the most important challenges, factors and/or elements for this phase. There are three constructs in this research. That is the reason why we intentionally map the question content into three categories. The first round of questionnaire is designed with open-ended solicitation so that all the experts from three different panelist groups could brainstorm any challenges and/or factors facing digital transformation in SCM, necessary steps and measures that shall be taken toward digital transformation in terms of desirability and feasibility for SCM, and commitment level from organizational leaders on building business analytic capability. The first two phased questionnaire, although validated by experts, still represent a broad coverage in their replies.

Therefore, the purpose of narrowing is to list the most important factors, steps, and elements that they think desirable and feasible in achieving a successful digital transformation from their prior broad coverage. Data from the prior two phases will be fully transcribed into a spreadsheet and coded independently by applying the process for the data reduction, data display, conclusion drawing, and verification technique described by Miles and Huberman (1994) who suggested qualitative analysis needs to be well documented. Therefore, the third questionnaire will be randomly arranged to cancel out bias in the order of the item listings. Each panelist will be asked to select (not rank) at least six factors and/or elements from each listed category that they consider important to the success of a digital transformation in terms of desirability and feasibility in the Big

Data era. When all panelists have returned their responses, we will analyze each panel separately to identify the factors and elements selected by over half of the experts in the panel; we will retain these results for each panel. This process will reduce the lists to a manageable size. The target size for ranking will be about 30 to 48 items.

The aim of the Ranking stage in the classic Delphi approach is to obtain consensus through the several rounds of questionnaires. I needed to have each panel group to list their relevant factors and/or elements within each group. The reason is that consensus is relatively easier to be reached within each panelist group than to gain a consensus from Delphi groups (Okoli & Pawlowski, 2004). Therefore, the panel design for consensus is the best for my purpose since the participants assigned to a specific panel group are deliberately selected given their demographic homogeneity by the researcher, in this way, the participants can have direct and adequate interaction over the issues in question.

The next step in the Ranking stage is to list the most important factors, challenges and/or elements on an individual basis within each panelist group in the order of their priorities. Each panelist will rank their listed items to a level at which only they think is necessary in terms of desirability and feasibility for a successful digital transformation. Meanwhile, we will also ask the experts of each panel in this round of questionnaire to give me their inputs as for why they rank these factors and/or elements in the order of their preference to justify their ranking.

Finally, we will ask the experts to provide us with their ranking explanation behind their reasoning. According to Schmidt (1997), solicitation of experts' comment on their reasoning can help understand experts' thought process from which their ranking is derived. Another reason, from researcher's perspective, is to gain insight behind each ranking. Sometimes, there might be a situation where a different item ranking shares the same reasoning at expert individual level, or there might be a case that the same reasoning from two different experts rank the same item in a different order given their differing perspective in the order of importance. When it is necessary for us to reiterate for consensus seeking within that panel, we could across reference these explanations to the same panelist group so that it is easy for them to review, revise, reevaluate each other's ranking to reach unanimity.

Data Analysis Plan

Completion of the three rounds of questionnaire will enable us to organize, sort, and categorize challenges, factors and elements that have been listed in the order of their importance based on individual expert's responses of each panelist group. To gain qualitative meaning of their responses, we will arrange them into two categories, i.e, desirability, and feasibility. Under each category, we will list the items in the order of the importance by panelist group, then we will rank them in priority order and code these items by meaning, i.e., if the item listed by different experts share the same meaning, we will code them the same so that we can further pare-down the list. After that, we could figure out patterns, and from these patterns, we will be able to derive themes under each category so that we could have a clear understanding of what stakeholders are thinking about a successful digital transformation as business analytics capability increases and leadership commitment in SCM is to be re-enforced. Since this is a qualitative analysis of the responses obtained from experts' feedback, different researchers might have differed interpretation of the pattern and themes that have been derived from category.

The ranking by individual experts varies with personal preference, which makes the researcher hard to list them in the order of priority when considering the most essential elements that shall be contained in a successful digital transformation in the Big Data era. Therefore, we must determine the ranking in a quantitative approach. In this regard, we will follow the guideline of non-parametric ranking by Schmidt (1997) as my analytic technique. The reason why we decide to take non-parametric ranking principle is that all these rankings are ordinal in nature, meaning nonparametric statistics does not rely on numbers, but rather on the order of sorting. For this specific research, the listing of items conveying individual preferences ranging from unsuccess to success in digital transformation would be considered ordinal data. we will then apply interquartile range (IQR) a statistical metric that represents the spread of data around the median. It includes the middle 50% of the observations. If the IQR is smaller than 1, it indicates that over 50% of all opinions are concentrated inside a 1-point range on the scale (De Vet et al., 2005). The IQR is commonly employed in Delphi studies and is well recognized as an unbiased and rigorous approach for establishing consensus (von der Gracht, 2012).

At the end of this ranking phase, we will have six ranked lists: two from each panel, representing the priorities that each of the panels placed on various factors in achieving the success in digital transformation in SCM in terms of desirability and feasibility. This rigorous process assures that the challenges, factors and/or barriers in the list are the most essential, and that the rankings are a valid indicator of a successful digital transformation. Based on these results, we will be able to figure out the reason of being lag behind and leadership strategies for a successful digital transformation in SCM. Meanwhile the theoretical observations from the literature, together with this research findings, we can offer propositions on desired relationships between organizational business analytic capability building and leadership commitment in affecting a successful digital transformation in SCM.

Issues of Trustworthiness

Delphi study is always vulnerable to criticism for lacking scientific rigor with vagueness of concepts from experts, lack of standard statistical analytical procedures and the findings being merely a collection of personal opinions subject to researcher bias (Ju & Jin, 2013). It is often a challenge for qualitative researchers to demonstrate trustworthiness in research findings with transparency in data collection and interpretation where bias is inevitable. Therefore, we won't intend to convince on how we build credibility, transferability, dependability, and conformability into our research, but to indicate what measures we have adopted to make this research finding as much objective as to be reflective of reality. From post-positivist perspective, human knowledge is based on a set of warranted conjecture, and these warrants can be modified and withdrawn in the light of further investigation (Lindlof & Taylor, 2017). In this view, our research findings can be credible, but are still subject to further empirical observation or study. We acknowledge that biases in the research process is undesirable but inevitable. Therefore, the researcher must work to detect and correct them as necessary

(Katherine, 2002. p. 35-45). Given this axiological perspective, we will address the trustworthiness of our research under this token.

Credibility

We have adopted a strict procedure for expert selection and back-to-back qualification assessment on the part of experts before they are actually assigned into different panelist group. The reason to phase in this process is to avoid homogeneity in terms of sharing the same experience from one industry. Thus, the inputs from the different panels will reflect differing views given their different work experience from different industries. Another outcome for this type of design is that it would be less subjective to authoritative power when these experts offer their own views because these experts are not familiar with one another. Hence, whatever feedback from individual expert is solely their own opinions, there is no influence among them. A big difference for this design also comes from the entire Delphi group as each panelist group act on their own pattern, there have no interaction between or among the panelist groups except interaction with the research facilitators. Moreover, to ensure the interpretations of data consistent and transparent, we conduct coding process through data analysis so that each description abstracted from data reading is interpreted individually in the research, then aggregate these interpretations into a reasonable understanding of the message thereby deriving patterns and themes. Therefore, the analytical result from each round of questionnaire is reliable in terms of coding process for each panel.

Transferability

In qualitative study, transferability means what we measured is based on what data we have collected (i.e., our data shall objectively reflect the reality and our research findings can be reproducible if the same procedures are followed by other researchers). Therefore, transferability is referred to as validity and the integrity that we applied in the methods undertaken and the findings accurately reflect the data. In this study, we have clearly indicated each step of the way in which I went from expert nomination, selection, questionnaire content design and generation, administration of rounds of questionnaire all the way through data collection, data organization and assortment, and data analysis, each of these processes were strictly followed the guideline stipulated by Schmidt (1997) and Delbeq et al. (1975) to prevent from data distortion and researcher's bias. For example, feedback from each individual expert is totally based on their own opinion, no dominating opinion is from authoritative power since these experts do not know each other in any of the panelist groups, they are free to express themselves throughout the entire questionnaire administration. we treated each individual expert equally in terms of feedback loop by my research facilitator. In coding process, we coded each entry individually, then synthesized to derive category, patterns, and themes accordingly. Finally, we have adopted a transparent procedure and method in the entire research process, which makes it easy for any researcher to reproduce the same result if the same procedures are followed.

Dependability

We build our panelist groups by inviting heterogeneous and qualified experts who come from different industries across the nation. Using heterogeneous panelist design would secure the stability and dependability of Delphi results (Cornick, 2006). Given the post-positivist perspective, a single, objective reality exists in human conjecture that is subjective to modification and/or withdrawn (Lindlof & Taylor, 2017) since both human beings and contexts change constantly (Wallendorf & Belk, 1989). Thus, we cannot guarantee that our results would be repeated if we replicate the research with similar experts in a similar context. Regardless, there shall be a boundary beyond which the dependability would be subjective to time frame constraints. It is recommended that we explore the boundaries of dependability by applying a longitudinal approach and repeating investigations later when things should have changed in various ways (Wallendorf & Belk, 1989). With the dynamics of the technology development and business environment, results vary with time should not be surprising. Although this might appear to be a limitation on this study, such challenge is unavoidable to all qualitative research approaches. Furthermore, we shall know that the Delphi method is not only used for theorizing, but also can furnish us with a snapshot of expert opinion at a specific moment in time (Maceviciute & Wilson, 2009; Thompson, 2009). If we take this into account for our study and combine it with a longitudinal design as deem fit, dependability should not be an issue with the Delphi method in the research. For triangulation, this research findings will be checked against relevant findings in the literature and see if my research results can be grounded in the prior empirical observations by other scholars and/or practitioners.

Confirmability

We establish the confirmability of our research by applying several procedural steps. As mentioned earlier, we have implemented strict criteria for expert selection from nomination all the way through expert role assignment. In solicitation of expert feedbacks, we follow exactly the conventional Delphi approach in which three stages of questionnaires are administered with the follow-up rounds based on the analysis of the prior result. The analysis of each round is a statistical process under which the experts' feedback of each panelist group is weighted so that the order of priority or importance can be found as a basis for the following round questionnaire. Therefore, the brainstorming serves as an initial source for us to discover what issues are involved in SCM digital transformation across different industries. For instance, the second round of the questionnaire can be narrowed down to ask for major issues facing different industries when calling for the digital transformation. To gain consensus on the topic, we administer the third round of questionnaire focusing on prioritizing the list of issues that each industry experiences. The entire solicitation process is leveraged with triangulation across researchers by involving multiple analysis, planning, execution of question surveys and consensus building as well as the analysis of textual data (Wallendorf & Belk, 1989). The most important of all, we have implemented an internal audit trail of data gathering and interpretation to increase confirmability in Delphi research (Skulmoski et al., 2007). We understand that any research cannot be objective and be free of biases, but we can remedy it by ourselves given the perspective of the post-positivists who consider our knowledge is based on conjectures of which can be later modified and withdrawn in the light of further investigation (Lindlof & Taylor, 2017). Moreover, as another layer of enhancing the objectivity, we will check our research findings against empirical observations by the MIT Center for Digital Application as an external audition to maximize confirmability. Finally, to achieve confirmability of our coding process, we leverage triangulation across researchers by aggregating and synthesizing feedback content to derive categories, patterns, and themes for the analysis of contextual data.

Ethical Procedures

This dissertation study aims to determine how a panel of 30 subject matter experts from the Institute of Supply Management in the United States views the desirability, feasibility, and importance of successful digital transformation of SCM through use of big data. To seek consensus from these experts, we have applied Delphi approach with three rounds of questionnaires. I obtained approval from Walden University's Institutional Review Board (IRB) before collecting data (approval no. 08-30-22-0667528). If there is anything that requires me to revise, amend, and edit, we will stick to these procedures for compliance.

For the selection of experts, participant contacting, participant qualification, panelist group assignment, and each round of feedback by panelist groups, I followed the guidelines stipulated in Delbe et al. (1997) and Linston and Turoff (1997). Selected participants will be contacted with a letter of consent, and they will be informed of my research purpose, duration of their participation, and requirement of their time dedication.

All these will be expressly indicated in their willingness to take part in my questionnaire survey with their signed letter of content. They are free to make their decisions on participation. In addition, all feedback is anonymously sought out, these experts would not have direct contact within their individual panelist group except for research facilitators. Collection of data and data storage, re-organization, assortment, process, and analysis of these data are only accessible to researchers. Unauthorized users would never be allowed to access data. I have established a procedure to transcribe all feedbacks from three rounds of questionnaires and maintain an environment of back-to-back discussion loop throughout the entire survey and store all survey responses in a database and recording notes on my analysis in Nvivo.

We will include at least 30 participants from both ISM associate members and non-associate members. All participants will complete all three surveys, and they will be assigned into two different panelist groups based on their membership status and be asked to complete anonymously through back-to-back feedback loop; there will be 50% of ISM associate members and 50% of non-associate member. These participants will be assigned into two panelist groups for researchers to compare different perspectives between ISM members and non-ISM members. This dissertation study is not in any conflict with any organizations in terms of prejudice or in the interest of financial favor to produce a preferential outcome on purpose.

Summary

Chapter 3 has been focused on the Delphi methodology and design with which this dissertation study is to be conducted. We have elaborated the procedures of each step that a Delphi approach will be undertaken from candidate nomination to participant selection all the way through panel group assignment. The design of questionnaire content and questionnaire administration are also introduced so that audience will be informed of the feedback process. Collection of data and data storage and access have also been regulated for compliance given IRB requirement and National Institutes of Health guidelines. Statistical tools and techniques used for data analysis are chosen based on the need of our research procedure. Interquartile range (IQR) is used to measure consensus because it is widely used in applied Delphi studies (Schmalz et al., 2021). IQR is applied for this statistical analysis as we need to rank the importance of priority according to experts' preferential feedback and measure the difference between rounds for saturation. To minimize biases in interpreting experts' feedback, we have applied synthesized content coding process from which the pattern, category and themes are derived. The implementation of the instrument and measurement is to make our research with rigor and objectivity in terms of credibility, dependability, transferability, and confirmability. Ethical issue has also been disclosed based on the compliant requirements in the light of the National Institutes of Health and IRB. In Chapter 4, I will present the research results along with a detailed explanation of what I found in terms of consensus building.

Chapter 4: Results

This qualitative classical Delphi study aims to determine how a panel of 30 subject matter experts from SCM professionals in the United States view the desirability, feasibility, and importance of successful digital transformation of SCM using big data. To gain consensus on the desirability, feasibility, and importance of successful digital transformation, I posed two questions to SCM professionals: (a) “What are the challenges and/or barriers that result in SCM lagging in digital transformation?” and (b) How is the desirability, feasibility, and importance of digital transformation of SCM impacted using big data?” This study's RQs were grounded in a forward-looking perspective to forecast the desirability and feasibility of a successful digital transformation in SCM in the big data era. In Chapter 4, we will detail the data collection process outlined in Delphi methodology that includes survey questionnaire design, platform selection, participant enrollment and qualifying, administration of three-round survey questionnaires, and data analysis between each round. The final study result is obtained through statistical processing of the collected data.

Setting

This Delphi study aims to determine how a panel of at least 30 SCM professionals can view the desirability, feasibility, and importance of successful digital transformation in SCM in the Big Data era. Initially, we chose the Institute for Supply Management (ISM) as the platform for data collection through the ISM Dallas local chapter. With IRB approval, I contacted the ISM Dallas chapter president and asked for his help administering a survey questionnaire to obtain data for this research. The chapter president showed great support and helped in this process by disseminating the survey questionnaire, IRB-approved letter of invitation, and consent form to about 200 ISM associate members within the Dallas chapter platform. However, the response rate did not meet the minimum required responses for data analysis for each round. To continue the research with the Delphi approach, we decided to enlarge the audience base by switching to a wider platform Interview that can pull the audience from all types of social media.

We officially used the User Interview platform with the IRB approval to continue participant enrollment and selection. To gain potentially qualified participants, I applied screening questions to qualify participants on the User Interview platform. The screening question aims to filter out participants who are neither SCM professionals nor familiar with using big data in SCM. Some of the screening questions, for example, were "Are you working as a supply chain professional for at least 2 years?" And "Do you have any experience in big data usage in SCM at either organizational or management levels?" These screening questions are included in Appendix B. Potential participants needed to meet the criteria set forth in the screening questions to be qualified for the survey. Before accessing the first-round survey questionnaire, qualified participants received the IRB-approved letter of invitation (see Appendix C) and consent form. Therefore, all participants are well informed of the purpose and duration of the survey for each round.

With a limited timeframe and policy of no compensation, we simplified the process of each round questionnaire from the originally complex design to avoid drop-out since the longer it takes, the more drop-out cases will occur. A ranking-type Delphi is used to reach a group consensus about the relative importance of issues (Strasser, 2017).

This Delphi Method uses an iterative-controlled feedback process that includes brainstorming, narrowing down, and ranking steps to identify and rank key issues (Schmidt, 1997). Therefore, the variant version of the Delphi method can still validate the interpretation of the study results (Strasser, 2017). Strasser (2017) studied variant Delphi methodologies and found that variant Delphi methods' generic features (anonymity, controlled feedback, iterative, and statistical aggregation) remain the same.

Demographics

There were 76 participants in total. After removing duplicate answers to the first-round survey questionnaire, answers to the first-round questionnaire from 64 participants were valid. The demographics of these 64 participants can be categorized into the following characteristics. In the survey, participants were only asked to provide their email address, number of years working as a SCM professional, and ISM membership. Also, participants were required to take screening questions before they were qualified to take the survey questionnaire. Therefore, the researcher knew that participants should have at least 2 years of working experience in SCM and were from various industries across the country. Given the collected information, the largest group of participants is from non-ISM membership, followed by participants from ISM membership. In these two groups, most participants have worked between 6 to10 years as SCM professionals, there are 15 participants with 2 to 5 years of working experience as SCM professionals, and we have 12 participants with 11 to 20 years working experience in the supply chain, and four participants with over 20 years of experience in the SCM. Among the final 32 participants, 17 are with ISM membership, and 15 are non-ISM members. We have no information on participants' ethnic group, their sex, and ages due to privacy concerns. Since the Delphi study requires three rounds of questionnaires, we often experience participants' drop-out during the following two rounds. Hence, the Delphi study takes longer than usual in data collection. This dissertation took us almost a year to collect data due to the frequent drop-out of participants in the data collection stage.

Data Collection

We used Okali and Paolowski's diagram (2004) to conduct three rounds of questionnaires. There are three stages involved in the process: brainstorming, narrowing, and ranking (Schmidt, 1997). Initially, the ISM Dallas chapter platform was used to administer survey questionnaires. After the survey questionnaires were disseminated for several months, the response rate was too low to meet the minimum requirement in headcount. With the IRB approval, the survey platform was switched to User Interview, which was able to drive potential participants to respond to the survey from LinkedIn, Twitter, and other social media. To qualify for participation, the researcher intentionally created a screening process for which the researcher can qualify participants. Potential participants must pass the screening questions before accessing the survey questionnaires. The screening questionnaire is included in Appendix B.

The first round is brainstorming, in which participants were treated as individual experts and asked to list relevant challenges, factors, and elements (not in any order) for digital transformation regarding desirability and feasibility. After removing exact duplicates and unifying terminology, we consolidated all listed challenges, factors, and elements into two separate lists from all experts, regardless of the panel, one for desirability and feasibility at the organizational level and the other for desirability and feasibility at the management level. Then, these lists were sent to individual experts for validation after this consolidation.

The second-round questionnaire was for narrowing down. At this stage, we listed two separate groups of questionnaires into six sub-groups so that we could present challenges, factors, and/or elements specifically for desirability, feasibilities, and barriers at organizational and management levels, respectively. For example, the questionnaire was presented to experts as "Please select at least 10 items among the factors, challenges, and elements in terms of feasibilities at the organizational level given the listings below" and "Please select at least ten items among the factors, challenges, and elements in terms of desirability at management level given the listings below." After the second round, responses from all participants were exported to Excel, where each expert's answer to all six sub-grouped questionnaires was calculated and consolidated according to the number of times these participants chose a specific item. Based on the number of times these participants chose a specific item, we can develop the most critical 20 challenges, factors, and barriers from the broadly listed items at both organizational and management levels contributing to the third round.

Ranking was the third round. It required participants to list the most critical challenges, factors, and barriers at both organizational and management levels according to their order of importance given their preference. To avoid confusion, we specifically asked the respondents to list challenges, factors, and barriers in ordinal order so that their preferences can be interpreted correctly. Most respondents listed their preferences in ordinal order, but only a few that were needed to follow up with their preference order via additional email contacts or took their order as initially listed. Nevertheless, the survey response is still valid because we can take their order as naturally indicated.

Data Analyses

As Franc et al. (2023) proposed, the Delphi method engages experts in a progressive series of iterative questionnaires to attain consensus. This study's primary focus was brainstorming feasibility, desirability, and barriers at both managerial and organizational levels. The qualitative nature of the three rounds featuring the conventional Delphi approach employed an inductive qualitative technique and quantitative analysis in the Delphi study.

Theme development through the Delphi qualitative method involves the extraction and refinement of recurring concepts, continuing until theme saturation is achieved, thus identifying pivotal thematic patterns. Spranger et al. (2022) highlight this method's emphasis on anonymity, allowing unbiased contributions and fostering consensus among participants. Ultimately, the Delphi method systematically explores and develops themes based on collective expertise and perspectives, facilitating comprehensive understanding within the research process (Franc et al., 2023). Within three rounds of survey questionnaires, the second-round questionnaire was built on the result of the first round. For this reason, the Delphi study involves quantitative analysis since the Delphi methodology involved collating input from a panel of 32 experts. Quantitative approaches were used to process the gathered data, involving numerical aggregation of responses and statistical assessments to ascertain expert consensus levels (Paré et al., 2013).

Despite its potential to significantly impact study quality and validity, this method has often needed more attention within the research methodology sections. Improved reporting guidelines could rectify this discrepancy, enhancing transparency in data accuracy and conclusive outcomes. Sekayi et al. (2017) applied the qualitative Delphi method, gathering experts' responses using closed-ended questions in the third round to ascertain consensus.

Data Analysis Approach

Analyzing qualitative data through the Delphi technique using NVivo involved a systematic approach integrating qualitative analysis methodologies with the iterative nature of the Delphi method. Here are the detailed steps used in the analysis:

1. Data Organization and Importation: The data collected from Microsoft Excel and Word, organized into distinct data sets representing each round of the Delphi method based on main categories and six significant domains, were imported into NVivo. This step facilitated easy accessibility and management of expert responses within NVivo.
2. Initial Review and Coding: Each round's data underwent a thorough review to comprehend the content, and preliminary themes were identified. Initial codes were created during this review to encapsulate respondents' ideas, opinions, and perspectives.

3. Iterative Analysis: Iterative coding was conducted for every round, employing NVivo's query tools like coding comparison queries, matrix coding queries, and code hierarchy. This approach aimed to compare coded segments across rounds, identifying changes and areas of consensus.
4. Consensus Building and Synthesis: Visualizations of coded comparisons aided in identifying convergence and consensus among experts. The analysis focused on pinpointing areas of agreement and divergence and exploring reasons behind conflicting viewpoints regarding managerial and organizational feasibilities, desirabilities, and barriers.
5. Refinement and Reporting: Insights gathered from visualizations and analysis refined subsequent rounds, addressing unresolved issues. Findings were documented, highlighting significant agreements and least prioritized areas among feasibilities, desirabilities, and barriers. A comparison between organization and management entities was drawn.
6. Continuous Review and Conclusion: Continuous review and refinement were conducted iteratively to draw comprehensive conclusions based on insights gathered from the entire Delphi process.

By employing these steps using strategic and authentic analysis processes (Braun & Clarke, 2006; Franc et al., 2023), the researcher used NVivo for qualitative data analysis that can minimize subjectivity, increase objectivity, and enhance the rigor and credibility of their analysis.

Theme Development

The current study's thematic development process involved an iterative approach where recurring themes and patterns surfaced from the participants' responses. These emergent themes were carefully identified, refined, and elucidated by integrating the collective input derived from the responses. Specifically, six axial codes were formulated based on narrative statements provided by the participants, encapsulating distinct aspects related to organizational and management levels. This thematic development process was essential to capture and categorize the insights conveyed by the participants systematically. By identifying these axial codes through iterative analysis, the study sought to elucidate multifaceted perspectives regarding organizational and management aspects. These emergent themes provided a structured framework to understand the feasibility, desirability, and barriers at both organizational and management levels, facilitating a comprehensive exploration of the research topic. Through this methodical approach, the study aimed to enhance the depth and clarity of understanding regarding the nuanced dimensions of organizational and managerial considerations expressed by the participants (Sekayi et al., 2017).

Evidence of Trustworthiness

Credibility

A strict process was followed from participant selection to coding. To avoid homogeneity, we used the third-party platform to pull potential respondents from all walks of life, and these potential participants were required to take screening questions to qualify themselves as potential respondents. Selected participants did not know each other since they came from different industries within the United States. Therefore, the answers to each round of the questionnaire were solely representative of their opinions without authoritative pressure.

Transferability

We have indicated how the study went from expert nomination, selection, questionnaire content design, and generation. The administration of questionnaire rounds through data collection, data organization and assortment, and data analysis strictly followed the guidelines stipulated by Schmidt (1997) and Delbeq et al. (1975) to prevent data distortion and researcher bias. For example, feedback from each expert is based on their own opinion; no dominating opinion is from authoritative power, and they are free to express themselves throughout the entire questionnaire survey. We treated each expert equally regarding the feedback loop by the research facilitator (third-party platform). We used the NVivo system to code categories, patterns, and themes accordingly. Finally, we have adopted a transparent procedure and method in the entire research process, which makes it easy for any researcher to reproduce the same result if the same procedures are followed.

Dependability

We built our panelist groups by inviting heterogeneous and qualified experts from different industries nationwide. A heterogeneous panelist design would secure the stability and dependability of Delphi results (Cornick, 2006). For example, the sampling population pool for this study was set for all SCM professionals regardless of sex, age, ethnicity, religion, and cultural background as long as the selected participants were qualified and given the screening questions. Also, these research findings will be checked against relevant findings in the literature for triangularity.

Confirmability

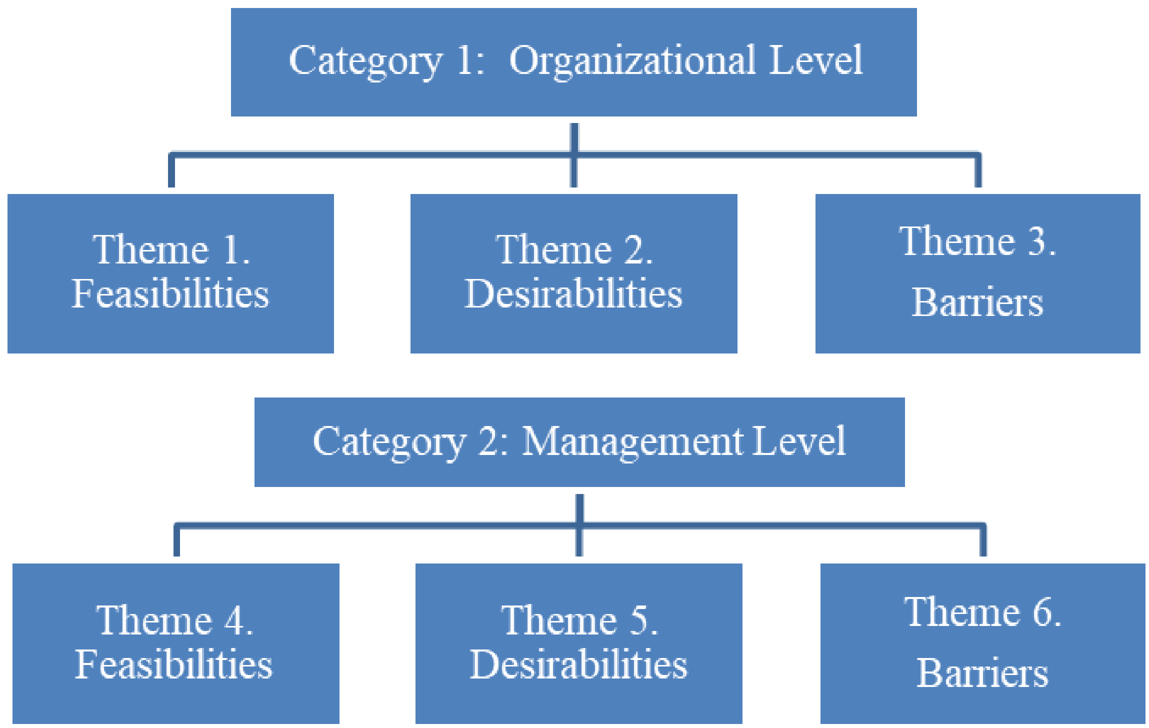
We followed the conventional Delphi approach in which three stages of questionnaires were administered with follow-up rounds based on the analysis of the prior result. The analysis of each round is a statistical process under which the experts' feedback of each round is weighted so that the order of priority or importance can be found as a basis for the following round questionnaire. Therefore, brainstorming is an initial source for discovering what issues were involved in SCM digital transformation across different industries. For instance, the second round of the questionnaire can be narrowed down to ask for significant issues faced at organizational and management levels when calling for digital transformation. To gain consensus on the topic, we administer the third round of questionnaires focusing on ranking the issues at both organizational and management levels. Then, these rankings were scored using interquartile rating (IQR) to derive consensus among these expert raters.

Coding Scheme

The coded units, derived from participants' feedback, underwent examination based on six categories (see Figure 3).

Figure 3

Categories and Themes



These coded units, reflective of diverse opinions and perspectives, were systematically organized into preliminary categories based on shared concepts, ideas, and axile codes (Spranger et al., 2022). Through an iterative process guided by the inductive qualitative technique, these preliminary categories were scrutinized and refined to identify overarching themes that encapsulated the essence of the participants' feedback. The progression from coded units to categories and subsequently to themes involved continual comparison, consolidation, and re-evaluation, ensuring coherence and relevance across the emerging representations (Franc et al., 2023). This iterative and rigorous process facilitated the extraction of central themes, contributing to a comprehensive understanding of the feasibility, desirability, and barriers evident at managerial and organizational levels, as highlighted in the qualitative Delphi study.

Results

Using the coding matrix, I explored the participants' ranked feasibilities at the organizational level (see Figure 4). The highest ranking feasibility was "Availability of technology, Scalability, Data accessibility, and strategic partnerships. After that, the respondents stated that "Identifying opportunities, Avoiding risks, Making better decisions, Improving efficiency, Enhancing innovation, Achieving goals, and Living a more fulfilling life," "Data availability, sharing can help planning, task execution, and efficiency," and "Preparedness, Planning, Motivating, Adaptability, Trendsetter" were the main feasibilities at the organizational level.

Figure 4

Feasibility at the Organizational Level

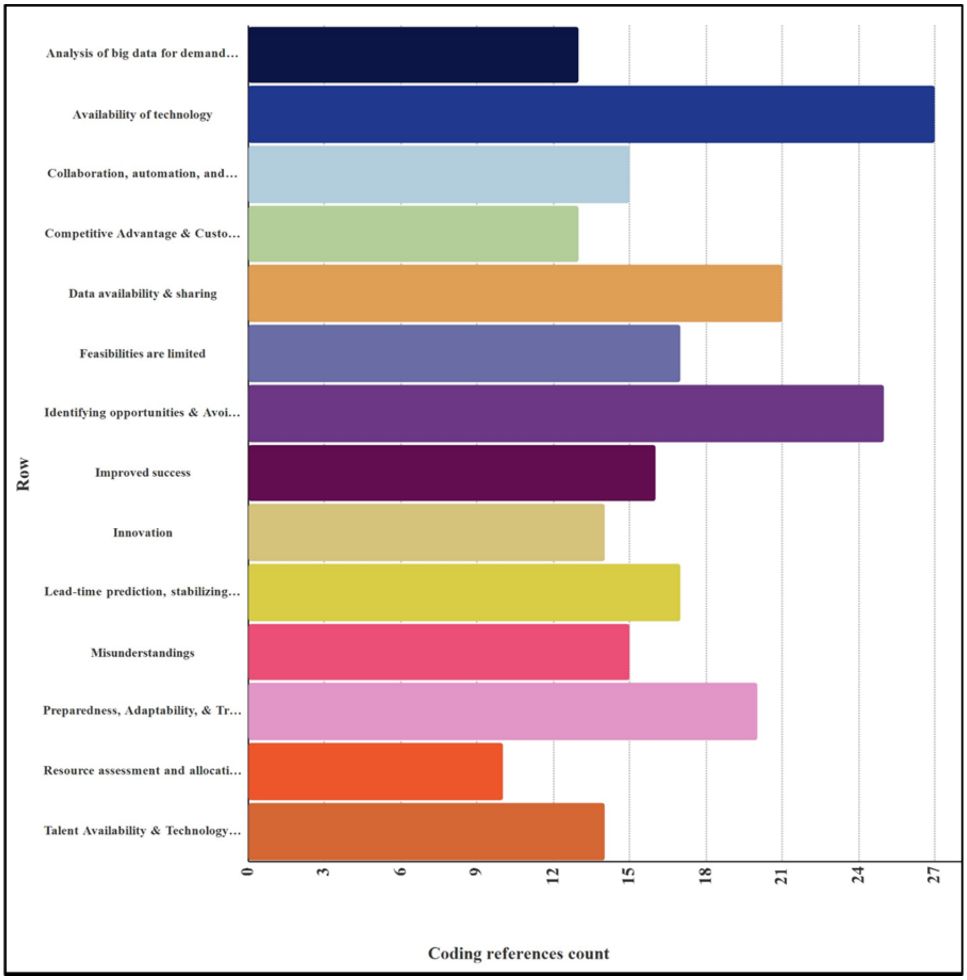
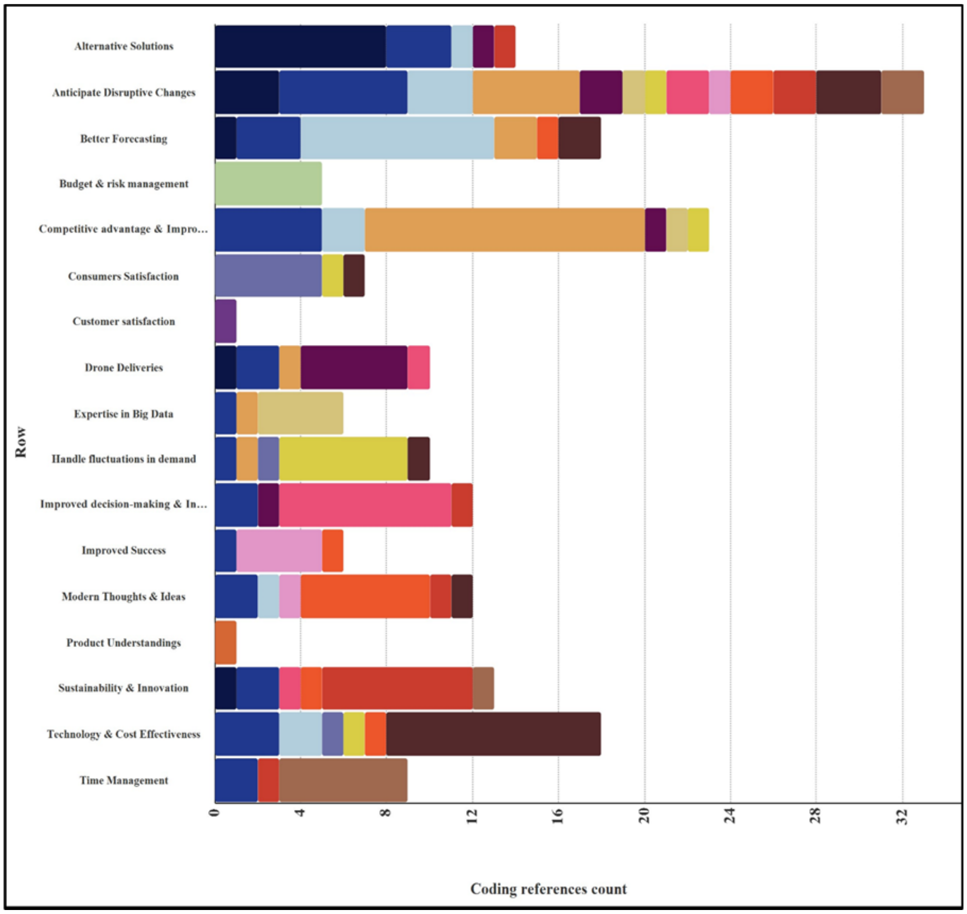


Figure 5 illustrates desirabilities at the organizational level. Under this category, the respondents ranked the desirabilities as “Anticipate Disruptive Changes, Strategic Planning, and Innovation” as greater desirability at the organizational level.

Figure 5

Desirabilities at the Organizational Level



Besides this, “Competitive advantage, Future-proofing, and Improved agility”, “Technology, Cost, Effectiveness, Access, Reliability, Performance,” “To better forecast, plan, purchasing decisions, and strategies in a way that is cost and time effective. Visibility and can be utilized to data-model multiple scenarios”, “To see where the business is falling short and create new solutions based on the data and allow the data to validate solutions,” and “Sustainability, innovation, competitive advantage, and agility and flexibility” are the most desirabilities at the organizational level.

Figure 6 reveals that there is a "lack of expertise, how to evaluate, too much data, insufficient staffing, "Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes," and "Hesitancy to partake in such an innovative and new type of data gathering for fear of miss use, and also monopolization, and privacy issue" are the most significant barriers to organizational level sustainability.

Figure 6

Barriers at the Organizational Level

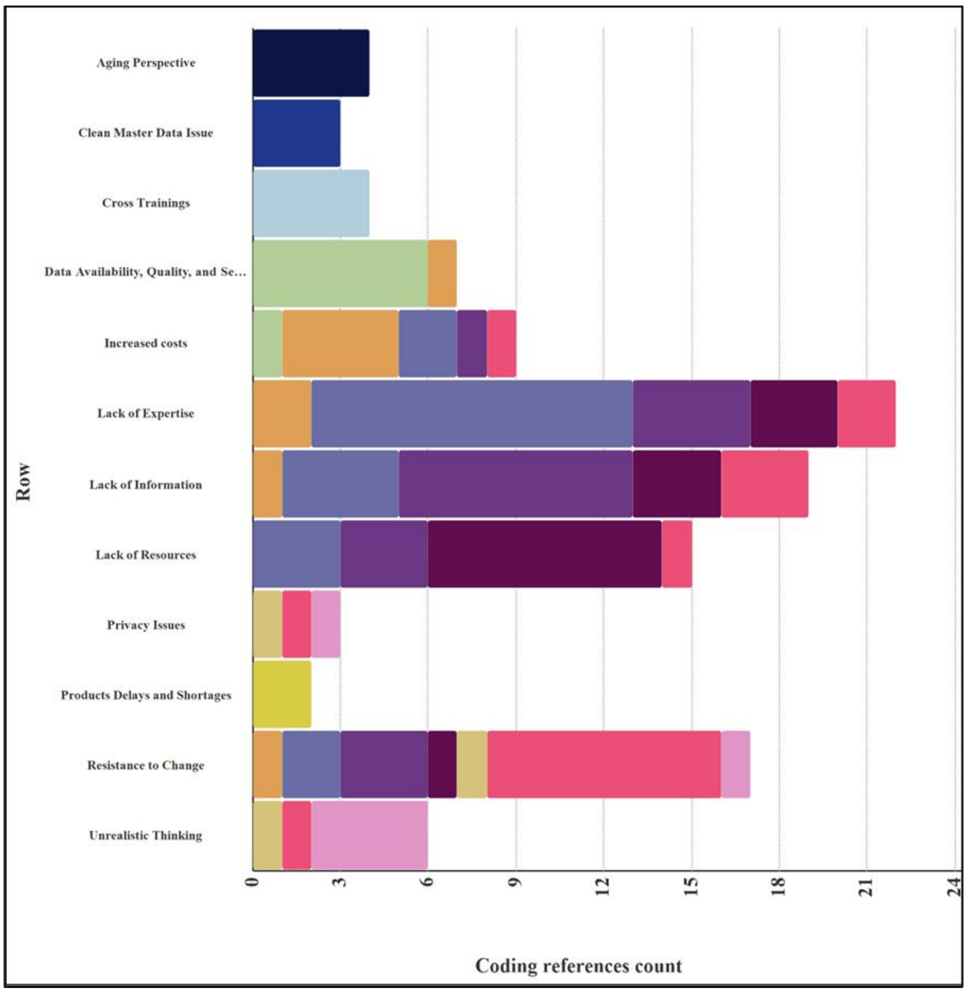


Figure 7 shows the coding matrix query based on several coded references to explore feasibilities at the management level. The visualization explored “Resource assessment and allocation, desired outcome to be achieved, team-building, management strategies, informed decision-making,” “Collaboration with partners, technology availability, data storage, and access,” “Enhanced Decision Making, Increased Agility, and Improved Collaboration,” Expertise as Understand when and what will happen”, “Financial and marketing”, “Staffing, experience, and training”, and “Technology Integration and data availability” are the top-ranked feasibilities at management level.

Figure 7

Feasibilities at the Management Level

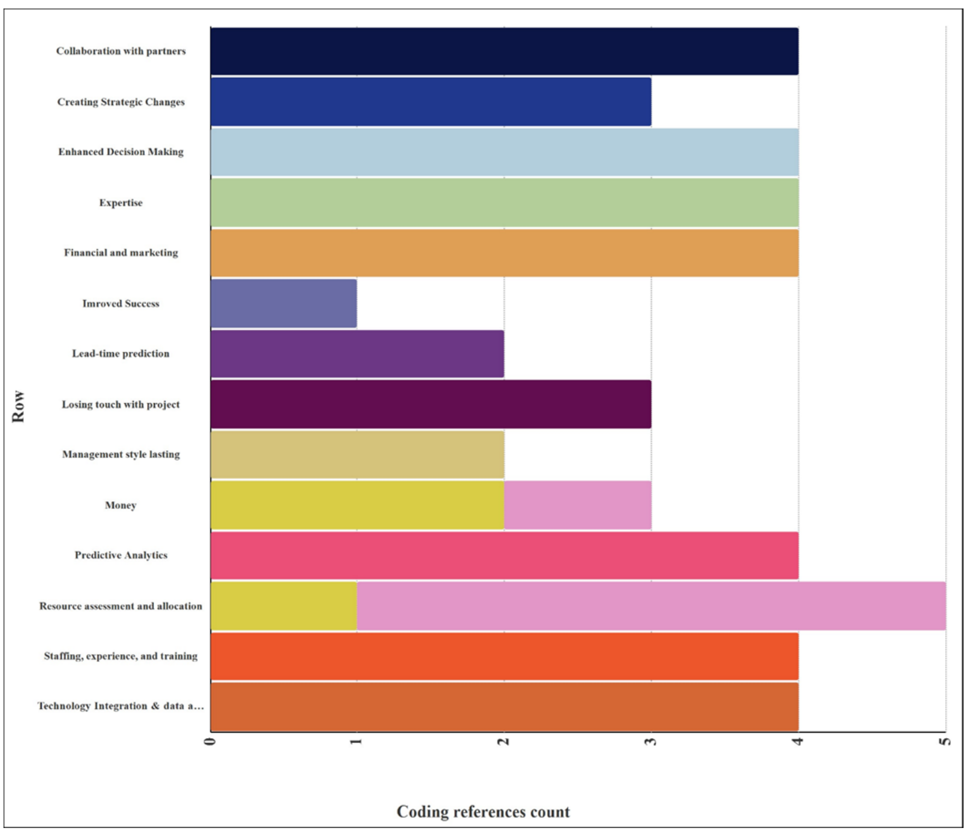
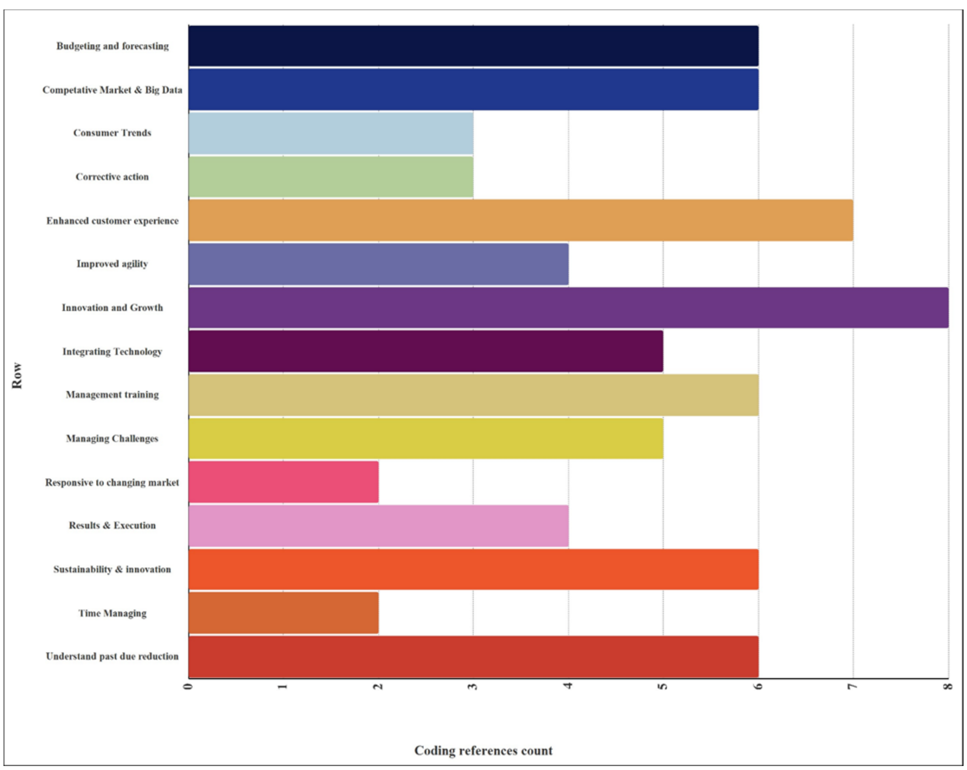


Figure 8 presents the desirabilities at the management level by the respondent's ranking order. The coding matrix of coded references revealed that the greater desirability at the management level is "Innovation and Growth, Improved Customer Satisfaction, and Competitive Advantage." The respondents revealed that "Competitive, enhanced customer experience, and efficiency," "Budgeting and forecasting," In a competitive market, big data can better planning, strategies, and retrospective," "Management training," "Sustainability, innovation, competitive advantage, and Agility and Flexibility," and "Understand past due reduction, lead-time, and cost impacts" as more effective desirabilities at management level.

Figure 8

Desirabilities at the Management Level



The management level within the organization also faced several barriers (see Figure 9). The results indicated that "Data quality and accuracy and security," "Resistance to change," "Integration with Legacy Systems, costs, and quality concerns," "Lack of Expertise," "Any type of delays could be catastrophic," "Lack of knowledge and understanding. Overwhelming amount of data. Customer resistance to change. The continual need to refresh data mining." and "A clean master data is always the immediate barrier" to the management level.

Figure 9

Barriers at the Management Level

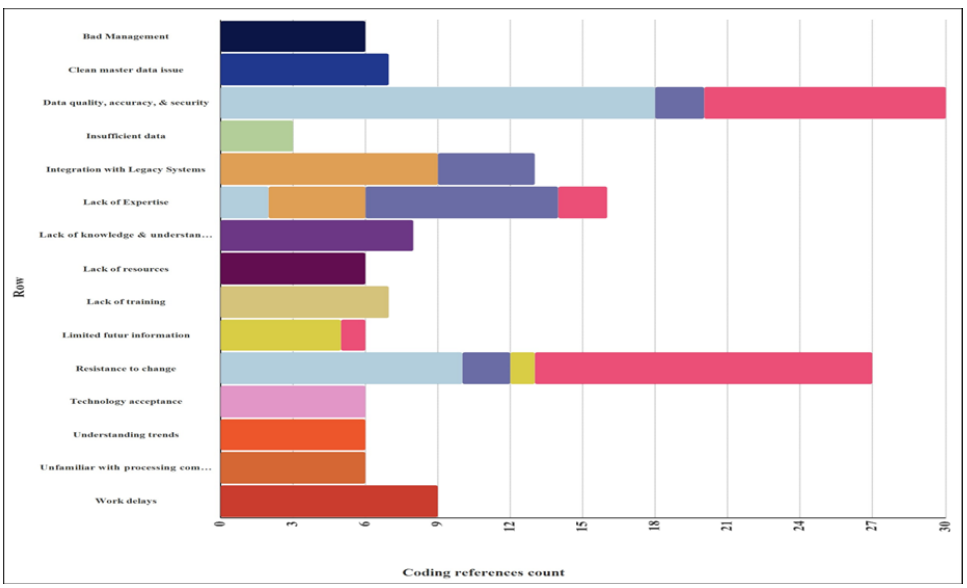
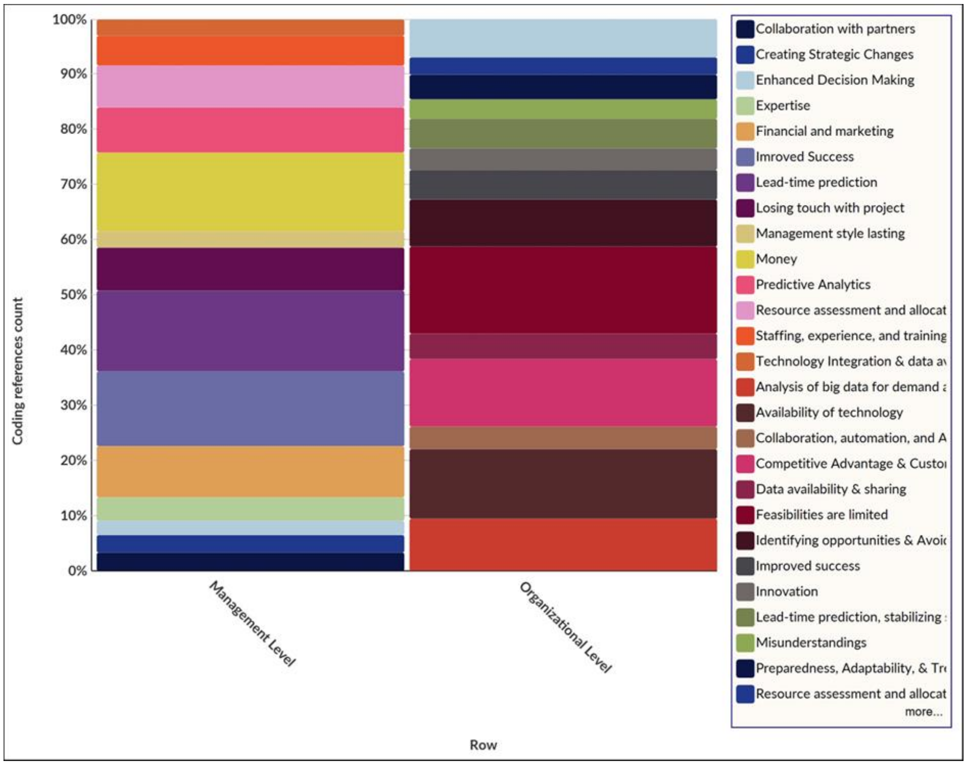


Figure 10 displays the comparison of organizational and management levels regarding feasibilities. The comparison of coded reference count explored that at the management level, lead-time prediction and stabilizing stocks (14.68%), money (14.18%), improved success (13.42%), financial and marketing (9.37%), predictive analytics (8.19%), and losing touch with projects (7.85%) are the most prominent feasibilities.

Figure 10

Comparison of Feasibilities Between Organizational and Management Levels

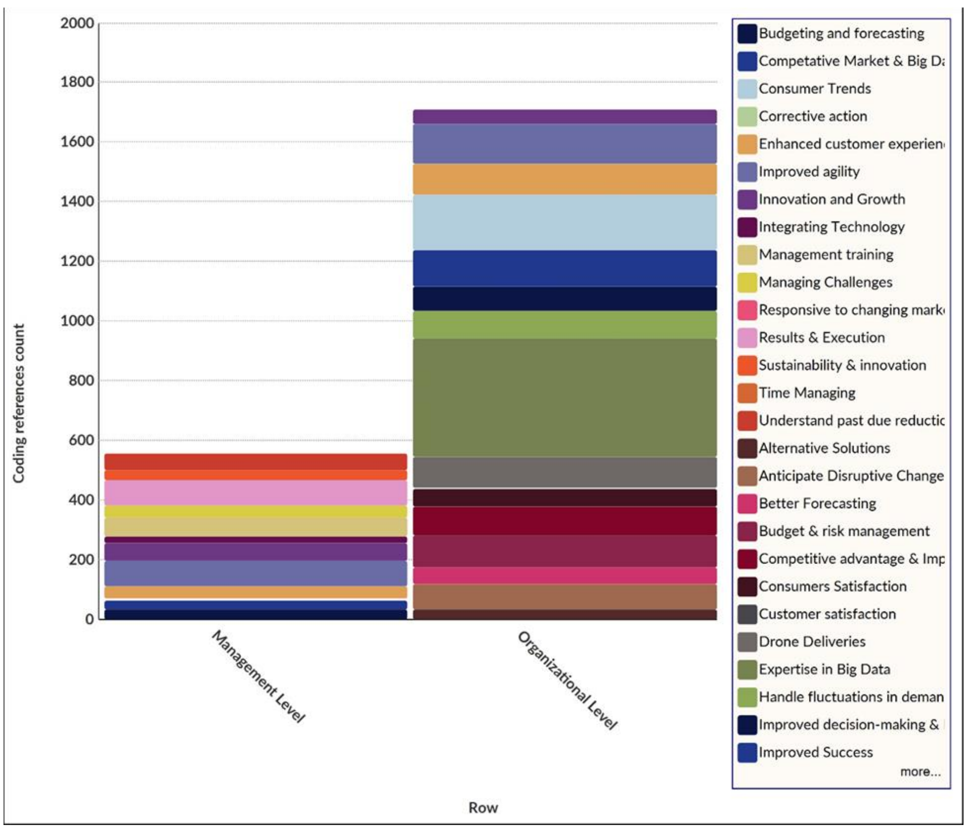


While at organizational level these "Feasibilities are limited by organizations not having the expertise, and customers are fixated on incumbent sources, which limits/hamstrings the ability to use big data to change suppliers" (15.90%), "Availability of technology, Scalability, Data accessibility, and strategic partnerships" (12.66%), staffing, experience, and training, "Competitive Advantage, Improved Customer Experience, and Increased Efficiency" (12.24%), and "Knowing how to analyze the overwhelming amount of big data and applying it the highly changeable future demand and customer requirements hamstrings the feasibility of using big data" (9.31%) are the most critical feasibilities at organizational level. Regarding coded references, the management level is found more with coded references than the organizational level. The result demonstrated that the feasibilities between organization management were found to be different.

Figure 11 shows the comparison of desirabilities between organization and management levels.

Figure 11

Comparison of Desirabilities Between Organizational and Management Levels



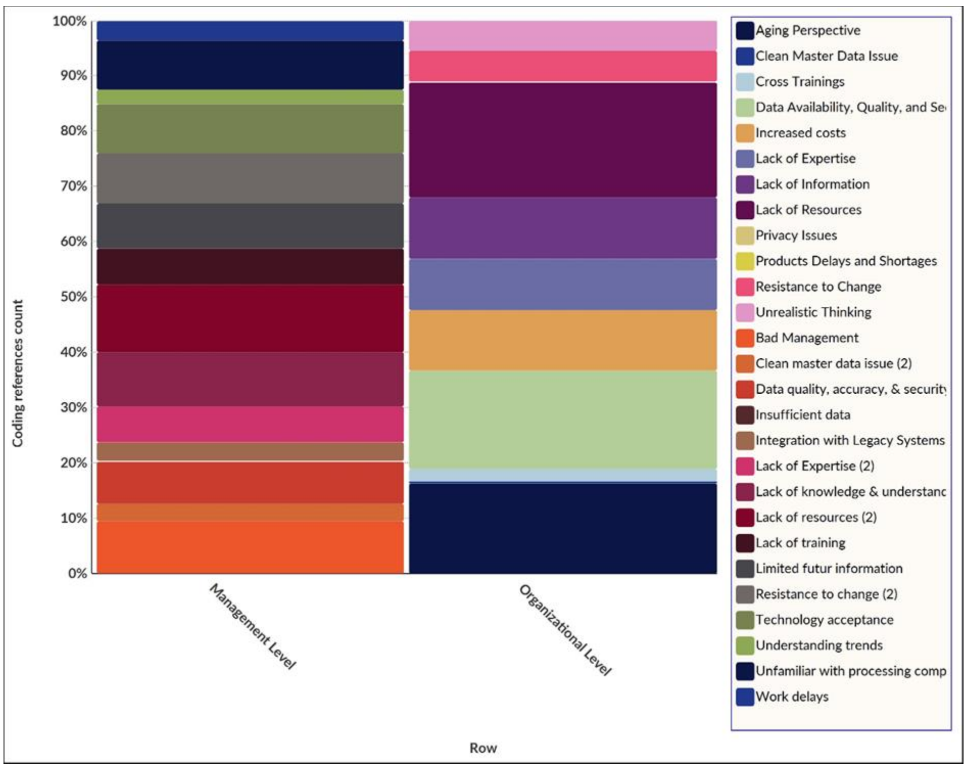
The results indicated that organization level had desirabilities of "Expertise in Big Data can better-sourcing decisions" (23.27%), "Thinking ahead, having modern thoughts and ideas" (10.88%), "Technology, Cost, Effectiveness, Access, Reliability, Performance"

(7.88%), improved success (7.13%), and “Drone deliveries, driverless cross-country shipments, & efficient transportation” (7.08%). Management level had the desirabilities of “Results, Execution, Effectiveness, Strategy” (15.16%), “Improved agility, better customer service, and cost-saving” (14.98%), “Innovation and Growth, and Improved Customer Satisfaction, and Competitive Advantage” (11.98%), management training (11.19%), and “Understand past due reduction, lead-time, and cost impacts” (9.75%). The desirabilities among organization and management levels were found to be different from their priorities.

Figure 12 illustrates the barriers at the organizational and management levels. The results indicated that the organization level faced barriers as organizations wanted to pay less for expertise. Management needs to understand big data, and there is no buy-in. Customers have preferred incumbents (20.75%). Moreover, organizations faced significant barriers of "Data Quality, Data Privacy and Security, and Implementation Challenge" (17.76%), "Age, thought perspective" (16.31%), "Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes" (11%), "Integration with Legacy Systems, increased costs, Lack of Expertise, and data quality can be compromised" (10.91%), and "Too much data, lack expertise, how to evaluate the data, insufficient staffing" (9.36%). On the other hand, the management level faced the barriers of "Lack of or insufficient data, resources, executive leadership support, time" (12.32%), "Lack of knowledge and understanding. Overwhelming amount of data. Customer resistance to change. Continual need to refresh data mining", (9.89%), bad management (9.41%), "Resistance to Change, Data Quality and Security, and Lack of Expertise" (9.12%), "Unfamiliarity with current processing Workflow complications, Interrupted work, Learning new routine, Time training" (8.92%), and "Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes" (8.15%).

Figure 12

Comparison of Barriers Between Organizational and Management Levels

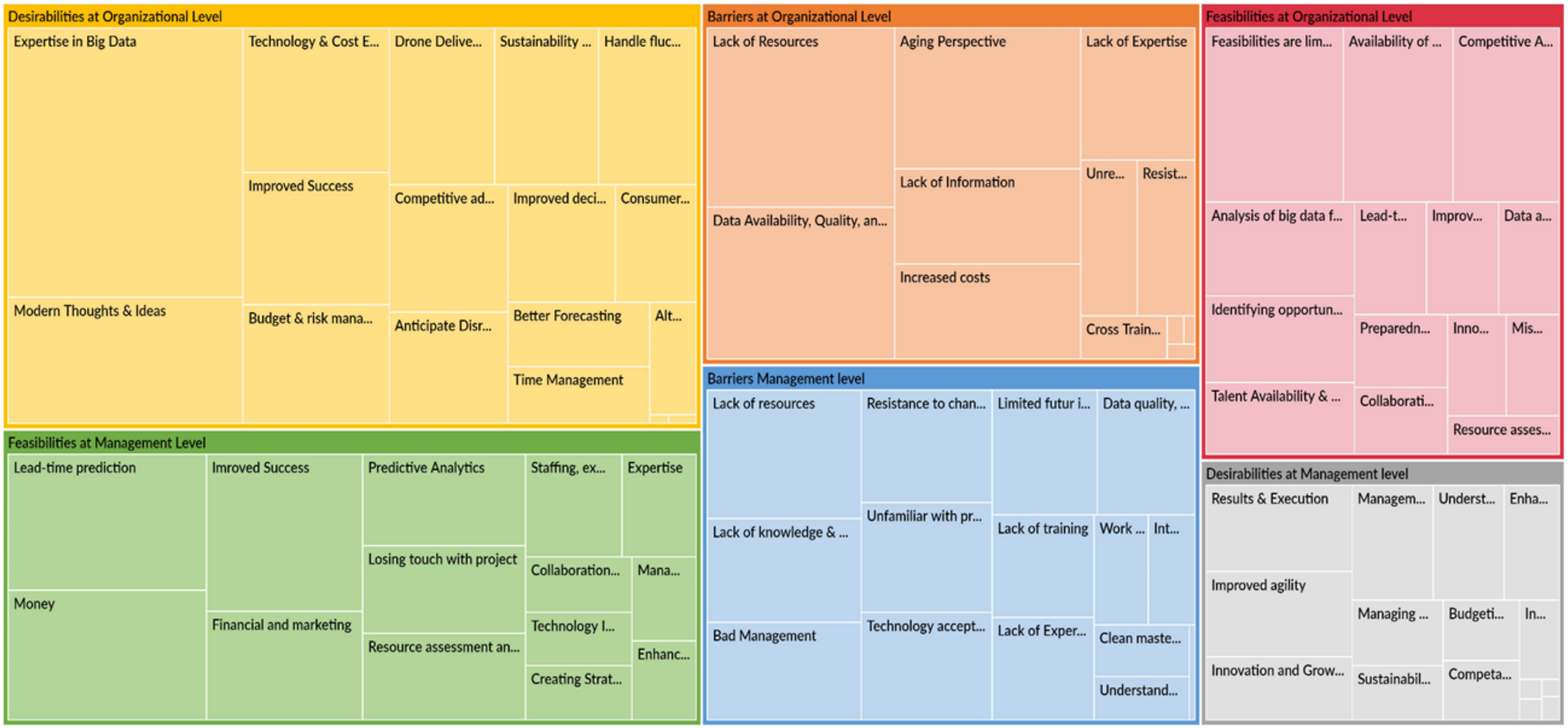


The most common barrier between an organization and management is a need for more resources, technology integration, and expertise to utilize the processes.

In the third round, the experts ranked a comprehensive list of factors, challenges, issues, and components pertinent to feasibilities, desirabilities, and barriers both organizations and management confront (see Figure 13).

Figure 13

Hierarchy of Coded References



The data analysis process unfolded across five key steps.

1. Identify the factors, challenges, elements, and categories arranged by the experts.
2. Discovering the frequency of each item the expert suggests for a specific rank.
3. Application of mean rank against each item and calculating rank score
4. Arranging final rank order
5. The final study results are presented in the data presentation phase through tabulation and interpretations.

Table 8 shows how the experts ranked each concept of factors, challenges, and elements in terms of feasibility at the organizational level. The rank scores were calculated using frequencies on each item. The lowest rank score indicated the highest importance. Based on the rank scoring, the top 10 feasibilities at the organizational level are

1. Knowledge of how to analyze the overwhelming amount of big data and apply it to the highly changeable future demand and customer requirements.
2. Competitive advantage, improved customer experience, and increased efficiency.
3. Availability of technology and access to data.
4. Resource assessment and allocation, desired outcome to be achieved, team building, management strategies, and informed decision-making.

5. Collaboration between different stakeholders, automation, and advanced analytics.
6. Improved success.
7. Availability of technology, scalability, data accessibility, and strategic partnerships.
8. Something new.
9. Misunderstanding.
10. Lack of expertise and customer fixation on incumbent sources.

Table 8

Experts' Ranking of Feasibility Factors at the Organizational Level

Statement	Rank order frequency										Rank score	Final rank
	1	2	3	4	5	6	7	8	9	10		
Knowing how to analyze the overwhelming amount of big data and applying it to the highly changeable future demand and customer requirements hamstrings the feasibility of using big data	9	6	2	0	0	1	0	0	3	0	60	1
Competitive advantage, improved customer experience, and increased efficiency.	3	8	3	1	2	0	0	1	1	2	79	2
Availability of technology, access to data	2	1	1	1	1	1	1	2	1	3	84	3
Resource assessment and allocation, desired outcome to be achieved, team building, management strategies, informed decision-making	4	2	7	1	2	1	1	0	3	1	93	4
To facilitate collaboration between different stakeholders, automation, and advanced analytics	0	3	2	0	2	3	4	1	2	0	94	5
Improved success	1	0	1	0	1	3	4	0	3	2	102	6
Availability of technology, scalability, data accessibility, and strategic partnerships	2	3	3	1	3	1	1	1	3	2	104	7
Something mew	1	3	4	0	3	3	3	2	1	2	118	8
Misunderstanding	1	2	2	2	2	2	4	4	0	2	121	9
Feasibilities are limited by organizations not having the expertise, the customers are fixated on incumbent sources which limits/hamstrings the ability to use big data to change suppliers.	3	0	2	7	1	5	0	3	1	2	125	10
Preparedness, planning, motivating, adaptability, trend setter	2	3	0	5	2	2	5	4	1	1	136	11
Lead-time prediction, stabilizing stocks	0	0	0	3	3	2	0	4	2	5	139	12
Talent availability, technology integration, and data availability	1	0	3	4	4	2	4	4	2	1	146	13
Data sharing can help planning, task execution, and efficiency	2	0	1	4	3	2	3	1	5	4	162	14

Identifying opportunities, avoiding risks, making better decisions, improving efficiency, enhancing innovation, achieving goals, and living a more fulfilling life	1	1	2	3	2	5	2	5	4	4	191	15

Table 9 presents the ranked concept of factors, challenges, and elements in terms of desirabilities at the organizational level. The rank scores were calculated using frequencies on each item. The lowest rank score indicated the highest importance. Based on the rank scoring, the top 10 desirabilities at the organizational level are

1. Customer satisfaction in terms of delivery, price, and quality can be positively influenced.
2. Expertise in big data can facilitate better-sourcing decisions.
3. Drone deliveries and driverless cross-country shipments, and efficient transportation.
4. Sustainability, innovation, competitive advantage, and agility and flexibility.
5. Improved success.
6. Time.
7. Competitive advantage and cost-saving.
8. Thinking ahead, having modern thoughts and ideas.
9. Anticipate disruptive changes, strategic planning, and innovation.
10. To better forecast, plan, purchasing decisions, and strategies in a way that is cost and time effective. Visibility and can be utilized to data-model multiple scenarios.

Table 9

Experts Ranking of Desirability Factors at the Organizational Level

Statement	Rank Order Count by Experts										Rank score	Final rank
	1	2	3	4	5	6	7	8	9	10		
Customer satisfaction in terms of delivery, price and quality can be positively influenced.	0	0	0	0	1	0	1	1	0	0	20	1
Expertise in big data can better-sourcing decisions.	3	0	0	2	2	0	0	1	2	2	67	2
Drone deliveries, driverless cross-country shipments, & efficient transportation.	0	1	4	5	2	2	3	0	0	1	87	3
Sustainability, innovation, competitive advantage, and agility and flexibility	1	3	2	4	2	1	2	2	1	1	94	4
Improved success	2	1	3	2	1	2	0	1	2	3	94	5
Time	3	3	2	1	0	5	3	1	2	1	106	6
Competitive advantage, and cost-saving.	4	1	1	0	4	0	2	2	2	3	107	7
Thinking ahead, having modern thoughts and ideas.	4	3	4	4	3	3	2	1	1	1	112	8
Anticipate Disruptive Changes, Strategic Planning, and innovation	1	4	0	0	0	0	5	3	4	2	124	9
To better forecast, plan, purchasing decisions, and strategies in a way that is cost and time effective. Visibility and can be utilized to data-model multiple scenarios	3	2	1	4	1	5	2	2	3	1	128	10
Budget management, risk management and overall profit	0	0	2	0	1	1	0	2	2	8	131	11
Improved decision-making, Increased efficiency, Enhanced innovation, Greater sustainability, and Strengthened relationships	1	4	3	3	3	2	5	2	3	0	135	12
Better able to handle fluctuations in demand; better ability to satisfy consumers	7	1	1	2	2	1	2	6	3	1	135	13
Technology, Cost, Effectiveness, Access, Reliability, Performance	0	2	4	3	6	2	2	2	2	2	138	14
To see where the business is falling short and create new solutions based on the data and allow the data to validate solutions.	3	3	2	0	3	3	2	2	4	3	144	15
Competitive advantage, Future-proofing, and Improved agility	0	4	3	2	2	5	1	4	2	3	152	16

Table 10 indicates the ranked potential barriers at the organizational level. Based on the rank scoring, the top 10 potential barriers at the organizational level are

1. Too much data, lack of expertise, how to evaluate the data, insufficient staffing.
2. Data quality, data privacy and security, and implementation challenge.

3. Too much data, lack expertise, how to evaluate the data, and insufficient staffing.
4. Cross training and updating protocols.
5. Organizations are not willing to pay more for expertise. Management needs to understand big data, and there is no buy-in. Customers have preferred incumbents.
6. Limited information about the future, biases, and assumptions; resistance to change; and lack of resources to implement changes.
7. Integration with legacy systems, increased costs, lack of expertise, and data quality can be compromised.
8. Continued delays and crashes, and shortages of products.
9. Fear of the unknown, lack of information, short-term thinking, lack of resources, and lack of support.
10. Clean master data is always the immediate barrier.

Table 10

Experts' Ranking of Potential Barriers at the Organizational Level

Statement	Rank Order Frequency										Rank Score	Final Rank
	1	2	3	4	5	6	7	8	9	10		
Too much data, lack expertise, how to evaluate the data, insufficient staffing.	1	0	0	0	0	1	1	1	1	2	51	1
Data Quality, Data Privacy and Security, and Implementation Challenge.	0	1	0	6	0	1	1	2	1	0	64	2
Too much data, lack expertise, how to evaluate the data, insufficient staffing	5	0	0	4	1	1	0	3	3	0	83	3
Cross training, updating protocols	2	4	2	1	3	0	1	2	1	2	87	4
Organizations are not willing to pay more for expertise. Management doesn't understand big data and there is no buy-in. Customers have preferred incumbents.	4	3	3	0	2	4	1	1	2	1	96	5
Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes	3	4	0	0	2	2	1	1	0	6	108	6
Integration with Legacy Systems, increased costs, Lack of Expertise, and data quality can be compromised	2	2	7	2	4	3	1	2	1	1	115	7
Continued delays and crashes; shortages of products.	1	2	4	1	3	3	0	3	2	2	116	8
Fear of the unknown, Lack of information, Short-term thinking, Lack of resources, and Lack of support	0	2	4	3	3	0	6	2	1	1	120	9
A clean master data is always the immediate barrier.	2	1	2	4	5	3	2	1	1	2	120	10
Money.	4	2	1	0	2	5	2	1	1	4	122	11
Age, attitude.	0	1	3	0	1	0	1	2	7	2	122	12
Data quality and availability, and Data security and privacy	2	4	2	3	1	2	2	0	2	5	127	13
Age, thought perspective	2	1	2	1	1	2	8	2	2	2	141	14
Hesitancy to partake in such an innovative and new type of data gathering for fear of miss use, and monopolization, and privacy issue	4	4	1	3	5	3	3	2	3	1	144	15
Unrealistic, Unreliable, Unsound, Faulty thinking.	0	1	1	3	1	3	2	8	3	2	165	16

Table 11 illustrates ranked concepts of challenges, elements, and feasibility at the management level. Based on rank scores, the list of top 10 feasibilities at management are

1. Staffing, experience, and training.
2. Lead-time prediction and stabilizing stocks.
3. Money.

4. Understanding when and what will happen.
5. Improved success.
6. Financial and marketing.
7. Enhanced decision-making, increased agility, and improved collaboration.
8. Resource assessment and allocation, desired outcome to be achieved, team building, management strategies, and informed decision-making.
9. Management style remains old.
10. Collaboration with partners, technology availability, and data storage and access.

Table 11

Experts Ranking of Feasibility Factors at the Management Level

Statement	Rank order frequency										Rank score	Final rank
	1	2	3	4	5	6	7	8	9	10		
Staffing, experience, and training.	6	1	3	2	1	3	1	0	1	1	74	1
Lead-time prediction, stabilizing stocks.	3	0	3	1	1	2	1	2	2	1	84	2
Money	2	1	1	3	1	0	1	4	2	1	91	3
Understand when and what will happen	2	3	2	2	1	0	1	5	2	0	92	4
Improved Success	0	1	3	0	1	2	1	1	1	4	92	5
Financial and marketing	3	4	2	4	2	3	3	1	0	1	100	6
Enhanced Decision Making, Increased Agility, and Improved Collaboration	2	3	0	1	4	3	2	0	1	3	103	7
Resource assessment and allocation, desired outcome to be achieved, team building, management strategies, informed decision-making	6	2	2	3	2	1	3	1	3	1	110	8
Management style remains old.	4	4	4	3	1	4	3	3	0	0	110	9
Collaboration with partners, technology availability, data storage and access	2	2	2	6	4	2	1	0	2	2	113	10
Predictive Analytics, Automation, and increased collaboration	0	4	1	2	2	3	2	2	2	2	115	11
Better future, creating strategic changes	2	4	3	2	3	3	4	1	0	2	116	12
Technology Integration and Data Availability.	0	1	4	2	1	1	2	3	2	3	119	13
Losing touch with the project or item.	0	1	2	2	4	3	1	1	5	1	124	14

Table 12 presents the ranked concept of factors, challenges, and elements regarding desirabilities at the management level. Based on the rank scoring, the top 10 desirabilities at the management level are

1. In product/service, with analysis of consumer trends, market research, and emerging technologies, it will aid decisions on product/service to meet customer's needs and wants.
2. Improved success.
3. Link technology use to value proposition, understand how technology can meet needs and concerns.
4. Management training.
5. Responsive to changing market, competitive, and gain market share.
6. Competitive, enhanced customer experience, and cost-saving.
7. In competitive market, big data can better planning, strategies, and retrospective.
8. Improved agility, better customer service, and cost-saving.
9. Budgeting and forecasting.
10. Time.

Table 12

Experts' Ranking of Desirability Factors at the Management Level

Statement	Rank order frequency										Rank Score	Final Rank
	1	2	3	4	5	6	7	8	9	10		
In product/service, with analysis of consumer trend, market research, and emerging technologies, it will aid decisions on product/service to meet customer's needs and wants	3	2	2	1	2	0	0	1	1	1	54	1
Improved success.	0	1	0	0	0	0	3	3	1	1	66	2

Link technology use to value proposition, understand how technology can meet needs and concerns	4	2	0	1	1	0	3	0	1	2	67	3
Management training.	4	6	3	1	2	1	1	1	1	0	69	4
Responsive to changing market, competitive, and gain market share.	2	4	0	1	0	1	1	3	1	1	70	5
Competitive, enhanced customer experience, and cost saving.	1	1	9	3	1	1	0	1	1	0	70	6
In competitive market, big data can better planning, strategies, and retrospective	1	2	0	6	3	2	1	1	0	1	81	7
Improved agility, better customer service, and cost saving.	1	0	0	1	5	2	3	0	0	2	83	8
Budgeting and forecasting	6	4	1	4	3	2	0	1	1	1	87	9
Time	1	2	2	1	0	1	2	3	2	1	87	10
Competitive, enhanced customer experience, and efficiency.	1	1	5	1	1	0	0	2	3	2	90	11
Results, Execution, Effectiveness, Strategy	0	1	2	1	1	3	0	0	3	3	92	12
Understand past due reduction, lead-time, and cost impacts	1	0	2	3	0	0	1	0	4	4	102	13

Table 13 indicates the ranked potential barriers at the management level. Based on the rank scoring, the top 10 potential barriers at the management level are

1. Resistance to change, data quality and security, and lack of expertise.
2. No training.
3. Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes.
4. Data quality, data privacy and security, and implementation challenges.
5. Data quality and accuracy and resistance to change.
6. Potential barriers from the supply chain manager may be adversity to change their process or accept new technology for the organization based on their lack of understanding of the positive attributes.
7. Lack of knowledge and understanding. Overwhelming amount of data. Customer resistance to change. The continual need to refresh data mining.
8. Integration with legacy systems, costs, lack of expertise, and quality concerns.

9. Any delay could be catastrophic.

10. Lack of data, resources, executive leadership support, and time.

Table 13

Experts' Ranking of Potential Barriers at the Management Level

Statement	Rank order frequency										Rank	Final
	1	2	3	4	5	6	7	8	9	10	score	rank
Resistance to Change, Data Quality and Security, and Lack of Expertise.	0	3	2	0	1	0	0	0	2	2	55	1
No training	1	2	0	1	1	1	0	2	1	3	75	2
Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes.	1	0	3	2	0	1	1	2	3	1	84	3
Data Quality, Data Privacy and Security, and Implementation Challenges	0	1	4	2	1	3	2	2	0	1	85	4
Data quality and accuracy and resistance to change	4	2	2	3	3	4	1	1	0	1	90	5
Potential barriers from the supply chain manager may be adversity to change their process or accept new technology for the organization based on their lack of understanding of the positive attributes.	4	5	2	4	2	2	2	0	1	1	91	6
Lack of knowledge and understanding. Overwhelming amount of data. Customer resistance to change. Continual need to refresh data mining.	3	1	2	3	3	2	1	1	2	1	93	7
Integration with Legacy Systems, costs, Lack of Expertise, and quality concerns	0	1	2	2	5	3	1	0	2	1	94	8
Any type of delay could be catastrophic	4	3	3	3	3	0	3	1	0	2	95	9
Lack of or insufficient data, resources, executive leadership support, time	6	1	2	0	1	2	0	1	4	2	95	10
Trends could change, customers, and supply issues.	1	4	0	3	2	1	2	2	1	2	96	11
Clean master data is always the immediate barrier	1	3	1	5	3	2	5	3	0	0	116	12
Money	3	1	1	2	3	3	1	4	1	2	117	13
Bad management	1	3	4	0	2	3	4	2	3	1	128	14
Unfamiliarity with current processing Workflow complications, Interrupted work, Learning new routine, Time training	2	0	3	3	0	1	3	4	4	2	138	15

Table 6 indicates the top 10 ranked potential barriers at the management level. They are 1) Resistance to Change, Data Quality and Security, and Lack of Expertise, 2) No training, 3) Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes. 4) Data Quality, Data Privacy and

Security, and Implementation Challenges, 5) Data quality and accuracy and resistance to change, 6) Potential barriers from the supply chain manager may be adversity to change their process or accept new technology for the organization based on their lack of understanding of the positive attributes, 7) Lack of knowledge and understanding. Overwhelming amount of data. Customer resistance to change. The continual need to refresh data mining, 8) Integration with Legacy Systems, costs, Lack of Expertise, and quality concerns, 9) Any type of delay could be catastrophic, and 10) Lack of or insufficient data, resources, executive leadership support, time. Given this rank, the potential barriers at management level fall into three aspects; resistance to change due to concern over data quality, data overwhelming, and data mining. Integration issues with cost, existing system, and expertise knowledge. Lack of leadership commitment is also a culprit.

Summary

In Chapter 4, discussions were about research ethics, trustworthiness, procedures, and results. We began this chapter with platform selection and procedures. Due to the limit in generating enough potential participants from the ISM Dallas chapter, we switched the platform to User Interview to broaden the participant pool with IRB approval. In the data collection process, participant selection procedures, and qualifications, we outlined each step in qualifying participants and forming two panelist groups. The demographics of participants were disclosed based on the available information collected. For evidence of trustworthiness, we reiterated our guidelines to ensure the research strictly follows credibility, transferability, dependability, trustworthiness, and conformity requirements. In data analysis, we detailed processes and procedures in coding terms and theme development, followed by qualitative and quantitative data analysis. We presented three groups of comparison on feasibility, desirability, and barriers between management and organization. I also calculated the IQR to generate ranking scores for items in ordinal order. IQR result was illustrated based on 32 expert feedbacks. Visual presentation and tabulations on feasibility, desirability, and barriers at management and organizational levels are displayed so readers can easily understand the research findings.

Research results are presented and discussed given NVivo analysis and IQR. Two categories with six themes were explained in the coding procedure. Study results showed that feasibility, desirability, and barriers at both organizational and management levels indicated a different focus given the ranking score from most important to least. Under each level, we analyzed three different themes to look closely into each topic to understand how these panelists think of feasibility, desirability, and barriers given their perspectives. This detailed analysis gives us insight into these differences between the two levels. Leaders at the organizational level are more on a macro basis, such as what an organization can do about it, whereas leaders at the management level pay more attention to things closely related to operative activities, like who can do it. Hence, at the macro level, executives are concerned about issues like lack of staffing, overwhelming data, and no expertise. In contrast, there needs to be more training; uncertainty about the future and unfamiliarity with workflow hinder managers from developing BDA skills for the existing work process. More discussion on how these results can shed light on practice and implications for future research will be illustrated in Chapter 5.

Chapter 5: Discussion, Conclusions, and Recommendations

This qualitative classical Delphi study aims to determine how a panel of at least 30 subject matter experts from SCM professionals in the United States views the desirability, feasibility, and importance of successful digital transformation of SCM through big data. The research results present a comprehensive understanding of consensus areas and disparities between the organizational and management levels regarding feasibilities, desirability, and barriers related to lead-time prediction, stock stabilization, and utilizing big data. At the management level, crucial feasibilities revolve around enhancing success rates, financial and marketing facets, and predictive analytics. Conversely, at the organizational level, emphasis is placed on technological availability, scalability, competitive advantages, and augmenting customer experience. Despite these aligned aspirations, management and organizations must overcome persistent hurdles. These shared challenges encompass insufficient resources, a need for more expertise, concerns over data quality/security, and resistance to change. Particularly noteworthy is the prominent shared obstacle—lack of resources, technology integration, and expertise highlighting the urgent necessity for investment and synchronization between management and organizational strategies.

Interpretation of the Findings

The research findings answered the two RQs, which were

RQ1. What challenges and/or barriers resulted in SCM being lagged in digital transformation?

RQ2. How is the desirability, feasibility, and importance of digital transformation of SCM impacted by the big data?

Data collection from the three rounds of questionnaires provided insight into the feasibility, desirability, and barriers at both organizational and management levels. We used two separate questionnaires, one at the organizational level and the other at the management level. At the organizational level, we applied three stages for each round, from brainstorming to ranking. The same pattern questionnaire was made at the management level. Data analysis indicated that challenges, factors, and barriers faced by organizations and management differ as each is emphasized differently. For example, at the organizational level, emphasis is placed on technological availability, scalability, competitive advantages, and augmenting customer experience, which coincidently aligned with Wamba et al.'s opinion that technological availability, scalability, competitive advantages, and improving customer experience in their research (Corte-Real et al., 2017; Wamba et al., 2017). At the management level, our findings echoed some scholars' research that enhancing success rates, financial and marketing facets (Brinch et al., 2018), and predictive analytics (Bradlow et al., 2017) are the primary concerns in business operations.

Furthermore, our research results disconfirmed that money is the key to digital transformation as the research findings indicated that organizations simply investing in BDA would not influence performance alone (Mandal, 2018), which study sheds light on the impact of the extensive data management capability on SCM performance. Therefore, the big data management capability in SCM activities means the entire organization can use BDA. Again, our study extended the concept of digital transformation to include the most common barrier between an organization and management: a need for more resources, technology integration, and expertise to utilize the processes. Finally, this research has contributed to the organizational theories that have been the significant framework in discussing big data and organizational performance (De Camargo Fiorini et al., 2018); our study extended the organizational theories on the synchronization between management and organizations (i.e., organizational change is a twofold concern). Feasibility, desirability, and barriers at both organizational and management levels differ due to different emphases given common challenges.

The analysis of feasibilities, desirability, and barriers at management and organizational levels revealed that lead-time prediction, stock stabilization, and utilizing big data reveal crucial insights. At the management level, key feasibilities center around improving success rates, financial and marketing aspects, and predictive analytics. Meanwhile, organizational feasibilities emphasize technological availability, scalability, competitive advantages, and customer experience enhancement. However, desires at both levels include better strategy execution, agility, innovation, and a deeper understanding of lead time and cost impact. Despite these aspirations, both management and organizations face persistent barriers. They grapple with challenges like insufficient resources, a lack of expertise, data quality and security concerns, and resistance to change. Notably, a shared barrier surfaces prominently—lack of resources, technology integration, and expertise, underscoring the critical need for investment and alignment between management and organizational strategies (Helfat et al., 2009)

Based on the comprehensive ranking of various feasibilities, desirability, and potential barriers, a holistic picture emerges regarding the significant determinants and challenges faced at both organizational and management levels in handling big data and technological integration. Critical factors like leveraging and applying big data effectively to meet future demands, achieving competitive advantages, and ensuring technological availability and scalability emerge as key feasibilities at the organizational level. However, limitations in expertise, data privacy concerns, and challenges in implementing changes appear as significant barriers. Concurrently, management-level feasibilities predominantly revolve around staffing, predictive analysis, financial aspects, and improved success rates. Conversely, barriers at this level center on resistance to change, data quality, and security concerns, among others.

Limitations of the Study

The same limitation arises as the other studies; this Delphi research was initially designed to obtain consensus from the ISM professional community. Due to the iterative feature of the Delphi approach, some participants dropped in the middle of a survey, which resulted in multiple repeating processes to meet the minimum head count. To maintain a relatively stable sampling size, we had to enlarge the sampling pool to include more possible participants, which process might exclude some potentially better participant candidates. Demographically, most participants did not want to share their personal information fully, such as salary, sex, ethnicity, education, workplace, and place of current living within the States. Therefore, we cannot demographically categorize our participants into three panelists, which limits our interpretation of the findings. Also, a cost issue limited our further rounds to gain better insight for consensus. Hence, we used IQR instead of Kendall’s W to generate rank scores to derive consensus areas. Finally, all samples were collected within the United States and the interpretation of the research findings is limited, therefore, we cannot apply the findings universally.

Recommendations

Our research findings have cleared some misconceptions about digital transformation in SCM, such as leaders' knowledge of digital technology in initiating digital transformation in medium to large organizations (Matt et al., 2015). This research indicated that feasibility and desirability for digital transformation were confronted differently at the organizational and management levels. In DCT, practitioners are informed to turn short-term competitive positions into long-term competitive advantages by combining the business's existing internal competency and external advantage. In this sense, our research findings indicated that focus on organization and management levels varies with differing emphasis. Change leaders at the organizational level shall know how to use feasibility and desirability to avoid barriers. The same token shall be applied at the management level while managers initiate process change. Synchronization between organizational and management levels in change strategy is imperative.

Recommendations for Practice

The significance of this study is two-fold. It can recommend to organizational leaders and managers what they must do to initiate digital transformation in SCM. The comparative table (see Table 14) summarizes feasibility, desirability, and barriers for organizational leaders and managers at their respective levels. In other words, at the organizational level, listing items ranked in ordinal sequence for feasibility, desirability, and barrier can inform organizational leaders what, where, why, and how these elements, factors, and issues will affect organizational changes. For example, at the organizational level, the reason why digital transformation is feasible is that the application of big data will help the organization gain a competitive advantage through data analysis; the importance of data analysis will bring a positive impact on customer satisfaction and take this change, leaders know what and how to overcome some challenges in this process.

The same logic will be used for managerial-level leaders when promoting digital transformation in the operative process. Managers are concerned about who can take the job, what skills their team workers will need, how these changes will impact the existing process, and where issues will arise during the change process. In Practice, this ranking summary can inform managers to prepare for these changes. For instance, managers can foresee lead-time predictions and make well-educated stocking decisions. If a digital transformation in SCM takes place, it will improve management performance. In achieving this goal, managers understand what barrier there is; in this case, if team workers can have enough training, their team will accomplish improved success.

At the management level, crucial feasibilities revolve around enhancing success rates, financial and marketing facets, and predictive analytics. Conversely, at the organizational level, emphasis is placed on technological availability, scalability, competitive advantages, and augmenting customer experience. Despite these aligned aspirations, management and organizations must overcome persistent hurdles. These shared challenges encompass insufficient resources, a need for more expertise, concerns over data quality/security, and resistance to change. Particularly noteworthy is the prominent shared obstacle—lack of resources, technology integration, and expertise highlighting the urgent necessity for investment and synchronization between management and organizational strategies.

Table 14

Comparative Summary of Items Ranking

	At Organizational Level			At Management Level		
Ranking Score	**Feasibility**	**Desirability**	**Barriers**	**Feasibility**	**Desirability**	**Barriers**
1	Knowing how to analyze the overwhelming amount of big data and applying it to the highly changeable future demand and customer requirements hamstrings the feasibility of using big data	Customer satisfaction in terms of delivery, price and quality can be positively influenced	Too much data, lack expertise, how to evaluate the data, insufficient staffing	Staffing, experience, and training	In product/service, with analysis of consumer trend, market research, and emerging technologies, it will aid decisions on product/service to meet customer's needs and wants	Resistance to Change, Data Quality and Security, and Lack of Expertise
2	Competitive Advantage, Improved Customer Experience, and Increased Efficiency	Expertise in Big Data can better-sourcing decisions	Data Quality, Data Privacy and Security, and Implementation Challenge	Lead-time prediction, stabilizing stocks	Improved success	No training
3	Availability of technology, access to data.	Drone deliveries, driverless cross-country shipments, & efficient transportation		Money	Link technology use to value proposition, understand how technology can meet needs and concerns	Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes.
4	Resource assessment and allocation, desired outcome to be achieved, team building, management strategies, informed decision-making	Sustainability, innovation, competitive advantage, and agility and flexibility	Cross training, updating protocols	Understand when and what will happen	Management training	Data Quality, Data Privacy and Security, and Implementation Challenges
5	To facilitate collaboration between different stakeholders, automation, and Advanced Analytics	Improved success	Organizations are not willing to pay more for expertise. Management doesn't understand Big Data and there is no buy-in. Customers have preferred incumbents	Improved Success	Responsive to changing market, competitive, and gain market share	Data quality and accuracy and resistance to change
6	Improved success	Time	Limited information about the future, biases and assumptions, resistance to change, and lack of resources to implement changes	Financial and marketing	Competitive, enhanced customer experience, and cost saving	Potential barriers from the supply chain manager may be adversity to change their

						process or accept new technology for the organization based on their lack of understanding of the positive attributes
7	Availability of technology, Scalability, Data accessibility, and strategic partnerships	Competitive advantage, and cost-saving	Integration with Legacy Systems, increased costs, Lack of Expertise, and data quality can be compromised	Enhanced Decision Making, Increased Agility, and Improved Collaboration	In competitive market, big data can better planning, strategies, and retrospective	Lack of knowledge and understanding. Overwhelming amount of data. Customer resistance to change. Continual need to refresh data mining
8	Something New	Thinking ahead, having modern thoughts and ideas	Continued delays and crashes; shortages of products	Resource assessment and allocation, desired outcome to be achieved, team building, management strategies, informed decision-making	Improved agility, better customer service, and cost saving	Integration with Legacy Systems, costs, Lack of Expertise, and quality concerns
9	Misunderstanding	Anticipate Disruptive Changes, Strategic Planning, and innovation	Fear of the unknown, Lack of information, Short-term thinking, Lack of resources, and Lack of support	Management style remains old	Budgeting and forecasting	Any type of delay could be catastrophic
10	Feasibilities are limited by organizations not having the expertise, the customers are fixated on incumbent sources which limits/hamstrings the ability to use Big Data to change suppliers	To better forecast, plan, purchasing decisions, and strategies in a way that is cost and time effective. Visibility and can be utilized to data-model multiple scenarios	A clean master data is always the immediate barrier	Collaboration with partners, technology availability, data storage and access	Time	Lack of or insufficient data, resources, executive leadership support, time
11	Preparedness, Planning, Motivating, Adaptability, Trend setter	Budget management, risk management and overall profit	Money	Predictive Analytics, Automation, and increased collaboration	Competitive, enhanced customer experience, and efficiency	Trends could change, customers, and supply issues
12	Lead-time prediction, stabilizing stocks	Improved decision-making, Increased efficiency, Enhanced innovation, Greater sustainability, and Strengthened relationships	Age, attitude	Better future, creating strategic changes	Results, Execution, Effectiveness, Strategy	Clean master data is always the immediate barrier
13	Talent Availability, Technology Integration, and Data Availability	Better able to handle fluctuations in demand; better ability to satisfy consumers	Data quality and availability, and Data security and privacy	Technology Integration and Data Availability	Understand past due reduction, lead-time and cost impacts	Money
14	Data sharing can help planning, task execution, and efficiency	Technology, Cost, Effectiveness, Access, Reliability, Performance	Age, thought perspective	Losing touch with the project or item		Bad management
15	Identifying opportunities, avoiding risks, making better decisions, improving efficiency, enhancing innovation, achieving goals, and living a more fulfilling life	Technology, Cost, Effectiveness, Access, Reliability, Performance	Hesitancy to partake in such an innovative and new type of data gathering for fear of miss use, and monopolization, and privacy issue			Unfamiliarity with current processing Workflow complications, Interrupted work, Learning

						new routine, Time training
16			Unrealistic, Unreliable, Unsound, Faulty thinking			

Recommendations for Research

Following the summary table, we recommend that future researchers focus on interactions among these elements, factors, and challenges since we primarily illustrated the importance of these elements, factors, and challenges in ordinal sequence. In other words, we figured out these elements, factors, and challenges from the most important to the least so that organizational leaders and managers better understand the feasibility, desirability, and barriers in digital transformation for SCM under the Big Data era. Since organizations are different in terms of their internal existing resources and external environment, the items ranked the most important can be of no significance at other organizations given a varying external setting. Therefore, we call for future Research to be conducted on the same topic in different parts of the world so that SCM leaders and managers from all walks of life can practically benefit.

Tackling the hindrances requires academically concerted efforts to address data management concerns, fortify technological infrastructure, and bridge skill deficiencies in future Research. Additionally, future Research shall also be conducted on the impact of customer allegiance to established sources since this poses a significant impediment for organizations aiming to leverage big data for supplier modifications, necessitating strategies to mitigate customer resistance. Finally, achieving strategic alignment, investing in resources, and employing proactive approaches to address these shared barriers are imperative for management and organizations to effectively leverage big data's potential and foster innovation within their respective domains in future studies.

Implications

The synthesis of responses underpins the importance of integrating data-driven insights into strategic decision-making for both management and organizational levels. The need for enhanced expertise, streamlined data management, and overcoming resistance to change are recurrent themes across both domains. Addressing these challenges is imperative to harnessing the full potential of big data, fostering innovation, and achieving competitive advantages in today's dynamic business landscape. This comprehensive analysis provides invaluable insights into the multifaceted nature of challenges and opportunities within big data utilization, guiding stakeholders toward informed strategies and proactive measures in addressing critical organizational and management concerns.

Implications for Practice

The study results informed that effective adoption of big data lies in a clear understanding of feasibility and desirability at both organizational and management levels. In other words, focusing on what is feasible and desirable is essential in effectively initiating digital transformation from the organizational and management perspective. Big data application at the organizational level means process changes and process change evolves, shifting management style. With findings from this study, we understand that changes in management and organization urge synchronization of management and organization. The context for changes lies in feasibility, desirability, and barriers facing management and organization. To successfully initiate these changes, executives at both management and organization shall take advantage of feasibility, desirability, and barriers in the change process. Therefore, this Research provides business managers and organization leaders with a guideline in preparing for organizational changes.

Implications for Research

As outlined in Chapter 1, this study could better understand how the product end-users envision leadership effectiveness in shifting the supply chain network from transforming customer experience and operational process through business model innovation. The Research could bring changes in a consumer society by complementing end-users with a group of suppliers through an ecosystem-based value-creating stream instead of a single, combined offering under a traditional buyer-supplier arrangement. In this sense, the organizations aiming to leverage big data for supplier modifications necessitate strategies to mitigate resistance among customers by addressing a significant impediment on the impact of customer allegiance to established sources.

Implications for Positive Social Change

SCM is closely related to people's daily lives since its operation covers the entire process from raw material procurement through finished product distribution, which affects all societal stakeholders. Application of the big data throughout the entire supply chain will change organizational incumbent process, bring about innovation, and result in better decision-making in swiftly meeting customers' demand; it will all end up with changing consumers' behavior such as shopping experience, cost-saving pattern, and buyer-supplier's relationship as well. Hence, our research results can significantly illuminate how to initiate the successful digital transformation of SCM in the Big Data era.

Conclusion

This study comprehensively understands consensus areas and disparities between the organizational and management levels regarding feasibilities, desirabilities, and barriers related to digital transformation in SCM, customer experience expectation, and utilizing big data among 32 experts. The result demonstrated that the feasibilities between organization and management were found to be different. The desirabilities among organization and management levels were found to be different from their priorities. The most common barrier between an organization and management is a need for more resources, technology integration, and expertise to utilize processes.

Despite these aligned aspirations, management and organizations must overcome persistent hurdles. Tackling these hindrances requires concerted efforts to address data management concerns, fortify technological infrastructure, and bridge skill deficiencies. Additionally, the impact of customer allegiance to established sources poses a significant impediment for organizations aiming to leverage big data for supplier modifications, necessitating strategies to mitigate resistance among customers. Ultimately, achieving strategic alignment, investing in resources, and employing proactive approaches to address these shared barriers are imperative for management and organizations to effectively leverage big data's potential and foster innovation within their respective domains.

References

Addo-Tenkorang, R., & Helo, P. T. (2016). Big data applications in operations/supply-chain management: A literature review. *Computers & Industrial Engineering*, *101*, 528–543. https://doi.org/10.1016/j.cie.2016.09.023

Ahmed, R., Vveinhardt, J., Ahmad, N., & Mujeeb, M. (2014). The business outsourcing in telecommunication industry: Case of Pakistan. *Transformations in Business & Economics*, *13*(2B, 32B), 760–779.

Ahmed, V., Tezel, A., Aziz, Z., & Sibley, M. (2017). The future of Big Data in facilities management: Opportunities and challenges. *Facilities*, *35*(13/14), 725–745. https://doi.org/10.1108/F-06-2016-0064

Alojairi, A., Akhtar, N., Ali, H. M., & Basiouni, A. F. (2019). Assessing Canadian business IT capabilities for online selling adoption: A net-enabled business innovation cycle (NEBIC) perspective. *Sustainability*. *11*(13), Article 3662. https://doi.org/10.3390/su11133662

Andal-Ancion, A., Cartwright, P. A., & Yip, G. S. (2003). The digital transformation of traditional businesses. *MIT Sloan Management Review*, *44*(4), 34–41. https://sloanreview.mit.edu/article/the-digital-transformation-of-traditional-business/

Anwar, M., Khan, S. Z., & Shah, S. Z. A. (2018). Big data capabilities and firm's performance: A mediating role of competitive advantage. *Journal of Information and Knowledge Management*, 17(4), Article 18500454. https://doi.org/10.1142/S0219649218500454

Arun, K., Şen, C., & Okun, O. (2020). How does leadership effectiveness related to the context? Paternalistic leadership on non-financial performance within a cultural tightness-looseness model? *Journal of East European Management Studies*, *25*(3), 503–529.

Arunachalam, D., Kumar, N., & Kawalek, J. P. (2018). Understanding big data analytics capabilities in supply chain management: Unravelling the issues, challenges, and implications for practice. *Transportation Research Part E: Logistics and Transportation Review*, *114*, 416–436. https://doi.org/10.1016/j.tre.2017.04.001

Bail, C. A. (2014). The cultural environment: Measuring culture with big data. *Theory and Society*, *43*(3–4), 465–482. https://doi.org/10.1007/s11186-014-9216-5

Barkham, R., Bokhari, S., & Saiz, A. (2022). Urban big data: City management and real estate markets. In P. M. Pardalos, S. Th. Rassia, & A. Tsokas (Eds.), *Artificial intelligence, machine learning, and optimization tools for smart cities: Designing for sustainability* (Vol. 186, pp. 177–209). Springer, Cham. https://doi.org/10.1007/978-3-030-84459-2_10

Barreto, I. (2010). Dynamic capabilities: A review of past research and an agenda for the future. *Journal of Management*, *36*(1), 256–280. https://doi.org/10.1177/0149206309350776

Belsky, G., & Gilovich, T. (2010). *Why smart people make big money mistakes and how to correct them: Lessons from the life-changing science of behavioral economics*. Simon and Schuster.

Benabdellah, A. C., Benghabrit, A., Bouhaddou, I., & Zemmouri, E. M. (2016). Big data for supply chain management: Opportunities and challenges. *2016 IEEE/ACS 13th International Conference of Computer Systems and Applications proceedings* (pp. 1–6). IEEE. https://doi.org/10.1109/AICCSA.2016.7945828

Benedict, K. (2018). “*Hard Decisions in Digital Transformation*” http://web2.sys-con.com/node/4136308

Berman, S. J. (2012). Digital transformation: opportunities to create new business models. *Strategy & Leadership*, *40*(2), 16–24. https://doi-org.ezp.waldenulibrary.org/10.1108/10878571211209314

Bolden, R., & Oregan, N. (2016). “Digital disruption and the future of leadership: an interview with Rick Hay Thornthwaite, Chairman of Centrica and Mastercard.” *Journal of Management Inquiry, 25(4).* https://doi.org/10.1177/1056492616638173

Bonnet, D., & Westerman, G. (2021). The New Elements of Digital Transformation. *MIT Sloan Management Review*, *62*(2), 82-89. • https://mitsmr.com/2UEVUzY

Bradlow, E. T., Gangwar, M., Kopalle, P., & Voleti, S. (2017). The role of big data and predictive analytics in retailing. *Journal of Retailing*, *93*(1), 79-95. DOI: 10.1016/j.jretai.2016.12.004

Braun, V. & Clarke, V. (2006). *Using thematic analysis in psychology, Qualitative Research in Psychology*, 3(2), 77-101.

Brinch, M., Stentoft, J., Jensen, J. K., & Rajkumar, C. (2018). Practitioners understanding of big data and its applications in supply chain management. *International Journal of Logistic Management, 29*(2), 555-574. https://doi.org/10.1108/IJLM-

05-2017-0115

Brown, D. (n.d.). *Digital labor promises major disruption to outsourcing*. KPMG. http://www.kpmginstitutes.com/content/dam/kpmg/sharedservicesoutsourcinginstitute/pdf/2017/digital-labor-outsourcing-disruptions.pdfBughin, J. (2017). The best response to digital disruption. *MIT Sloan management review*, *58*(4). https://sloanreview.mit.edu/article/the-right-response-to-digital-disruption/

Büyüközkan, G., & Göçer, F. (2018). Digital Supply Chain: Literature review and a proposed framework for future research. *Computers in Industry, 97*, 157-177. https://doi.org/10.1016/j.compind.2018.02.010

Cadorin, L., Bagnasco, A., Tolotti, A., Pagnucci, N., & Sasso, L. (2017). Developing an instrument to measure emotional behaviour abilities of meaningful learning through the Delphi technique. *Journal of Advanced Nursing*, *73*(9), 2208–2218. https://doi-org.ezp.waldenulibrary.org/10.1111/jan.13273

Cantrill, J. A., Sibbald, B., & Buetow, S. (1996). The Delphi and nominal group techniques in health services research. *International Journal of pharmacy practice*, *4*(2), 67-74. https://doi.org/10.1111/j.2042-7174.1996.tb00844.x

Chen, D. Q., Preston, D. S., & Swink, M. (2015). How the Use of Big Data Analytics Affects Value Creation in Supply Chain Management. *Journal of Management Information Systems, 32(4), 4-39.* doi:10.1080/07421222.2015.1138364

Cornick, P. (2006). Nitric oxide education survey–Use of a Delphi survey to produce guidelines for training neonatal nurses to work with inhaled nitric oxide. *Journal of Neonatal Nursing*, *12*(2), 62-68. Doi.org/10.1016/j.jnn.2006.01.005

Corte-Real, N., Oliveira, T., & Ruivo, P. (2017). Assessing business value of Big Data Analytics in European firms. *Journal of Business Research,* 379. https://doi.org/10.1016/j.jbusres.2016.08.011

Daniel, E., & White, A. (2005). The future of inter-organizational system linkages: findings of an international Delphi study. *European Journal of Information Systems*, *14*(2), 188–203. https://doi-org.ezp.waldenulibrary.org/10.1057/palgrave.ejis.3000529

De Camargo Fiorini, P., Seles, B. M. R. P., Jabbour, C. J. C., Mariano, E. B., & de Sousa Jabbour, A. B. L. (2018). Management theory and big data literature: From a review to a research agenda. *International Journal of Information Management, 43*,112-129. https://doi.org/10.1016/j.ijinfomgt.2018.07.005

De Mauro, A., Greco, M., & Grimaldi, M. (2016). A formal definition of Big Data based on its essential features. *Library Review*. https://doi.org/10.1108/LR-06-2015-0061

De Vet, E., Brug, J., De Nooijer, J., Dijkstra, A., & De Vries, N. K. (2005). Determinants of forward stage transitions: a Delphi study. *Health education research*, *20*(2), 195-205.

Del Vecchio, P., Di Minin, A., Petruzzelli, A. M., Panniello, U., & Pirri, S. (2018). Big data for open innovation in SMEs and large corporations: Trends, opportunities, and challenges. *Creativity and Innovation Management*, *27*(1), 6-22. Doi.org/10.1111/caim.12224

Dillman, D. A., Smyth, J. D., & Christian, L. M. (2014). *Internet, phone, mail, and* *mixed-mode surveys: the tailored design method*. John Wiley & Sons.

Dimitrijević, B., Simic, V., Radonjic, V., & Kostic-Ljubisavljevic, A. (2012, June). The Delphi method as a research tool: an application in transportation and logistics systems evaluations. In The 6th International Quality Conference. Center for Quality, Faculty of Engineering, University of Kragujevac (Serbia). Https://doi. org/10.13140/RG (Vol. 2, No. 1798.6646).

Dong, J. Q., & Yang, C. H. (2020). Business value of big data analytics: A systems theoretic approach and empirical test. *Information & Management, 57*(1), 103124. https://doi.org/10.1016/j.im.2018.11.001

Dossi, A., & Patelli, L. (2010). You Learn from What You Measure: Financial and Non-financial Performance Measures in Multinational Companies. *Long Range Planning, 43*(4), 498–526. https://doi.org/10/bsff4 k

Douma, S., & Schreuder, H. (2002). *Economic Approaches to Organizations* (3rd ed.). Financial Times Prentice Hall.

Drath, R., & Horch, A. (2014). Industrie 4.0 – Hit or hype? *IEEE Industrial Electronics Magazine, 8(2)*, 56–58. Doi.org/10.1109/mie.2014.2312079.

Durach, C. F., Kembro, J., & Wieland, A. (2017). A New Paradigm for Systematic Literature Reviews in Supply Chain Management. *Journal of Supply Chain Management*, *4*, 67. https://doi.org/10.1111/jscm.12145

Erevelles, S., Fukawa, N., & Swayne, L. (2016). Big Data consumer analytics and the transformation of marketing. *Journal of Business Research*, 69(2), 897-904. https://doi.org/10.1016/j.jbusres.2015.07.001

Fan, S., Lau, R. Y. K., & Zhao, J. L. (2015). Demystifying Big Data Analytics for Business Intelligence Through the Lens of Marketing Mix. *Big Data Research*, 2, 28–32. https://doi.org/10.1016/j.bdr.2015.02.006

Franc, J. M., Ching Hung, K. K., Pirisi, A., & Weinstein, E. S. (2023). Analysis of Delphi study 7-point linear scale data by parametric methods: Use of the mean and standard deviation. *Methodological Innovations*. https://doi.org/10.1177/20597991231179393

Francisco, E. D. R., Kugler, J. L., Kang, S. M., Silva, R., & Whigham, P. A. (2019). Beyond Technology: Management Challenges in the Big Data Era. *Revista de Administração de Empresas, 59(6),* 375-378. https://doi.org/10.1590/s0034-759020190603

Frederico, G. F., Garza-Reyes, J. A., Anosike, A., & Kumar, V. (2019). Supply Chain 4.0: concepts, maturity, and research agenda. *Supply Chain Management: An International Journal. https://doi.org/10.1108/SCM-09-2018-0339*

Gartzia, L., & Baniandrés, J. (2016). Are people-oriented leaders perceived as less effective in task performance? Surprising results from two experimental studies. *Journal of Business Research*, *69*(2), 508-516.

Gawankar, S. A., Gunasekaran, A., & Kamble, S. (2020). A study on investments in the big data-driven supply chain, performance measures and organizational performance in Indian retail 4.0 context. *International Journal of Production Research*, *58*(5), 1574-1593. https://doi.org/10.1080/00207543.2019.1668070

Goldsby, T. J., & Zinn, W. (2016). Technology innovation and new business models: can logistics and supply chain research accelerate the evolution? *Journal of Business Logistics,37*(2), 80-81.

Gunasekaran, A., & Ngai, E. W. (2004). Information systems in supply chain integration and management. *European journal of operational research*, *159*(2), 269-295.

Gunasekaran, A., Papadopoulos, T., Dubey, R., Wamba, S. F., Childe, S. J., Hazen, B., & Akter, S. (2017). Big data and predictive analytics for supply chain and Organizational performance. *Journal of Business Research*, *70*, 308–317. https://doi-org.ezp.waldenulibrary.org/10.1016/j.jbusres.2016.08.004

Gunasekaran, A., Yusuf, Y. Y., Adeleye, E. O., & Papadopoulos, T. (2018). Agile manufacturing practices: the role of big data and business analytics with multiple case studies. *International Journal of Production Research, 56*(1/2), 385–397. https://doi.org/10.1080/00207543.2017.1395488

Gupta, M., & George, J. F. (n.d.). Toward the development of a big data analytics capability. *Information & Management, 53(*8), 1049–1064. https://doi.org/10.1016/j.im.2016.07.004

Gupta, R., Tanwar, S., Tyagi, S., & Kumar, N. (2020). Machine Learning Models for Secure Data Analytics: A taxonomy and threat model. *Computer Communications*, *153*, 406–440. https://doi-org.ezp.waldenulibrary.org/10.1016/j.comcom.2020.02.008

Hajli, N., Tajvidi, M., Gbadamosi, A., & Nadeem, W. (2020). Understanding market agility for new product success with big data analytics. *Industrial Marketing Management*, *86*, 135-143.

Hazen, B. T., J. B. Skipper, J. D. Ezell, and C. A. Boone. 2016. Big Data and Predictive Analytics for SC Sustainability: A Theory-Driven Research Agenda. *Computers & Industrial Engineering* 101: 592–598.

Heavin, C., & Power, D. J. (2018). Challenges for digital transformation–towards a conceptual decision support guide for managers. *Journal of Decision Systems, 27*(sup1), 38-45. https://doi.org/10.1080/12460125.2018.1468697

Helfat, Constance E.; Finkelstein, Sydney; Mitchell, Will; Peteraf, Margaret; Singh, Harbir; Teece, David; Winter, Sidney G. (2009). *Dynamic Capabilities: Understanding Strategic Change in Organizations*. John Wiley & Sons.

Hermann, M., Pentek, T., & Otto, B. (2016). Design principles for industrie 4.0 scenarios. 49th Hawaii international conference on system sciences (HICSS) (pp. 3928–3937). http://dx.doi.org/10.1109/HICSS.2016.488.

Hofmann, E., Sternberg, H., Chen, H., Pflaum, A., & Prockl, G. (2019). Supply chain management and Industry 4.0: conducting research in the digital age. *International Journal of Physical Distribution & Logistics Management*. https://doi.org/10.1108/IJPDLM-11-2019-399

Horton, J., Kerr, W. R., & Stanton, C. (2017). "*Digital Labor Markets and Global Talent Flows"* NBER Program(s): Labor Studies, Productivity, Innovation, And Entrepreneurship

Huang, Y., & Handfield, R. B. (2015). Measuring the benefits of ERP on supply management maturity model: a "big data" method. *International Journal of Operations & Production Management, 35(*1), 2. Doi :10.1108/IJOPM-07-2013-

0341.

Huntemann, N. B. (2015) Introduction: Digital Labor behind the Screen. *Critical Studies in Media Communication, 32(3),* 158-160. https://doi.org/10.1080/15295036.2015.1061681

Inside Supply Management (2015 Ed.). https://www.ismworld.org/globalassets/pub/magazine/ismmagazine20150102-dl.pdf

Jacobides, M. G., Cennamo, C., & Gawer, A. (2018). Towards a theory of ecosystems. *Strategic management journal*, *39*(8), 2255-2276.

Jazdi, N. (2014). Cyber physical systems in the context of Industry 4.0. 2014 IEEE automation, quality and testing, robotics, 2–4. http://dx.doi.org/10.1109/AQTR.20146857843.

Jeble, S., R. Dubey, S. J. Childe, T. Papadopoulos, D. Roubaud, and A. Prakash. 2018. Impact of Big Data and Predictive Analytics Capability on Supply Chain Sustainability. *International Journal of Logistics Management* 29 (2): 513–538. Doi:10.1108/IJLM-05-2017-0134.

Ju, B., & Jin, T. (2013). Incorporating nonparametric statistics into Delphi studies in library and information science. *Information Research: An International Electronic Journal*, *18*(3), n3. http://InformationR.net/ir/18-3/paperxxx.html]

Kache, F., & Seuring, S. (2017). Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International Journal of Operations & Production Management, 37*(1), 10–36.

https://doi.org/10.1108/IJOPM-02-2015-0078

Kadigi, W. R., Ngaga, Y. M., & Kadigi, R. M. (2021). Perceptions of smallholder farmers on nature-based income generating activities as potential livelihood and biodiversity conservation strategies in Uluguru Mountains, Tanzania.

Kamble, S. S., & Gunasekaran, A. (2020). Big data-driven supply chain performance measurement system: a review and framework for implementation. *International Journal of Production Research*, *58*(1), 65–86. https://doi-org.ezp.waldenulibrary.org/10.1080/00207543.2019.1630770.

Kane, G. C., Palmer, D. Phillips, A. N., Kiron, D., & Buckley, N. (2016). "*Digitally savvy executives are already aligning their people, processes, and culture to achieve their organizations' long-term digital success*" Retrieved from https://sloanreview.mit.edu/projects/aligning-for-digital-future/

Kazim, F. A. (2019). Digital Transformation and Leadership Style: A Multiple Case Study. *The ISM Journal of International Business, 3*(1), 24-33. https://www.researchgate.net/profile/Michael_Neubert7/publication/337007715_How_Do_Corporate_Valuation_Methods_Re_ect_the_Stock_Price_Value_of_SaaS_So_ware_Firms/links/5dbff9a64585151435e52988/How-Do-Corporate-Valuation-Methods-Re-ect-the-Stock-Price-Value-of-SaaS-So-ware-Firms.pdf#page=25

Kazmi, S. A. Z., Takala, J., & Naaranoja, M. (2015). *Sustainable solution for competitive Team formation., 17(9).*

Keil, M., Cule, P. E., Lyytinen, K., & Schmidt, R. C. (1998). A framework for identifying software project risks. *Communications of the ACM*, *41*(11), 76-83. https://doi.org/10.1145/287831.287843

Khan, Z., & Vorley, T. (2017) Big data text analytics: an enabler of knowledge management, *Journal of Knowledge Management*, *21*(1),18-34. Klein, A. (2017). Fixing your supply chain with BIG DATA: Distilling millions of granules of information into operational decisions will separate tomorrow's winners and losers. *Industrial Engineer: IE*, *49(9)*, 39–43.

Krittika, Vishvakarma, N. K., Sharma, R. R. K., & Lai, K. K. (2017). Linking big data analytics to a few industrial applications: A conceptual review. *Journal of Information and Optimization Sciences*, *38*(6), 803-812. https://doi.org/10.1080/02522667.2017.1372130

Kumar, N (2015). Leveraging Emotional Intelligence for the Enhancement of the Organizational Effectiveness – Paradigms and Paragons. Integral Review. *Integral Review: A Journal of Management*, *8*(2).

Lamba, K., & Singh, S.P. (2016), Big data analytics in supply chain management: some conceptual frameworks, *International Journal of Automation and Logistics*, *2* (4), 279-293. https://doi.org/10.1504/IJAL.2016.080341

Lamba, K., & Singh, S. P. (2017). Big data in operations and supply chain management: current trends and future perspectives. *Production Planning & Control*, *28(11/12*), 877. doi:10.1080/09537287.2017.1336787

Lamba, K., & Singh, S. P. (2018). Modeling big data enablers for operations and supply chain management. *The International Journal of Logistics Management* https://doi.org/10.1108/IJLM-07-2017-0183

LaValle, S., E. Lesser, R. Shockley, M. S. Hopkins, and N. Kruschwitz. (2011). Big Data, Analytics, and the Path from Insights to Value. *MIT Sloan Management Review* 52 (2): 21

Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons 60(3)*, 293–303. https://doi.org/10.1016/j.bushor.2017.01.004

Linstone, H. A., & Turoff, M. (Eds.) (2002), The Delphi Method: Techniques and Applications, Addison-Wesley Publishing Company Inc, Reading, M.A. Available at: http://www.is.njit.edu/pubs/delphibook

Lindlof, T. R., & Taylor, B. C. (2017). *Qualitative communication research methods*. Sage publications.

Loughlin K.G. & Moore L.F. (1979) Using Delphi to achieve congruent objectives and activities in a pediatrics department. *Journal of Medical Education 54*(2), 101-106. DOI: 10.1097/00001888-197902000-00006

Ludwig, G., & Pemberton, J. (2011). A managerial perspective of dynamic capabilities in emerging markets: The case of the Russian steel industry. *Journal of East European Management Studies*. *16 (3)*: 215–236. Doi:10.5771/0949-6181-2011-3-215.

Maceviciute, E., & Wilson, T. D. (2009). A Delphi investigation into the research needs in Swedish librarianship. *Information Research: An International Electronic Journal*, *14*(4), n4. https://eric.ed.gov/?id=EJ869360

Mandal, S. (2018). Exploring the influence of big data analytics management capabilities on sustainable tourism supply chain performance: the moderating role of technology orientation. *Journal of Travel & Tourism Marketing, 35*(8), 1104-1118. https://doi.org/10.1080/10548408.2018.1476302

Manyika, J., M. Chui, B. Brown, J. Bughin, R. Dobbs, C. Roxburgh, and A. H. Byers. 2011. *Big Data: The Next Frontier for Innovation, Competition, and Productivity*. San Francisco, CA: McKinsey Global Institute.

Marshall, A., Mueck, S., & Shockley, R. (2015). How leading organizations use big data and analytics to innovate. *Strategy & Leadership, 43*(5), 32–39. https://doi.org/10.1108/SL-06-2015-0054

Matt, C., Hess, T., & Benlian, A. (2015). Digital transformation strategies. *Business & Information Systems Engineering, 57*(5), 339-343. https://doi.org/10.1007/s12599-015-0401-5

Matthias, O., I. Fouweather, I. Gregory, and A. Vernon. 2017. Making Sense of Big Data Can it Transform Operations Management? *International Journal of Operations and Production Management* 37 (1): 37–55. doi:10.1108/IJOPM-02-2015-0084.

Mazzarol, T. (2015). SMEs Engagement with E-commerce, E-business, and E-marketing. *Small Enterprise Research, 22(1), 79-90*. doi:10.1080/13215906.2015.1018400

McAfee, A., & Brynjolfsson, E. (2012, October). Big data: The management revolution. *Harvard Business Review*. https://hbr.org/2012/10/big-data-the-management-revolution

Mengual-Andrés, S., Roig-Vila, R., & Mira, J. (2016). Delphi study for the design and validation of a questionnaire about digital competences in higher education. *International Journal of Educational Technology in Higher Education*, *13*(1), 1–11. https://doi-org.ezp.waldenulibrary.org/10.1186/s41239-016-0009-y

Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly, 36*(4). https://doi-org.ezp.waldenulibrary.org/10.1016/j.giq.2019.06.002

Merendino, A., Dibb, S., Meadows, M., Quinn, L., Wilson, D., Simkin, L., & Canhoto, (2018). Big data, big decisions: The impact of big data on board level decision-making. *Journal of Business Research, 93,* 67-78. https://doi.org/10.1016/j.jbusres.2018.08.029

Migliore, L. A., & Chinta, R. (2017). Demystifying the Big Data Phenomenon for Strategic Leadership. *SAM Advanced Management Journal (07497075), 82*(1), 48–58.

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook.* Sage.

Miller, K. (2002). *Communication theories. Perspectives, processes, and contexts.* McGraw-Hill Companies.

Nelson, R. R. (1982). *An Evolutionary Theory of Economic Change*. Belknap Press of Harvard University Press.

Nguyen, T., Zhou, L., Spiegler, V., Ieromonachou, P., & Lin, Y. (2018). Big data analytics in supply chain management: A state-of-the-art literature review. *Computers and Operations Research*, 98254-264. https://doi.org/10.1016/j.cor.2017.07.004

Okoli, C., & Pawlowski, S. D. (2004). The Delphi method as a research tool: an example, design considerations and applications. *Information & management*, *42*(1), 15-29. doi:10.1016/j.im.2003.11.002

Oliveira, M. I. S., Lima, G. D. F. B., & Lóscio, B. F. (2019). Investigations into Data Ecosystems: a systematic mapping study. *Knowledge and Information Systems*, 1-42. https://doi.org/10.1007/s10115-018-1323-6

Paré, G., Cameron, A.-F., Poba-Nzaou, P. and Templier, M. (2013) 'A systematic assessment of rigor in information systems ranking-type Delphi studies', *Information & Management*, vol. 50, no. 5, pp. 207–217

Pauleen, D. J., & Wang, W. Y. (2017). Does big data mean big knowledge? KM perspectives on big data and analytics. *Journal of Knowledge Management*, *21*(1), 1-6. https://doi.org/10.1108/JKM-08-2016-0339

Powell, C. (2003). The Delphi technique: myths and realities. *Journal of advanced nursing*, *41*(4), 376-382. https://doi.org/10.1046/j.1365-2648.2003.02537.

Ram, J., Zhang, C., & Koronios, A. (2016). The implications of Big Data analytics on Business Intelligence: A qualitative study in China. *Procedia Computer Science, 87*, 221-226. https://doi.org/10.1016/j.procs.2016.05.152

Raut, R. D., Mangla, S. K., Narwane, V. S., Gardas, B. B., Priyadarshinee, P., & Narkhede, B. E. (2019). Linking big data analytics and operational sustainability practices for sustainable business management. *Journal of Cleaner Production*, *224*, 10-24. https://doi.org/10.1016/j.jclepro.2019.03.181

Rescher (1998): *Predicting the Future,* (Albany, NY: State University of New York Press, 1998)

Richey, R. G., Morgan, T. R., Lindsey-Hall, K., & Adams, F. G. (2016) A global exploration of Big Data in the supply chain, *International Journal of Physical Distribution & Logistics Management, 46* (8), 710-739. https://doi.org/10.1108/IJPDLM-05-2016-0134

Roßmann, B., Canzaniello, A., von der Gracht, H., & Hartmann, E. (2017). The future and social impact of Big Data Analytics in Supply Chain Management: Results from a Delphi study. Technological Forecasting & Social Change, Doi: 10.1016/j.techfore.2017.10.005

Ross D.F. (2015) *Information Technology and Supply Chain Management. In: Distribution Planning and Control*. Springer, New York, NY. https://doi.org/10.1007/978-1-4899-7578-2_15

Sanders, N. R. (2016). How to Use Big Data to Drive Your Supply Chain. *California Management Review, 58(3), 26-48.* https://doi.org/10.1525/cmr.2016.58.3.26

Santos, M. Y., e Sá, J. O., Andrade, C., Lima, F. V., Costa, E., Costa, C., ... & Galvão, J. (2017). A big data system supporting bosch braga industry 4.0 strategy. *International Journal of Information Management*, *37*(6), 750-760. https://doi.org/10.1016/j.ijinfomgt.2017.07.012

Schmalz, U., Spinler, S., & Ringbeck, J. (2021). Lessons learned from a two-round Delphi-based scenario study. MethodsX, 8, 101179.

Doi.org/10.1016/j.mex.2020.101179

Schmidt, R. C. (1997). Managing Delphi surveys using nonparametric statistical techniques. *Decision Sciences, 28*(3), 763-774. https://doi.org/10.1111/j.1540-5915.1997.tb01330.x

Sekayi, D., & Kennedy, A. (2017). Qualitative Delphi Method: A Four Round Process with a Worked Example. *The Qualitative Report,* 22(10), 2755-2763. https://doi.org/10.46743/2160-3715/2017.297

Shamim, S., Zeng, J., Shariq, S. M., & Khan, Z. (2018). Role of big data management in enhancing big data decision-making capability and quality among Chinese firms: A dynamic capability views. *Information & Management*, 103135. https://doi-org.ezp.waldenulibrary.org/10.1016/j.im.2018.12.003

Shamout, M. D. (2019). Does Supply Chain Analytics Enhance Supply Chain Innovation and Robustness Capability? *Organizacija, 52*(2), 95-106. http://organizacija.fov.uni-mb.si/index.php/organizacija/article/view/983

Shields, A. (2018). Quantum Cryptography: a new age in data security: Dr Andrew Shields highlights the importance of quantum cryptography in ensuring the future of data security. *Scientific Computing World*, (163), 16.

Sibanda, M., & Ramrathan, D. (2017). Influence of Information Technology on Organization Strategy. *Foundations of Management, 9(1), 191-202.* http://dx.doi.org.ezp.waldenulibrary.org/10.1515/fman-2017-0015. Retrieved from http://ezp.waldenulibrary.org/login?url=https://search-proquest-com.ezp.waldenulibrary.org/docview/1965463093?accountid=14872.

Siddique, M. N. A., Hasan, K. W., Ali, S. M., Moktadir, M. A., Paul, S., & Kabir, G. (2021). Modeling drivers to big data analytics in supply chains. *Journal of Production Systems and Manufacturing Science*.

Silahtaroğlu, G., & Alayoglu, N. (2016). Using or Not Using Business Intelligence and Big Data for Strategic Management: An Empirical Study Based on Interviews with Executives in Various Sectors. *Procedia - Social and Behavioral Sciences, 235*, 208–215. https://doi-org.ezp.waldenulibrary.org/10.1016/j.sbspro.2016.11.016

Skog, D. A., Wimelius, H., & Sandberg, J. (2018). Digital disruption. *Business & Information Systems Engineering*, *60*(5), 431-437. https://doi.org/10.1007/s12599-018-0550-4

Skulmoski, G. J., Hartman, F. T., & Krahn, J. (2007). The Delphi method for graduate research. *Journal of Information Technology Education: Research*, *6*(1), 1-21. https://www.learntechlib.org/p/111405/

Spil, T., Pris, M., & Kijl, B. (2017). Exploring the BIG Five of e-leadership by developing digital strategies with mobile, cloud, big data, social media, and the Internet of things. *E-proceedings IC Management Leadership &Governance, Johannesburg South Africa*.

Spranger, J., Homberg, A., Sonnberger, M., & Niederberger, M. (2022). Reporting guidelines for Delphi techniques in health sciences: A methodological review. *Zeitschrift für Evidenz, Fortbildung und Qualität im Gesundheitswesen*, *172*, 1-11.

Strasser, A. (2017). Delphi method variants in information systems research: Taxonomy development and application. *Electronic Journal of Business Research Methods, 15(2),* pp120-133.

Sundram, V. P. K., Bahrin, A. S., Abdul Munir, Z. B., & Zolait, A. H. (2018). The effect of supply chain information management and information system infrastructure. *Journal of Enterprise Information Management, 31(*5), 751–770. https://doi.org/10.1108/JEIM-06-2017-0084

Teece, D., Pisano, G., & Shuen, A. (1997). Dynamic Capabilities and Strategic Management. *Strategic Management Journal*. *18 (7):* 509–533. https://doi.org/10.1002/(SICI)1097-0266(199708)18:7<509:AID-SMJ882>3.0.CO;2-Z

Thompson, M. (2009). Considering the implication of variations within Delphi research. *Family Practice, 26(5),* 420–424. https://doi.org/10.1093/fampra/cmp051

Tiwari, S., Wee, H., & Daryanto, Y. (2018). Big data analytics in supply chain management between 2010 and 2016: Insights to industries. *Computers & Industrial Engineering,*115319-330. doi: 10.1016/j.cie.2017.11.017

Tjahjono, B., Esplugues, C., Ares, E., & Pelaez, G. (2017). What does industry 4.0 mean to supply chain? *Procedia manufacturing*, *13*, 1175-1182. https://doi.org/10.1016/j.promfg.2017.09.191

Tseng, M., Lim, M., & Wong, W. P. (2015). Sustainable supply chain management. *Industrial Management & Data Systems, 115*(3), 436–461. https://doi.org/10.1108/IMDS-10-2014-0319

ur Rehman, M. H., Yaqoob, I., Salah, K., Imran, M., Jayaraman, P. P., & Perera, C.

(2019). The role of big data analytics in industrial Internet of Things. *Future Generation Computer Systems*, *99*, 247-259. https://doi.org/10.1016/j.future.2019.04.020

Vera-Baquero, A., Colomo Palacios, R., Stantchev, V., & Molloy, O. (2015). Leveraging big data for business process analytics. *Learning Organization*, *22*(4), 215–228. https://doi.org/10.1108/TLO-05-2014-0023

Verma, S., Bhattacharyya, S. S., & Kumar, S. (2018). An extension of the technology acceptance model in the big data analytics system implementation environment. *Information Processing & Management*, *54*(5), 791-806. https://doi.org/10.1016/j.ipm.2018.01.004

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research*, *261*(2), 626–639. https://doi.org/10.1016/j.ejor.2017.02.023

Vijayarani, S., & Sharmila, S. (2016). Research in big data: an overview. *Inf Eng Int J*, *4*, 1-20.

Vilkinas, T., Murray, D. W., & Chua, S. M. Y. (2019). Effective leadership: Considering the confluence of the leader's motivations, behaviors, and their reflective ability. *Leadership & Organization Development Journal*, *41*(1), 147–163. https://doi-org.ezp.waldenulibrary.org/10.1108/LODJ-12-2018-0435

von der Gracht, H. A. (2012). Consensus measurement in Delphi studies: Review and implications for future quality assurance. *Technological Forecasting & Social Change*, *79*(8), 1525–1536. https://doi.org/10.1016/j.techfore.2012.04.013

Wallendorf, M., & Belk, R. W. (1989). Assessing trustworthiness in naturalistic consumer research. *ACR special volumes*. https://www.acrwebsite.org/volumes/12177/volumes/sv07/SV-0

Waller, M. A., & Fawcett, S. E. (2013). Data Science, Predictive Analytics, and Big Data: A Revolution That Will Transform Supply Chain Design and Management. *JOURNAL OF BUSINESS LOGISTICS*, *34*(2), 77–84. https://doi-org.ezp.waldenulibrary.org/10.1111/jbl.12010

Wamba, S. F., & Akter, S. (2019). Understanding supply chain analytics capabilities and agility for data-rich environments. *International Journal of Operations & Production Management*. https://doi.org/10.1108/IJOPM-01-2019-0025

Wamba, S. F., Gunasekaran, A., Akter, S., Ren, S. J.-F., Dubey, R., & Childe, S. J. (2017). Big data analytics and firm performance: Effects of dynamic capabilities. *Journal of Business Research, 356. https://doi.org/10.1016/j.jbusres.2016.08.009*

Westerman, G., Bonnet, D., & McAfee, A. (2014). The nine elements of digital transformation. *MIT Sloan Management Review*, *55*(3), 1-6.

Witjas-Paalberends, E. R., van Laarhoven, L. P. M., van de Burgwal, L. H. M., Feilzer, J., de Swart, J., Claassen, E., & Jansen, W. T. M. (2018). Challenges and best practices for big data-driven healthcare innovations conducted by profit-non-profit partnerships–a quantitative prioritization. *International Journal of Healthcare Management, 11*(3), 171– 181.

Wright, L. T., Robin, R., Stone, M., & Aravopoulou, D. E. (2019). Adoption of big data technology for innovation in B2B marketing. *Journal of Business-to-Business*

Marketing, *26*(3-4), 281-293. https://doi.org/10.1080/1051712X.2019.1611082

Yadegaridehkordi, E., Hourmand, M., Nilashi, M., Shuib, L., Ahani, A., & Ibrahim, O. (2018). Influence of big data adoption on manufacturing companies' performance: An integrated DEMATEL-ANFIS approach. *Technological Forecasting and Social Change, 137*, 199-210.

Yaniv, I. (2011). Group diversity and decision quality: amplification and attenuation of the framing effect. *International Journal of Forecasting*, *27*(1), 41-49. https://doi.org/10.1016/j.ijforecast.2010.05.009

Yin, S., & Kaynak, O. (2015). Big data for modern industry: challenges and trends [point of view]. *Proceedings of the IEEE, 103*(2), 143-146.

Yousuf, M. I. (2007). The Delphi technique. *Essays in Education*, *20*(1), 8.

Yu, W., Chavez, R., Jacobs, M. A., & Feng, M. (n.d). Data-driven supply chain capabilities and performance: A resource-based view. *Transportation Research Part E-Logistics and Transportation Review*, 114371-385.

Zikopoulos, P., DeRoos, D., Parasuraman, K, Deutsch, T., Corrigan, D. and Giles, J. (2013). *Harness the Power of Big Data*. McGraw-Hill.

Appendix A: Search Results and Article Selection Process

Table A1

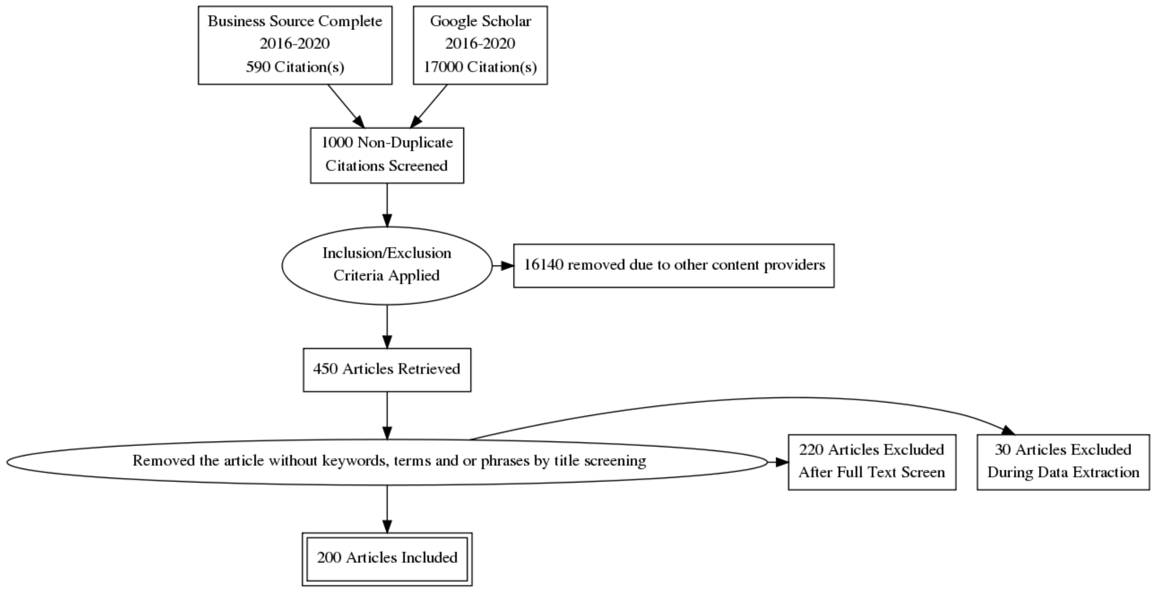
Databases, Search Engines, Keywords, and Search Parameters for Literature Search

Database/search engine	Search date range	Search string (Boolean phrase)	Discipline	Expander	Limiter	Language	No. of results
Walden Library Search	2016–2020	"big data analytics and supply chain management"	Business and Management	1. Apply related words using the EBSCOhost Thesaurus. 2. Apply search within the full text of the articles. 3. Apply equivalent subjects.	Scholarly (peer-reviewed) journals, reports. Year range	English	325
Google Scholar*	2016–2020	"Big data analytics and supply chain management"	Any		Year range	English	18,500

Note. Google Scholar had no filters for discipline(s), expanders, limiters, or content providers.

Figure A1

Article Selection Process



Note. Adapted from "Preferred Reporting Items for Systematic Reviews and Meta-Analyses: The PRISMA Statement," by D. Moher, A. Liberati, J. Tetzlaff, D. G. Altman, & The PRISMA Group, 2009, *PLOS Medicine*, *6*(7), Article e1000097 (https://doi.org/10.1371/journal.pmed.1000097). CC BY.

Appendix B: Screening Questions

Screening Questions

1. **Question 1 (**Pick one)

   Are you working as a supply chain professional for at least two years?
   - Yes (accept)
   - No (reject)
   - Not sure (reject)

2. **Question 2 (**Pick one)

   Do you know big data concept
   - Yes (accept)
   - It depends where it is used (accept)
   - No (reject)

3. **Question 3 (**Pick one)

   Do you have any experience in big data usage in supply chain management at either organizational level or management level?
   - Yes, at both levels (accept)
   - Only at either level (accept)
   - Not at any level (reject)

4. **Question 4 (**Pick one)

   Can you commit to complete entire survey since this Delphi Study requires a three-round questionnaire so that we could issue you the following round questionnaire to obtain your feedback if you are selected?
   - Yes (accept)
   - Not sure (reject)
   - No (reject)

5. **Question 5 (**Pick one)

   Do you reside in the United States of America
   - Yes (accept)
   - Resided before but not now or temporarily stay (reject)
   - No (reject)

Appendix C: Letter of Invitation

Walden University

Letter of Invitation to Participate in Research

Title of study: What Makes an Effective Leader of Supply Chain Management in the Big Data Era

Date: Aug 30, 2022

Dear Participants

You are invited to participate in a research study conducted by Doctoral candidate Tianshu (James) Wu from Walden University under committee chair Dr. Richard Dool.

The purpose of this study is to determine how a panel of 30 subject matter experts from supply chain management in the United States views the desirability, feasibility, and importance of successful digital transformation of supply chain management through use of the Big Data. You are eligible to participate in this study since you work as a supply chain professional. I will ask you to complete three rounds of questionnaires which should take approximately 10-15 minutes for each round questionnaire. The questionnaire will be administered at three different time frames. This survey contains questions about:

1) What are the challenges and or barriers that result in supply chain management being lag behind in digital transformation? Please list them in any order.

2) How is the desirability, feasibility, and importance of digital transformation of supply chain management impacted by use of the Big Data? Please list them in any order.

Your responses will be confidential.

Your participation in this study is entirely voluntary. If you are interested in participating, please read attached consent form which contains additional information about the study. You may discontinue participation at any time during the survey and or choose any questions you wish to answer. There is no any obligation regardless participation or choose not to participate. Feel free to contact me at tianshu.wu@waldenu.edu if you have any further questions.

Sincerely,

Tianshu (James) Wu