Big Data Analytic Capabilities Playing a Critical Role in Sustainability performance of Supply Chain at Australian Organisations

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This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

This research is supported by the Australian Government Research Training Program.

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2. Conference Papers

Cetindamar, D., Shdifat, B., & Erfani, S. (2020, January). Assessing big data analytics capability and sustainability in supply chains. In Proceedings of the 53rd Hawaii International Conference on System Sciences.

Shdifat, B., Cetindamar, D., & Erfani, S. (2019, August). A literature review on big data analytics capabilities. In 2019 Portland International Conference on Management of Engineering and Technology (PICMET) (pp. 1-6). IEEE.

3. Journal Papers

Cetindamar, D., Shdifat, B., & Erfani, E. (2021). Understanding Big Data Analytics Capability and Sustainable Supply Chains. Information Systems Management, 1-15.

Abstract

Climate change is undoubtedly one of the key challenges facing sustainability for contemporary business and society. It is widely recognized that current violations associated with climate change are going to make addressing it a critical issue for future generations. Unfortunately, Australia faces significant environmental and economic impacts of climate change across several sectors. Thus, focusing on short-term temporary solutions may lead to poor sustainability. Consequently, sustainability performance has become a necessity. Supply chain management is one of the driving forces to achieving business's sustainability. To attain a sustainable supply chain, an organisation has to social, economic, and environmental concerns across its entire supply chain.

Nowadays, organisations are dealing with large amounts of data, not only for important decisions but also in their day-to-day activities. A considerable amount of records or data, known as Big Data (BD) has become a new source for boosting sustainable supply chain performance (SSCP) because it allows the efficient use of vast volumes of strategic, operational, and tactical information across the supply chain phases. Embracing the advantages of big data is not enough towards addressing sustainability issues, investing in human and technology capabilities of big data analytics(BDA) is seen as a strategic capability that will help a business respond to social, environmental, and economic issues in an uncertain environment. By doing so, big data analytics capabilities(BDACs) can improve an organisation's sustainable performance.

The main goal of this study is to provide empirical evidence concerning the influence of BDACs on SSCP and obtain insights regarding its impacts. Therefore, two key motivations behind this research. Firstly, even though BDA has received more attention from scholars and practitioners because of the predicted valuable benefits, such as increased productivity and future economic growth, few empirical studies investigate data analytics from a capability perspective. Many prior studies

have also primarily paid more interest to infrastructure and analytics tools (non-human capabilities). Nonetheless, they do not offer a holistic picture of BDACs (BDA human and non-human capabilities). Furthermore, there is a scarcity of measurement scales for BDACs and SSCP. Secondly, there is a limited managerial and academic understanding as to how organisations can harvest the maximum benefit from BDA to respond to supply chain sustainability issues by adopting and reconfiguring appropriate BDA human and non-human capabilities. Empirical studies of the relationship between BDACs and SSCP have hardly been conducted. Prior empirical studies investigate the influence of BDACs on three sustainability dimensions (environment, social, and economic), but they do not consider all sustainability dimensions simultaneously

There are two adopted research strategies to meet the thesis's core objectives and answer the research questions. Firstly, to set the foundations for BDACs and SSCP, we carried out a systemic literary review. Secondly, we conducted a questionnaire-based survey method to collect data from Australian IT-related managers. Quantitative data (73 responses) were used to empirically evaluate and test causal relationships (proposed hypotheses) between research variables. Our findings suggest that BDACs have a positive influence on an organisation's sustainability performance in the supply chain. However, this impact is direct without a moderated effect.

Our study yields some interesting theoretical and empirical contributions. Firstly, a capability-based measurement for BDACs and a multi-dimensional measurement of SSCP, including environmental, social and economic performances, is proposed. Secondly, a novel empirically validated BDACs-SSCP model is developed, using the fragmented and disconnected relevant literature (Big Data and sustainable supply chain literature) as a baseline. This model successfully assesses the impact of BDACs on sustainability performance in supply chains and can act as a guiding mechanism for organisations. Finally, this thesis provides a case study from Australia for the extant literature on BDACs. In practical respect, organisations can achieve sustainability performance outcomes by employing BDA human and non-human capabilities. Additionally, practitioners might build long-term strategies to develop their capabilities

and organisational culture to transform their businesses into a sustainable future. Last but not least, the developed sustainability of companies will further improve their social and environmental performances, which will benefit all of society.

Keywords:

Big data analytics capabilities, Supply chain management, Sustainable supply chain performance, Social performance, Environmental performance, and Economic performance.

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Abbreviations

BD	Big Data
BDA	Big Data analytics
BDACs	Big Data analytics capabilities
SC	Supply chain
SCM	Supply chain management
SSCM	Sustainable supply chain management
SSCP	Sustainable chain supply performance
SP	Social performance
ENP	Environmental performance
ECP	Economic performance
CMV	Common method bias
CIO	Chief Information Officer
IS	Information System
IT	Information Technology
IoT	Internet of Things
RBV	Resource-based view
DCV	Dynamic capabilities view
AVE	Average variance extracted
FA	Factor analysis
CR	Composite reliability
GoF	Goodness-of-Fit
Q	Predictive relevance

Chapter 1. Introduction

This chapter represents an overview of the present study. Section 1.1 draws the research background based on existing knowledge. The research questions follow this in Section 1.2. Section 1.3 displays the research plan, and Section 1.4 demonstrates the significance of the study objectives. Section 1.5 briefly introduces the research methods involving the philosophical stance and research approach.

1.1 Research Background

Data is considered a backbone in sustaining a thriving business. Recently, the accelerated advancement of information technologies, like cloud computing and the internet of things, has created and accumulated enormous data known as Big Data. Big Data (BD) has been defined primarily in five Vs.: volume, variety, velocity, veracity, and value (Wamba et al., 2015). Academics and practitioners have paid more attention to analysing BD as a novel technology for achieving competitive advantage, increasing productivity and innovation, and future economic growth (Bollier & Firestone, 2010). Big data analytics (BDA) is defined as processes and tools applied on extensive and separate datasets to extract valuable and meaningful insights (Ghasemaghaei & Hassanein, 2015). Even though multiple success criteria for using BD are involved in BDA definitions, the organisational resources required to extract actionable insights from BD are not observed in these definitions. Therefore, researchers have launched the term 'BDA capability' (BDACs) to indicate a company's ability to leverage BD to extract actionable insights (Mikalef et al., 2018). Although BDACs has been defined as the "ability to assemble, integrate, and deploy its Big Data-based resources." (Gupta & George, 2016, p. 1050), a comprehensive picture of BDACs appears lacking (Mikalef et al., 2018). Thus, the primary aim of this study is to contribute to BDA literature by addressing a gap through depicting a comprehensive picture of BDAC, which involves BDA human and non-human capabilities.

BDA has a revolutionary role in several domains. BDA is especially relevant to the supply chain management (SCM) domain as it provides valuable and meaningful insights to support decision-making in increasingly global, volatile, and dynamic value networks. Recently, studies concerning supply chains have paid more attention to sustainability issues. IT-based SCM systems contribute to organisational outcomes by combing materials, funds, and information flow with the organisation's supply chain partners (Dehning et al., 2007). Sustainability, in terms of the triple bottom line (TBL, consisting of environmental, economic, and social performance), has become a more significant interest for business. In this context, firms aim to achieve sustainability through addressing social and environmental issues whilst increasing efficiency in those areas and improving financial performance (Hazen et al., 2016). Attaining sustainability criteria is based on the operational and strategic capabilities of firms. Thus, BDA provides valuable analytics to improve firms' decision-making processes, which will lead to developing their organisational and strategic capabilities. Furthermore, they positively influence sustainability performance (Hazen et al., 2016).

Despite the above, empirical studies of the relationship between BDACs and SSCP have hardly been conducted. Prior empirical studies investigate the influence of BDACs on three sustainability dimensions (environment, social, and economic), but they do not consider all sustainability dimensions simultaneously (Song et al., 2017). For instance, some studies investigate the impact of BDACs on economic performance (Gupta & George, 2016; Akter et al., 2016; Ji-fan Ren et al., 2017; Wamba et al., 2017; Gunasekaran et al., 2017). Similarly, Koseleva and Ropaite (2017) indicate the impact of BDACs on environmental sustainability. However, there is a lack of empirical evidence on the role of BDACs in social sustainability (Song et al., 2017; Liu and Zhang, 2017). Consequently, studies that focus on the influence of BDACs on the TBL dimensions of sustainability in combination are still in their infancy. In order to address this gap, our current research draws on the dynamic capabilities view (DCV) (Teece et al., 1997) to investigate the association between BDACs and the supply chain's sustainable performance.

1.2 Research Questions

Even though existing literature concerning BD and sustainability performance offers profound insights, addressing some research gaps could enrich current knowledge and practice. In particular, a focus on building BDACs in firms and the impact of building BDACs on sustainable supply chain performance (SSCP) appears to be a fruitful endeavor. Based on the research gap given above, the primary purpose of this research is to provide empirical evidence concerning the effect of BDACs on SSCP.

Given such a backdrop, the key question of this research is formulated as follows:

"What is the effect of Big Data analytics capabilities on sustainable supply chain performance?"

The following sub-questions are then posed:

RQ1: What capabilities are required to build Big Data analytics?

RQ2: What constitutes the dimensions of SSCP?

RQ3: To what extent can BDAC's enhance SSCP?

RQ4: To what extent does supplier integration influence the relationship between BDACs and SSCP?

RQ5: To what extent does alignment of business strategy with BDACs influence the relationship between BDAC and SSCP?

RQ6: To what extent does corporate social responsibility influence the relationship between BDAC and SSCP?

1.3 Research Significance

This study strives to connect two disparate research streams, i.e., BDACs and SSCP. Despite advances in the BD and sustainability performance of supply chain literature, there are research gaps in the current knowledge regarding the building of BDACs in organisations and the influence of BDACs on SSCP.

Big data analytics have valuable benefits such as increased productivity, innovation, and future economic growth, leading to more attention from researchers and practitioners. However, according to a capability perspective, many prior studies focus on technical capabilities and thus do not provide a comprehensive picture of BDACs (Mikalef et al., 2018, Gupta & Georg, 2016). Accordingly, this study's major significance lies in depicting a comprehensive view of BDACs that involves human and non-human capabilities.

In recent years, increasing attention to sustainability issues has been evidenced across published studies in the supply chain realm (Chiesa & Przychodzen, 2020; Gimenez et al., 2012; Missimer & Mesquita, 2022). The reason for this is responding to environmental, economic, and social issues (Brandenburg et al., 2014; Klassen & Vereecke, 2012). In this regard, many advanced businesses are still striving to understand, analyse, and design sustainable dimensions and respond to the rising demands on business operations ((Adam et al., 2019)Gunasekaran et al., 2014; Marques et al., 2010; Park-Poaps and Rees, 2010). However, organisations are often restricted in evaluating the sustainable impact on their supply chain due to inadequate data concerning sustainability issues and a lack of transparency between supply chain partners. So, businesses try to utilise BDA to find an appropriate solution to problems resulting from a lack of transparency between supply chains(Chiappetta Jabbour et al., 2020).

Even though there are many studies in the literature on how supply chain management may utilise predictive analysis and data science, empirical evidence has hardly investigated the impact of BDACs on supply chain sustainability. Some existing empirical studies indicate the influence of BDACs on three dimensions of sustainability (i.e., environmental, social, and economic). Yet, they do not consider all sustainability dimensions simultaneously (Song et al., 2017). Hence, insufficient empirical evidence on the relations between adopting BDACs and supply chain sustainability performance outcomes motivate us to pursue a more empirical investigation. This study contributes to ongoing research related to the impact of BDACs on the sustainability performance of the supply chain.

1.4 Research Plan

This section shows the research plan, which provides a guide to completing this research. Figure 1.1 shows the research plan for achieving the key goals of this thesis.

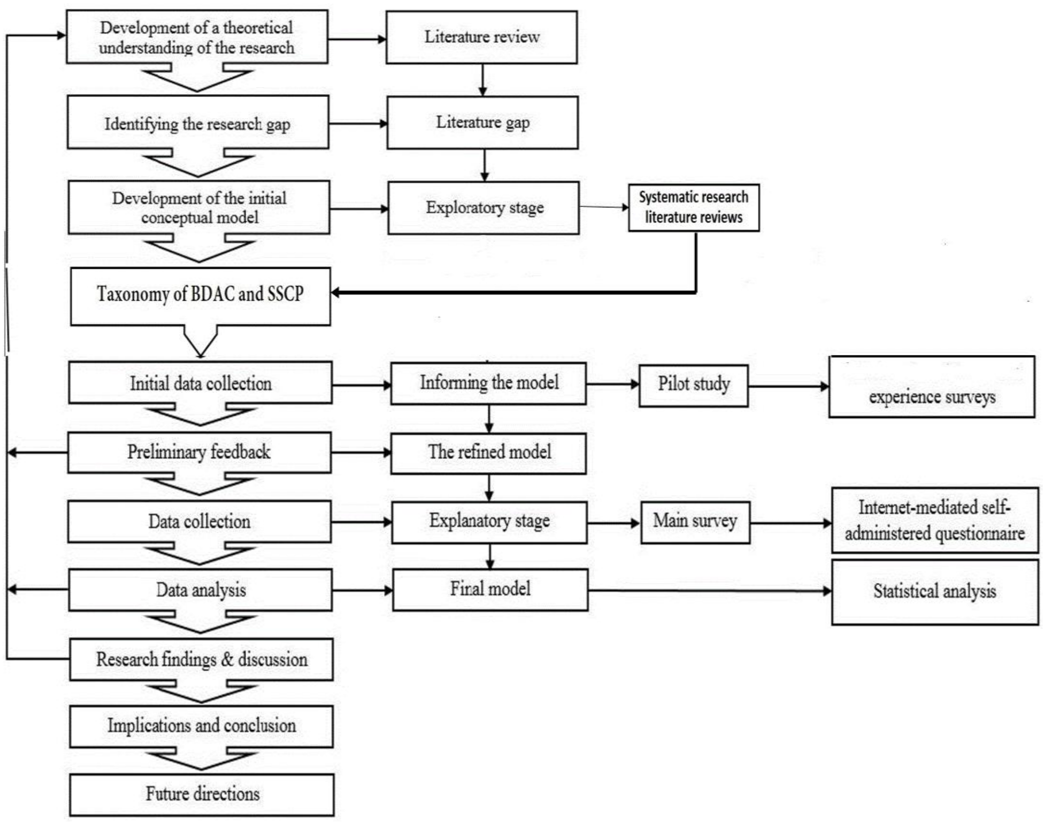

Figure 1-1 Research plan

1.5 Research Methodology

This study is classified as an explanatory (descriptive) research study, relevant to achieving the research objectives and answering the research questions. In fact, explaining cause-and-effect relationships between research variables is an appropriate reason to apply explanatory research. Furthermore, this thesis's principal objective is to conduct an empirical study using accurate data, consistent with a positivist perspective.

A quantitative method is adopted in light of the research objectives and questions. Indeed, conducting an empirical investigation of the research model and hypotheses requires such an approach. Deductive reasoning is used to construct and test hypotheses based on current knowledge using empirical observations (Saunders et al., 2019). Drawn on this approach, the causal correlation model was conceptualised via a comprehensive literature review of the research phenomenon, from the general to the specific.

Overall, this thesis adopts two research strategies: systematic literature review (SLR) and survey, to answer the proposed research questions and meet the thesis's core objectives. Moreover, the questionnaire-based survey method was conducted to collect data and test the research model. The Partial Least Squares Structural Equation Modelling (PLS-SEM) method was employed to assess the research model, helping to ensure that indicators and constructs were satisfied with validity and reliability.

1.6 Thesis structure

This thesis is systematised into six chapters. The following paragraphs present a brief for each chapter.

Chapter1(Introduction) presents an overview of this thesis. It reviews the background of this study and focuses on the research gap to formulate the research questions and relevant objectives to address the research problem. After that, research significance is outlined, followed by a presentation of research plan and finally a summary outlining how thesis chapters are structured

Chapter 2 (Literature Review) presents detailed literature to lay out the research context on this study phenomenon and answer key issues about the research questions. The literature of theoretical domains of big data and supply chain management and sustainability are reviewed. A review of the literature on the relation between BDACs and SSCP is conducted to identify the research gap. Drawing on theoretical perspectives and research gaps, the research model is established. Consequently, some hypotheses are developed which concerned with the effects BDACs on SSCP.

Chapter 3 (Research Methodology) contains a detailed outline of philosophical and methodological considerations of this study, including the research philosophy, the research approach, the research strategy, research method. In addition to this, a detailed explanation of the research measures, and questionnaire development and design is provided. Finally, the ethical considerations, population and sample size, and data collection process are explained.

Chapter 4 (Data Analysis and Results) describes descriptive analyses of the quantitative data collected via an online questionnaire. Based on the target population's results, this study has conducted a set of related analyses by using both SPSS 21 and Smart PLS 3. SPSS was used to extract the descriptive analyses. On the other hand, the Smart-PLS was used to evaluate the PLS_SEM model, which involves two main approaches. Firstly, assessing the quality of the measurement model involves evaluating reliability and validity. Secondly, assessing the structural model, which used the bootstrapping procedure to assess the relationships among the model's constructs through hypotheses testing.

Chapter 5 (Discussion) highlights in detail the findings of the study. This study's results were achieved by analyzing and assessing the research model, testing each proposed hypothesis in light of the results presented in Chapter 4. This chapter offers critical discussions concerning the research questions, explaining the causal relationships between BDACs and all pillars of sustainability performance.

Chapter 6 (conclusion) identifies the main contributions of this research along with the key managerial implications elicited from this research investigation. It also finishes with the research limitations and recommends future directions offering further research opportunities.

Chapter 2. Literature Review

This chapter presents the relevant literature to set the research context and answer key research questions. Section 2.1 provides an overview of the composition of BDACs. Secondly, Section 2.2 provides background on supply chain management and sustainability. Finally, Section 2.3 discusses the implementation of BDA in all pillars of the sustainability performance of the supply chain and identifies the research gaps.

2.1 Basics of Big Data Analytics Capabilities

2.1 What is Big Data

Data is considered a key element in building a thriving organisation. The accelerated advancement of information technologies, such as the internet of things (IoT) and cloud computing, has created and accumulated a significant amount of data (Zhao et al., 2017). This can be considered the reason for coining the term "Big Data" (BD). Big Data was launched to describe the data explosion, particularly in the digital world. Cisco estimated that devices' total data would reach 847 ZB per year by 2021 (Cisco, 2018). Big Data has played a revolutionary role in business and management (McAfee et al., 2012) as it has significant transformational abilities concerning management, business and research. Consequently, it comes as no surprise that researchers and practitioners have come to pay more attention to it (Akter et al., 2016; Chen & Zhang, 2014).

Big Data is becoming a part of the daily routines of corporations and government institutions at an overwhelming pace because it has achieved its maturity(Raban & Gordon, 2020; Yaseen & Obaid, 2020). Therefore, the rapid and broad evolution of Big Data as a concept results in various interpretations. For example, Jeble et al. (2016) and (Maras & Wandt, 2019)highlight large data sets as the common element of the Big Data concept. Maras and Wandt (2019) define Big Data as "extremely large data sets that can be analysed to reveal patterns, trends and associations, especially relating to human behaviour and interactions" (p. 161). According to

Jeble et al. (2016), Big Data refers to " datasets with terra-bytes and petabytes of data created in a short span of few hours" (p.4). De Mauro et al. (2016) also provide a comprehensive definition that implicit factors related to Big Data which defines as “ the information asset characterized by such a high volume, velocity, and variety to require specific technology and analytical methods for its transformation into value" (p. 127).

Some definitions of BD are recommended by Forbes (2014). The first definition is the “shift (for enterprises) from processing internal data to mining external data”. The second one is “new attitude by businesses, non-profits, government agencies, and individuals that combining data from multiple sources could lead to better decisions”. Therefore, internal and external BD are significant for companies. In addition to the data source, the value created from analysing these data brings many benefits to businesses, such as competitive advantage, growth, and innovation (Manyika et al., 2011). Table 2-1 represents several definitions of BD.

Table 2-1 Several Definitions of BD (derived from Wamba et al., 2015)

Author, Date	Definition
Jacobs (2009)	Big Data: Data that is too large to be placed in a relational database and analysed with the help of a desktop statistics/visualization package—data, perhaps, whose analysis requires massively parallel software running on tens, hundreds, or even thousands of servers. (p.44)
Rouse (2011)	Big Data: The voluminous amount of unstructured and semi-structured data a company creates or data would take too much time and cost too much money to load into a relational database for analysis.
Manyika et al. (2011)	Big Data: datasets with a size beyond the ability of typical database software tools to capture, store, manage, and analyse.
IBM (2012b)	Big Data: data captured from sensors, posts to social media sites, digital pictures and videos, purchase transaction records, cell phone GPS signals, etc.
Davenport et al. (2012)	Big Data: data from everything, including clickstream data from the Web to genomic and proteomic data from biological research and medicine.
Fisher et al. (2012)	Big Data: data that cannot be handled and processed straightforwardly (p. 53)
Boyd and Crawford (2012)	Big Data: a cultural, technological, and scholarly phenomenon that rests on the interplay of (1) Technology: maximizing computation power and algorithmic accuracy to gather, analyse, link, and compare large data sets. (2) Analysis: drawing on large data sets to identify patterns in order to make economic, social, technical, and legal claims. (3) Mythology: the widespread belief that large data sets offer a higher form of intelligence and knowledge that can generate insights that were previously impossible, with the aura of truth, objectivity, and accuracy. (p. 663).
Havens et al. (2012)	Big Data: data that you cannot load into your computer's working memory (p. 1130)

Johnson (2012)	Big Data: extremely large sets of data related to consumer behaviour, social network posts, geotagging, and sensor outputs (p. 21).
IDC (2013)	Big Data has three main characteristics: the data itself, the analytics of the data, and the presentation of the analytics results. Then there are the products and services that can be wrapped around one or all of these Big Data elements (p. 1)
Sun et al. (2015)	Big data: massive data from heterogeneous and autonomous resources, with diverse dimensions, by "size that is beyond the capacity of conventional processes or tools to effectively capture, store, manage, analyse, and exploit them," with "complex and dynamic relationships."
Akter et al. (2016)	Big data is defined regarding five 'Vs.:' volume, velocity, variety, veracity, and value.
Mikalef et al. (2018)	Big data has seven main characteristics in 'Vs.:' volume, velocity, variety, veracity, value, variability, and visualization.

Cox and Ellsworth launched the concept of Big Data in the late 1990s, which refers to three Vs (i.e., Volume, Velocity, and Variety), also widely used in previous studies (Burke, 2012; Kwon & Sim, 2013; McAfee et al., 2012; Russom, 2011). 'Volume' refers to a significant amount of available data. 'Velocity,' on the other hand, can be either the frequency or speed of data creation or delivery, whilst 'Variety' refers to data generated from various sources and formats (Russom, 2011). Other studies defined BD by four 'Vs.': Volume, Velocity, Variety, and Value. 'Value' indicates the economically worthy insights and benefits generated from BD by extraction and transformation (Dijcks, 2012). By considering the importance of data quality and BD resources reliability, White (2012) suggests the fifth dimension of BD, 'Veracity'. It ensures that the data used are trusted, authentic, and protected from unauthorised access and modification (Demchenko et al., 2013). Figure 2.1 illustrates the different characteristics of Big Data.

The BD concept can be defined by way of its use. This study considers BD as 5'Vs: 'Volume, Velocity, Variety, Value, and Veracity. The five V's reflect the growing popularity of BD. A further two dimensions are often added to BD characteristics, i.e., visualisation and variability. Variability denotes the dynamics concerning the rates of data flow (Gandomi & Haider, 2015). Through artificial intelligence technologies that produce models, 'visualisation' reveals data representation in meaningful ways. (Seddon and Currie 2017). Until now, there appears to be no clear definition for BD, and more Vs will be observed in the future (Mikalef et al., 2018).

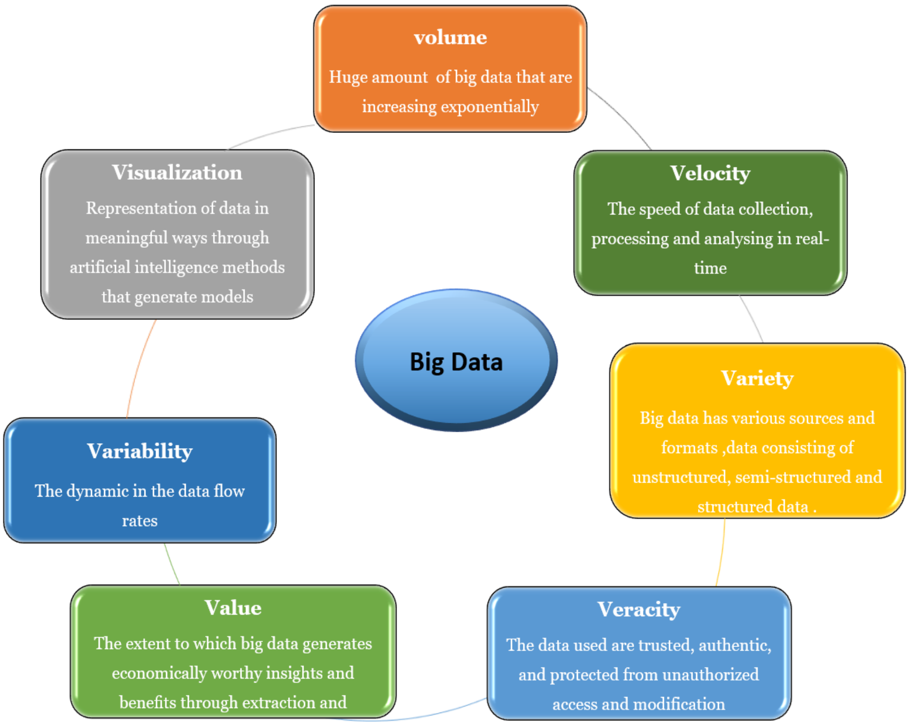

Figure 2-1 Different Characteristics of Big Data

2.2 Big Data Analytics

Big Data has released torrents of terabytes into every sector of the world's economy. Thus, companies have different forms of data such as customer transaction records, customer-generated content, and user logs(Chen et al., 2012). Companies could implement two phases to extract valuable business insights from BD. Firstly, data management involves different processes: data acquisition and recording; extraction, cleaning, and annotation; and integration, aggregation, and representation. Secondly, analytics encompasses modeling, analysis, and interpretation (Gandomi & Haider, 2015). Thus, BD analytics (BDA) is an effective tool to enrich understanding of how BD is utilised to leverage valuable business insights (Cetindamar et al., 2019).

The concept for BDA is defined from diverse viewpoints. BDA is defined as analytical techniques, procedures, tools, and infrastructure (Kwon et al., 2014) (Lamba & Dubey, 2015). Others concentrate on the process of examining BD via advanced technologies to reveal helpful information (e.g., hidden patterns) that can be used to improve business processes across functions or enterprises. (Waller & Fawcett, 2013). Big Data analytics is sometimes also defined as technologies (e.g., database and data mining tools) and techniques (e.g., analytical methods) that a company can employ to analyse large-scale, complex data for various applications intended to augment firm performance in multiple dimensions (Kwon et al., 2014). Further, BDA is also described as using different analytic approaches to handle the diversity of BD to produce descriptive, actionable, predictive, and prescriptive outcomes (Lamba & Dubey, 2015). Some other definitions of BDA encompass multi-critical elements to the success of BD. For instance, some define BDA as procedures and tools frequently employed in massive and distributed datasets to acquire significant insights (Ghasemaghaei & Hassanein, 2015).

Big Data analytics has some key benefits in different fields. For instance, BDA could accurately set cost reduction areas across the health system in the healthcare sector, reducing operational costs (Wang & Hajli, 2017). In retail industries, BDA has improved the customer experience and reduced fraud (Wamba et al., 2015). In addition, BDA also provides potential benefits to the bank sector by analysing customer log files and handling customer interactions. Big Data analytics can predict client behaviours by analysing their behaviours to upgrade services, detect frauds, and determine financial risk assessments (Zhong et al., 2016).

From the supply chain perspective, BDA capabilities have been applied in different aspects of SCM. BDA can boost visibility, mitigate risk and improve competitiveness (Raut et al., 2021). Dubey, Gunasekaran and Childe (2019) explore the role of BDAC to improve supply chain agility and competitive advantage. In addition, Mandal (2019) investigates the impact of BDA management capabilities on supply chain resilience. BDA capability assists in sustainable supply chain performance (Bag et al., 2020; Raut et al., 2019). Mani et al. (2017) examine how BDA can be applied to mitigating social risk in the supply chain.

Promoting the BDA capabilities of an organization can result in several outcomes. BDA has a significant positive impact on green innovation, competitive advantage, and HRM practices (El-Kassar & Singh, 2018)2019). Interestingly, many empirical studies agree that BDA could affect economic performance, such as profitability (Wang et al., 2018), sales (Shahbaz et al., 2020), and better customer services(Lee, 2017).

BDA is considered a facilitator for the adoption of the circular economy paradigm and can effectively create a basis for achieving economic, ecological, and social benefits(Gupta et al., 2019). Wang et al. (2020) investigate BDA capability has a positive moderating effect on the relationship between external corporate social responsibility and green supply chain management. Significantly, developing BDA capability assists to achieve superior organizational performance(Gupta et al., 2020)and co-innovation(Lozada et al., 2019).

Despite involving multiple significant elements in BDA definitions, the organisational resources essential to turning BD into actionable insights do not appear to be a prominent theme. Consequently, the term "BDA capability" (BDAC) has been coined by researchers to describe a business's ability to use BD to acquire significant insights (Akter et al., 2016).

2.3 Dimensions of Big Data Analytics Capabilities

System infrastructure has received considerable attention from current BD studies, involving: 'networking’, 'storage,' 'data capture,' and ‘distributed system parallel computing' (Gupta & George, 2016; Kearns & Lederer, 2003). However, these studies have not looked into beneficial BDACs related to a firm, such as the capabilities of system infrastructures (McAfee et al., 2012; Shuradze & Wagner, 2016), organisational learning (Gupta et al., 2020; Waqas et al., 2021), data-driven culture(Yasmin et al., 2020) and basic resources(Ferraris et al., 2019; Gupta et al., 2020; Waqas et al., 2021). Consequently, the term "BDA capability" has been coined, which indicates “the ability of a firm to provide insights using data management, infrastructure, and talent to transform a business into a competitive force" (Akter et al., 2016). Olczak (2014) defines BDACs as "the ability of an organisation to integrate, build, and reconfigure the information resources, as well as business processes, to address rapidly changing environments"(p.1106). Big data analytics capabilities are defined in other studies as "a firm's ability to assemble, integrate, and deploy its Big Data-specific resources" (Gupta & George, 2016, p. 1050). Interestingly, Wamba et al. (2017) suggest classifying BDACs into three categories: infrastructure, data management, and talent as key capabilities for transforming the firm into a competitive force. Likewise, BDAC's fundamental dimensions highlight management, infrastructure, and staff skills capabilities (Akter et al., 2016).

In the context of healthcare, Wang and Hajli (2017) defines BDACs as "the ability to acquire, store, process and analyse large amounts of health data in various forms, and deliver meaningful information to users, which allows them to discover business values and insights in a timely fashion"(p.290). In addition, as the principal capabilities for BDACs in healthcare, predictive analytics and analytical capability are suggested (Wang & Hajli, 2017; Wang et al., 2018). While some research has previously investigated and introduced some BDACs, a comprehensive picture of BDACs appears lacking (Mikalef et al., 2018).

2.3.1 BDA Human capabilities

Implementing BDA is infeasible without human capabilities. Big Data analytics is about more than just technology; it also extensively depends on the knowledge and skills of BDA staff to be effectively employed. Human capability refers to the professional ability of BDA staff (e.g., knowledge and skills in using data analysis, analytical technologies, and decision making) in conducting BDA (Bharadwaj, 2000; Kim et al., 2012).

In light of the study by Cetindamar et al. (2020), 72% of the studies indicate human capabilities as a prominent pillar of the BDACs. Similarly, staff expertise capability is considered a cornerstone of BDACs (Wamba et al., 2017). Aligned with such a study, people with analytical experience and knowledge play an instrumental role in organisational maturity concerning BD (Coleman et al., 2016). Recent BD studies have noted the shortage of BDA specialists who possess the necessary knowledge and skills to conduct BDA (Dubey & Gunasekaran, 2015; Rialti et al., 2018). According to the study of Cetindamar et al. (2020) and Cetindamar et al. (2021), two fundamental human capabilities form BDACs: skills and knowledge of BDA staff. This study focuses on staff skills as human capabilities.

2.3.1.1 Skills

Prior IT capability research has revealed crucial human resource components, such as managerial and technical skills (Bharadwaj, 2000; Chae et al., 2014). In this vein, this research suggests that managerial and technical skills are critical components of BDACs.

Technical Skills

Technical skills refer to "the know-how to use new technology to extract meaningful information from massive data volume" (Gupta & Georg, 2016, p.1052). These skills require diverse competencies such as machine learning, data extraction, and statistical analysis (Gupta & George, 2016; Russom, 2011). Dealing with BD requires new types of managerial and technical skills that are not usually taught in universities, so companies are confronted with substantial difficulty in training current employees and recruiting talent in the specific skills of BD (Gupta & George, 2016).

The primary issue in adopting BDA for some organisations may not be the technology itself, but instead finding data scientists to work with these technologies. Oracle, Cisco, and IBM had a total of 26,488 unfilled careers requiring BD staff in 2015(Grover et al., 2018). In the same vein, according to Bain & Company's survey, 56 percent of chief executive officers stated their firms to be short of the capabilities to create meaningful, data-driven insights (Grover et al., 2018).

Managerial Skills

Another element of human capability necessary for performing BDA is management skills. It refers to employees' competencies to comprehend and interpret the insights and results gained from big data,, based on knowing what customers, partners, and other business units require now and, in the future, (Gupta & Georg, 2016).

According to BDACs importance in the firm context, the valuable insights that have been extracted from massive data volumes will be useless unless the managers observe a deep understanding of how and where to apply these insights. Hence, managers should possess the ability to predict the requirements of customers, partners, and other business units (Mata et al., 1995). Additionally, soft skills, like interpersonal skills and the capacity to build trust between BDA managers and other functional managers, are essential for effectively using BDACs (Kearns & Lederer, 2003; Mata et al., 1995). As a result, the organisation can develop exceptional human capabilities of BD over time, which rivals will find challenging to imitate.

2.3.2. BDA Non-Human Capabilities

In addition to human capabilities forming BDACs, a wide range of technical BDA capabilities are illustrated in previous studies. According to the study by Cetindamar et al. (2020) and Cetindamar et al. (2021), five vital non-human capabilities form BDAC: data, primary resources, BDA infrastructure capabilities, organisational learning and data-driven culture. BDA Infrastructure capability is an essential pillar of BDACs. The previous studies (Akter et al., 2016; Zhu et al., 2022) indicate that BDACs predominantly depend on advanced IT infrastructure. Robust IT infrastructure plays an instrumental role to integrate and analyze data from different resources to create novel insights (Grover, 2018). IT infrastructure also is one reason big data projects are often fruitful (LaValle et al.,2011). McAfee et al. (2012) also state technology infrastructure as a critical capability across organizations' data economy. Therefore, BDA require more appropriate IT infrastructures to gather, integrate and analyze high-quality data. Consequently , this study focuses on BDA infrastructure capabilities as non-human capabilities.

2.3.2.1 BDA Infrastructure Capabilities

The infrastructure capability of BDA indicates the ability to hold hardware and applications that allow BDA employees to rapidly improve, support and deploy the business's essential system components (Kim et al., 2012). In addition, infrastructure enables the firm to gather, store and transmit data (Coleman et al., 2016). When faced with unpredictable business situations, it is critical to strengthen the flexibility of the BDA infrastructure (Coleman et al., 2016). Infrastructure facilitates the alignment of resources with long-term and short-term business goals, like strategic alliances (Akter et al., 2016). Businesses might acquire and link multiple data, develop applications and tools and generate compatible data-sharing channels via flexible architecture to adapt to changing requirements. As a result, connectivity, modularity, and compatibility are mainly perquisites of a business's BDAC infrastructure (Wamba et al., 2017).

2.2 Supply Chain Management and Sustainability

2.2.1 Supply Chain Management

The concept of supply chain management (SCM) has seen considerable advancement since its origin (Stock et al., 2010). During the 1990s, practitioners have paid more attention to SCM due to the significant advantages of deeper comprehension and managing their supply in general (Mentzer et al., 2001). Supply chain management has made substantial efforts to react to continuous fluctuations in a dynamic business market, for instance, accelerated globalisation, government regulations, business competition, and consumer demands. These pressures drive businesses to engage in long-term partnerships with their supply chain network partners (Mentzer et al., 2001).

Supply chain management(SCM)is considered an interdisciplinary and integrated topic that has progressed to become a new discipline. Through the literature, there are several definitions of SCM as a whole. SCM refers to moving material, information, and money systematically across various business partners (Erboz and Szegedi, 2020; Turkenand Geda, 2020). Nevertheless, this study embraces the most widely cited definition of SCM. Mentzer et al. (2001) define SCM as "the systematic, strategic coordination of traditional business functions and tactics across these business functions within a particular company and across businesses within the supply chain, to improve the long-term performance of the individual companies and the supply chain as a whole" (p.22).

The globalisation of the supply chain imposes negative environmental and social impacts. The environmental matters may include hazardous materials, greenhouse gas emissions, resource depletion, and toxic chemicals (Sanders, 2011). In addition, supply chains increasingly face social concerns, for instance, violation of union rights and the use of under-aged workers (Lindgreen et al., 2009). That is why supervising supply chain partners' performance, integrating (globally) all sustainability (environmental, social, and economic) goals, has become a continuous necessity in the supply chain.

2.2.2 Sustainable Supply Chain Management

Community pressures, concern about natural resource scarcity, and increased customer demand for green products have motivated firms to use sustainable raw materials into their supply chains to produce more sustainable services or products (Sarkis, Gonzalez-Torre, et al., 2010; Seuring & Müller, 2008a). That, indeed, has played 'a paradigm shift' from the traditional supply chain focusing on economic benefits to the sustainable supply chain approach that accounts for all environmental, social, and economic goals ((Taghikhah et al., 2019)Carter and Rogers, 2008). In 2007, the sustainable supply chain management (SSCM) concept was recommended by Linton et al. (2007) which focus on incorporating the core functions of the SC namely including product design, manufacturing by-products, by-products produced during product use, product life extension, product end-of-life, and recovery processes at end-of-life. Since then, many related studies have been accomplished.

Sustainable supply chain management has garnered the increasing interest of scholars and practitioners(Sajjad et al., 2020). Many researchers have provided several definitions of sustainable supply chain management to achieve a better understanding of it. The two following definitions of SSCM have been introduced by Seuring and Müller (2008b) and Carter and Rogers (2009), which could be considered the initial foundation of SSCM conceptualisation. Carter and Rogers (2008) describe SSCM as "the strategic, transparent integration and achievement of an organisation's social, environmental, and economic goals in the systemic coordination of key inter-organisational business processes for improving the long-term economic performance of the individual company and its supply chains" (p. 368). This definition underlines two key aspects. Firstly, it emphasises integrating all sustainability dimensions (economic, social, and environmental). Secondly, it suggests extra attention be paid to creating a coordinated supply chain at the level of inter-organisational business among participants to increase sustainability performance.

Seuring and Müller (2008b) highlight the significance of three pillars of sustainability, stakeholder and customer perspectives. Sustainable supply chain management is explained as "the management of material, information, and capital flows as well as cooperation among companies along the supply chain while taking goals from all three dimensions of sustainable development, i.e., economic, environmental, and social, into account which are derived from customer and stakeholder requirements" (Seuring & Müller, 2008, p.1700).

Another description of SSCM, which involve coordination, efficiency, and effectiveness, this one is more comprehensive and holistic, which indicates SSCM as "the creation of coordinated supply chains through the voluntary integration of economic, environmental, and social considerations with key inter-organisational business systems designed to efficiently and effectively manage the material, information, and capital flows associated with the procurement, production, and distribution of products or services to meet stakeholder requirements and improve the profitability, competitiveness, and resilience of the organisation over the short- and long-term." (Ahi & Searcy, 2013, p. 339).

Recently, uncertainty and disruption have been generated across the supply chain by the COVID-19 pandemic (Joshi & Sharma, 2021; Kusrini & Maswadi, 2021). Therefore, supply chain management is imperative to incorporate economic, social, and environmental dimensions (Joshi & Sharma,2021). Additionally, abuse or absence of any dimension of sustainability can result in several risks which influence long-term viability (Joshi & Sharma,2021). Therefore, SSCM integrates the concepts of supply chain management and sustainability and indicates all activities of companies to enhance sustainability of their supply chains(Lis et al., 2020; Seuring, 2013). Most of the research has widely acknowledged economic, social, and environmental aspects as the key pillars of the sustainability concept(Gao & Bansal, 2013). For example, sustainable SSCM focuses on the conservation of balance between social responsibility, protection of the environment, and economic viability throughout the supply chain functions (Sánchez-Flores et al., 2020). However, few studies take into account all dimensions of sustainability (Panigrahi et al., 2019; Sajjad et al., 2020), especially the social dimension

SSCM depicts every business as a part of an integrated system, part of a broader socio-natural system. It involves co-operative with suppliers, as well as with recipients and other stakeholders and managers to make a positive impact on the relationships between these systems(Kot, 2018; Kozma, 2017; Ślusarczyk, 2017). One of the recent definitions of SSCM is presented by Zhiwen and Wenbing (2021, p. 2)" a process of planning, organizing, leading, and controlling to coordinate material, information, and capital flows along the supply chain through continuous innovation and decision-making, in order to realize an organization's social, environmental, and economic goals, which are derived from stakeholder requirements over the short and long term".

2.2.3. Dimensions of SSCM

Having reviewed the SSCM concept, the following sub-sections provide a better and more comprehensive depiction of the main dimensions of SSCM.

2.2.3.1 Environmental Performance

Raw materials and natural resources are used in manufacturing all the time. Therefore, firms' environmental sustainability has received much attention due to being vital in association with sustainability.

Environmental sustainability encourages firms to embrace environmental initiatives to maintain a natural environment. Environmental sustainability has become a hot topic for academia and industries (Brandenburg et al., 2014) due to two main drivers: customer demand for ecologically friendly goods and services and environmental regulations. Environmental sustainability refers to the natural environment conservation and enhancement (Shrivastava & Hart, 1992) and the efforts of organisations regarding ecological concerns (Henriques & Richardson, 2013). These efforts can be affected by the business's goal to achieve a long-term competitive advantage (internal factors), legislation, or public concern (external factors). The environmental pillar (environmental performance) also requires a proactive practice that does not threaten the next generation by minimising its ecological footprint. In essence, these practices focus on cutting pollution such as greenhouse gas emissions, waste management, and efficient utilisation of natural recourses. Alhaddi (2015), for example, cited a study that was conducted by Kearney (2009). This study indicated that embracing eco-friendly practices assists organisations in achieving financial benefits by reducing operational costs (from decreasing water and energy usage) and increasing profits (from developing green products) (Kearney, 2009).

The environmental performance addresses corporations' behaviour and how environmental management strategies are utilised to improve a company's image and boost revenues. Environmental performance assesses the extent to which companies meet their stakeholders' expectations regarding environmental responsibility through the efficient utilisation of energy resources and the minimisation of ecological footprints (Elkington, 1997).

The fundamental motivation for businesses is to maximise profits that may cause prominent and harmful influences on the natural environment (Paulraj et al., 2017). As a result, regulations and customers are bringing growing pressure on firms to reduce their environmental footprint (Morali & Searcy, 2013). The key objective of decreasing ecological footprint is not limited to a business's confines but extends to businesses' efforts to reduce their environmental footprint across their whole supply chain.

Moreover, unethical behaviour by supply chain partners harms international businesses' brand image. Nestle, for example, has been accused of the destruction of rainforests by its palm oil suppliers (Coombs, 2014). Consequently, a collaboration between corporations and their supply chain partners might create environmentally friendly services and products (Gold et al., 2010).

Attaining environmental performance draws on embracing environmental standards to create a valuable contribution to reducing the ecological impact. These requirements can be applied in two ways: environmental performance measurements (e.g., resource utilisation and pollution control) and environmental practices (processes and policies such as regularly auditing and discharge monitoring) (Beske et al., 2008).

According to the study of Cetindamar et al. (2020) and Cetindamar et al. (2021), previous studies took into account the following indicators to achieve environmental performance: decrease in consumption of harmful/hazardous/toxic materials, increase in energy saving, drop in the use of natural resources, reduction in air pollution due to efficiency improvements and conservation. In essence, this study's environmental performance measures the extent to which a business enhances the effectiveness of pollution control and natural resources usage (Jacobs et al., 2010; Pullman et al., 2009).

2.2.3.2 Social Performance

Several advanced businesses worldwide have still struggled to understand, analyse, and address social matters. Nevertheless, social sustainability has drawn more interest among researchers and practitioners caused by increasing public awareness about social concerns like inequality, poverty and gender discrimination. That is why, from a practitioners' perspective, large international corporations like Nike and Apple have embraced SC social sustainability practices, like creating contact with local communities, monitoring supplier labour standards and enhancing product safety (Klassen & Vereecke, 2012). From the researchers' perspective, Lafferty and Langhelle (1999) describe social sustainability as an ethical code of human progress and existence that should be equitably and wisely accomplished. While Sarkis, Helms, et al. (2010) portray social sustainability as social resources management such as people skills, interpersonal connections, and social values, different social issues have garnered increasing attention across the supply chain in the last two decades. Examples of these include health and safety issues, child labour, living conditions, and equity problems. Consequently, social sustainability strives to respond to and address these issues. Nonetheless, organisations discriminate between stakeholder and social concerns, and focus on issues that have a greater impact on stakeholders than on society (Clarkson, 1995).

Firms have paid significant attention to social issues in SCs in response to rising demands from stakeholders, NGOs, customers, and government (Mani et al., 2016). In this regard, firms recognise the significance of joining social sustainability practices at their SC and corporate levels (Vachon & Klassen, 2007). Accordingly, firms can achieve social sustainability only if they can assess their social performance. Assessing social performance is more complex than assessing other sustainability dimensions (environmental and economic performance) due to the difficulty in identifying which consequences should be taken into account (Hutchins & Sutherland, 2008) as well as how to measure such effects (Beske-Janssen et al., 2015). Measuring social performance focuses on the organisation's interaction with the community and reacts to concerns such as community participation, fair salaries and employee relations (Goel, 2010). According to Cetindamar et al. (2020) and Cetindamar et al. (2021), previous studies took into account the following indicators to achieve social performance: improvement in employees' rights, investments in social projects (culture, education and sports), community health and safety, child labour, male vs. female full-time and employee training and education. These indicators are related to a firm's social sustainability performance as engaging in social sustainability practices could attract customers, improving firms' social reputation and corporate image. Fundamentally, in this thesis, social performance assesses the extent a business enhances results for employees and the community.

2.2.3.3 Economic performance

Different commercial operations are critical to the economic system's long-term viability, not just for the current generation but also for future generations. All these operations strive to maximise business profits. Conventionally, traditional accounting measures measure a company's financial success, like revenue and profit. Undoubtedly, profit is considered the backbone of a business to survive in a competitive market and reinforce its long-term sustainable growth.

Even though businesses strive to adopt sustainability practices that draw on return on investment and business self-interest (Siegel, 2009), effective use of natural resources will develop economic performance and lead to economic development and sustainability (Singa Boyenge, 2007). Consequently, when a company achieves economic sustainability, it becomes economically viable. Economic sustainability refers to the efficient use of an organisation's assets while balancing economic, social, and environmental concerns to achieve long-term growth and profitability (Oberoi, 2014). Moreover, economic sustainability in the context of a company entails increasing short- and long-term shareholder value while also laying a solid financial foundation for the company's long-term survival (Steurer et al., 2005).

In light of the TBL approach, the economic pillar relates to the organisation's business activities on the economic system (Elkington, 1997). The economic pillar also connects company growth to economic growth and, as a result, contributes to the long-term (Spangenberg, 2005). In other words, it focuses on how the business's operations influence the economy and wealth without threatening future generations' needs (Kovacic, 2009).

When organisations make substantial efforts to integrate social and environmental considerations into their supply chain procedures and corporate strategy and operations, they can attain economic benefit and support people in the future (Ross, 2015). IKEA, a Swedish furniture firm, is one well-known example. It increased its sales to US$ 37.6 billion in 2016, but profit was not consumed. Instead, it reinvested its revenues in recycling waste material, such as tree remains, which were then converted into new items. IKEA is now recognised as an enterprise with a “zero waste to landfill” operating system" (Parinduri et al., 2019). According to Cetindamar et al. (2020) and (Cetindamar et al., 2021), previous studies focused on the following indicators to achieve economic performance: reducing costs associated with purchased materials, energy consumption, waste disposal and treatment, and waste discharge. Moreover, profit, brand image, and sales are alternative measures of economic performance (Schaltegger & Burritt, 2014). These alternative measures are linked to a company's sustainability performance because a company's sustainable practices may attract customers, resulting in increased revenues and brand image (Schaltegger & Burritt, 2014). In this thesis, economic performance indicates how a business enhances profit and market outcomes.

2.2.4 Sustainable Supply Chain performance

With rising concerns regarding the environmental and social impacts of supply chains, organisations meet different pressures from all stakeholders to reduce the harmful effects in their supply chains (Chang et al., 2019; Ortas et al., 2014). Additionally, because of generating uncertainty from the COVID-19 pandemic and disruption across supply chain management (Matos et al., 2020), sustainability of the supply chain is considerd a fundamental prerequisite for achieving competitive benefits post COVID-19(Joshi & Sharma, 2021; Karmaker et al., 2021; Kusrini & Maswadi, 2021). According to several scholars, a sustainability concept extends beyond any business's boundaries and can affect a product at any stage of its lifecycle (Anvari, 2021). As a result, organisations are in a position to be held accountable for their supply chains and are consistently required to measure, control, and report their sustainability performance and the sustainability performance of their whole supply chain (Taticchi et al., 2013). Despite growing interest towards sustainable performance measurement in SCs, especially using the TBL concept, environmental and economic dimensions are dominant due to receiving more attention from scholars and practitioners. In contrast, the social dimension has gained the least attention (Chiesa & Przychodzen, 2020; Garlock et al., 2022; Missimer & Mesquita, 2022;Morais & Barbieri, 2022).

To assess sustainability performance, it is significant to consider and balance the three dimensions of sustainability and their intersections (Cagno et al., 2019), individually integrating the social and environmental measures with the economic one (Chiappetta Jabbour et al., 2020; Seuring & Müller, 2008b). Improvements in sustainable supply chain performance (SSCP) can provide competitive advantages to companies. Ortas et al. (2014, p. 333) describe SSCP as is "a company's capacity to reduce the use of materials, energy, or water and to find more eco-efficient solutions by improving supply chain management". Sustainability performance in the manufacturing industry is defined as "the extent to which the manufacturing firms have reduced its harm and produced regenerative impacts on natural and social systems"(Adam et al., 2019, p. 138). Sustainability performance also measures the extent to which an organisation embraces economic, environmental, and social aspects, eventually impacting its performance and society (Artiach et al., 2010). Accordingly, this definition aligns with the TBL of sustainability, economic, environmental, and social performance. In this study, SSCP assesses the extent to which an organisation improves sustainability performance by considering economic performance (profit-oriented and market-oriented outcomes), social performance (employee- and community-oriented outcomes), and environmental performance (pollution control and resource efficiency).

2.3 The Relationship Between Big Data Analytics and Sustainability Performance

Even though SSCM has drawn rising interest from academics and practitioners, there is a shortage of understanding in how businesses respond to SSCM issues. Many studies are mainly concerned with the sustainability strategy. Other studies also observed further matters, such as measuring sustainability performance, information technology utilisation, and governance. Various studies are conducted in the SSCM domain, such as ethically or socially responsible sourcing (Kelly & Bhutta, 2010) and green supply chain management (Chiarini, 2014; Coyle et al., 2015). Previous research also has more interest in exploring environmental sustainability within the SCM framework; however, social sustainability is scarce. (Chiesa & Przychodzen, 2020; Garlock et al., 2022; Klassen & Vereecke, 2012; Missimer & Mesquita, 2022; Morais & Barbieri, 2022; Seuring & Müller, 2008b).

On the other hand, existing research has not addressed the role of BDA to solve environmental, economic, and social concerns (Jeble et al.,2018; Song et al., 2017). According to the advanced technology of BD, adopting BDA could assist in solving sustainability challenges. The influence of BDACs on business environmental, social, and economic performance is shown in the following subsections.

2.3.1 Impact of BDA on Environmental Performance

Profit maximising is undoubtedly the primary aim of a business. However, this aim may cause prominent and harmful influences on the natural environment (Paulraj et al., 2017). As a result, regulations and customers bring growing pressure on firms to reduce their environmental footprint (Morali & Searcy, 2013). In truth, the objective of decreasing ecological footprint is not limited to the confines of a business, but also extends to businesses' efforts in declining their environmental footprint across their whole supply chain. Moreover, unethical behaviour by supply chain partners harms international businesses' brand image. For instance, Nestlé was criticised for rainforest devastation by its palm oil suppliers (Coombs, 2014). Consequently, a collaboration between corporations and their supply chain partners might create environmentally friendly services and products (Gold et al., 2010).

Rising public concerns focus on addressing environmental sustainability issues in light of new insights and forms of analytics extracted from BD. Employing BDA has brought many benefits, such as improving sustainability by looking for hidden patterns, unknown trends, and correlations (Wu et al., 2016). Many environmental matters like waste, pollution, ecology disruption and resource depletion have received attention from several BDA studies. For example, to protect human health from controlling air pollution and improving urban air quality, a semi-supervised learning method is proposed, which consists of a spatial classifier involving spatial-related features (e.g., length of highways) and a time classifier involving temporally-related features (e.g., traffic) (Zheng et al., 2013). This method offers fine-granularity air quality prediction in real-time based on limited air quality monitor stations. Another exciting advantage of Big Data's real-time analytics is processing data instantaneously. IBM's mainframe computer called "Deep Thunder" is designed to provide local, high-resolution weather predictions (Mukred & Jianguo, 2017). It could be used to predict the locations where the public will face outages due to weather conditions. Therefore, any company using "Deep Thunder" can take the necessary steps to prevent that or fix it right on time, reducing the cost and optimising energy use for the company (Mukred & Jianguo, 2017).

Environmental resources are steadily depleting, making it essential to find and implement improved ways to reduce and manage them using sustainable practices. Utilising BDA is one way to deal with this problem. Two significant contributions of BDA in environmental performance, i.e., improved natural resource utilisation and reduced CO2 and other greenhouse gases, are discussed in the following subsections.

2.3.1.1 Reduced-Emission of CO2 and Other Greenhouse Gases

Emerging technologies, such as extensive data analysis based on the Global Positioning System (GPS), have played a key role in systems management and planning (Lucas et al., 2019). A study supported by the European Council declared the transport sector contributes a large portion of greenhouse gas emissions. Switching to free or low carbon fuels and improving fuel efficiency are the two main methods of decreasing greenhouse gas emissions (De Gennaro et al., 2016). In that study, researchers developed a methodology for offering a holistic overview of data processing platform applications designed to take advantage of the tremendous data potential of road transport policies in Europe. Data was collected from different resources such as navigational systems and mobile computer systems used by that platform. Two sets of conventional fuel vehicle data were compiled using GPS systems onboard in a preliminary pilot study, and its basic algorithms were created. The emissions model illustrates how evaporative emissions from fuel vehicles can be measured draw on real-world driving data. Therefore, technologies of BDA could contribute to reducing emissions and achieving sustainable development (De Gennaro et al., 2016).

2.3.1.2 Improved Natural Resource Utilisation

Natural resources have a significant contribution towards achieving sustainable development. An economy's rapid growth might adversely affect the ecosystem. For this reason, manufacturing enterprises must take steps to manage human capital and ecological resources in a sustainable way (Song et al., 2017). As an example, Unilever, a multinational corporation with over 240 manufacturing plants in 67 countries, has attained its 'zero waste to landfill' goal in 2015 (Unilever, 2015). In 2017, it lowered water usage by 20% across 90 sites through BDA and Internet-of-Things-enabled sensors. In addition, it increased its renewable energy consumption to 28% per year, like solar and wind power. With a zero coal dependence, Unilever intended to cut its carbon footprint by 43% in 2020 (Howells, 2017). Reduced natural resource consumption and improved sustainability are the results of those actions.

2.3.2 Impact of BDA on Social Performance

Social sustainability has emerged in the supply chain due to a growing call from researchers in dealing with diverse social issues like inequality, gender discrimination, wages, and poverty. Businesses have strived to tackle social problems through various tactics, including corporate social responsibility (CSR) reports. CSR reports are available on the corporate websites of around 60% of the world's largest corporations (Jose & Lee, 2007). Their social activities are shared with varying degrees of clarity in these reports. For instance, certain businesses have provided statistics on the number of days off because of several injuries to show the healthy environment in businesses where employees work (Tate et al., 2010). Although some degree of dedication may be evident in the reports (Jose &

Lee, 2007), it is difficult to determine if a firm has reported satisfying stakeholders or engaging in socially responsible practices (Kolk, 2003). This motivates finding more reliable techniques to collect data about social sustainability criteria and social concerns.

The significant growth in digital and sensor technologies provides opportunities for every partner in a supply chain to collect large-scale data. Those data bring beneficial advantages for the supply chain, such as reducing the lack of knowledge regarding confronting social breaches and criteria of social sustainability. As a result, employing BDA assists in finding proper and accurate predictions to mitigate social violations and enhance supply chain transparency to achieve social sustainability (Keeso, 2014; Song et al., 2017; Wu et al., 2016). According to Mani et al. (2017), BDA has been engaged to mitigate the social risk of the supply chain and show the extent to which mitigation will assist to achieve sustainability. The results of this study confirm that companies embrace BDA to predict social problems such as fuel consumption, monitoring workforce safety, workforce health, the physical condition of vehicles, security and unethical behaviour - demonstrating how implementing information management procedures would reduce social disruptions. BDA has significant contributions to solving or mitigating social issues such as child labour and health and safety, discussed in the following subsections.

2.3.2.1 Child Labour

Child labour is one of the most visible issues in social sustainability, consequently attracting researchers' attention. However, this and other social issues were not in the mind of many businesses. According to the International Labour Organisation, "Child labour concerns work by children under the age of 15 that prevents school attendance and work by children under the age of 18 that is hazardous to the child's physical or mental health."(Yawar & Seuring, 2017, p. 625)

Although many countries are raising the awareness of child labour and undertaking steps to cease child labour, changes in this issue do not come easily or quickly due to the engraining in society's socio-cultural and economic structure. Policy reforms are essential to combat child labour, but they must accompany efforts to change societal attitudes since they are intricately related.

Performance monitoring is an effective technique to measure supplier performance, identifying the breach level of social issues across the supplier base. It includes comprehensive audits using the code of conduct and focused assessments in specific high-risk areas such as child labour. However, auditing for child labour in the lower tiers of supply chains can be complex due to a poor capability to capture and report information about child abuse (Syafrudin et al., 2017). As a result, investment in advanced technologies for data gathering and analysing from suppliers will assist in monitoring the performance (Mamic, 2005), which will ultimately help managers decide how to reduce social violations in supply chains to achieve social sustainability.

An example of the use of BDACs comes from the work of Thöni et al. (2018). This study developed a novel model for social sustainability monitoring in supply chains based on a Bayesian network and BDA (text mining). The quantitative risk model continuously ranks suppliers based on their risk of breaching sustainability standards on child labour. A Bayesian network uses various data sources such as statistical data, social media (Twitter), audit results and public reports of child labour incidents. They help to determine the likelihood of a breach for each supplier location. The model is based on observations that are statistically derived from previous child labour issues that are automatically included from publicly available news sources using text-mining algorithms. This model might have a significant contribution in reducing the risk of child labour in the supply chain.

2.3.2.2 Health and Safety

Social media has become an essential channel used by firms to spread information and communicate with external parties. Official firm websites can acquire vast amounts of diverse information regarding firm performance and development. According to this phenomenon, Taiwanese light-emitting diode (LED) firms have pushed to acknowledge social media information. In addition, they work to develop related capabilities, which agree with customer and stakeholder expectations for sustainability and mitigating risk. According to the study, various data types about LED firms include qualitative data from management, social media data (Big Data from websites), and quantitative data regarding operations. That study employed a novel method based on BDA and fuzzy and grey Delphi methods to identify a set of reliable attributes(Wu et al., 2017). Based on those attributes, Big Data is converted to a manageable scale to consider the impact of attributes. The application of expert judgment has been used to develop sustainability through strengthening their capabilities to mitigate social risks, such as health and safety. The international company can determine the likelihood of a breach along the supply chain base. As a result, this information helps managers make decisions regarding reducing social violations in supply chains to achieve social sustainability.

2.3.3 Impact of BDA on Economic Performance

The primary driver of companies is profit-maximisation. Therefore, managers draw on businesses' return on investment (ROI) and self-interest to embrace sustainability practices (Siegel, 2009). Nevertheless, increased efficiency and effectiveness in using natural resources will develop economic performance and lead to economic development and sustainability (Singa Boyenge, 2007).

Firms greatly rely on information systems and data analytics to attain their competitive advantage (Chen et al., 2012; LaValle et al., 2011). There has been an exponential growth in the data collected, stored, and processed by organisations (LaValle et al., 2011). The massive amount of data usually contains valuable information about the business market, customers, and the firm itself. As a result, some businesses are increasingly looking at managing their business more effectively using BDA. Interestingly, many empirical studies investigate the impact of BDA on economic performance, such as profitability (Wang et al., 2018), sales growth (JP, 2012), return on investment (ROI) (Court, 2015), and customer retention (Davenport, 2006).

Other recent research has indicated factors that play instrumental roles in BDA employment. Gupta and George (2016) demonstrate that investing in BDACs is associated with increased operation performance, market performance, and superior firm performance. Similarly, Akter et al. (2016) and Wamba et al. (2017) investigate the impact of BDACs (management capability, infrastructure capability, personnel expertise capability) on firm performance. According to a systematic literature review (Arunachalam et al., 2018), Studies show the role of BDACs in driving organisational decision-making, leading to positive firm performance. The study results by Gunasekaran et al. (2017) indicate the positive impact of Big Data and predictive analytics (BDAP) assimilation as a capability on organisational and supply chain performance. There are many significant contributions of BDA to improve economic performance, such as profitability and sales growth, discussed in the following subsections.

2.3.3.1 Profitability

Predictive analytics-based BDA and text mining can benefit organisations in healthcare by reducing costs (i.e., waste and fraud reduction) (Wang et al., 2018). For example, in an Australian healthcare organisation, CMC-I+Plus is an advanced analytical application that uses claims to predictive modelling techniques, applied to hospital and medical claims data, to provide claim-based intelligence to facilitate customers' claim governance, balance cost and quality and evaluate payment models (Srinivasan & Arunasalam, 2013). As a result, managers can use predictive analytics-based BDA and text mining patterns to review a cost and profit summary related to each healthcare service, identify any claim anomalies and make proactive decisions by utilising productive models (Wang et al., 2018).

2.3.3.2 Sales Growth

BDA can enhance business value and firm performance, for example, a personalised recommendation system in Amazon. In its second financial quarter, it earned 29% of sales, which grew to US$12.83 billion (JP, 2012). The success of this recommender system depends on advanced data analytic tools and methods. It combines data from different sources: search and web browsing history, purchase history, other customers' purchase and browsing history, related products available and current items in shopping carts. Amazon immediately creates recommendations for new or existing customers by applying sophisticated mathematical algorithms (Linden et al., 2003).

2.4 Research Model

In the light of the aspects stated in Chapter 1, Section 1.2 to 1.4, literature review of the relationship between BDACs and SSCP in Chapter 2, and the theoretical perspectives discussed in Chapter 2, Section 2.6, we attempt to develop a research framework that depicts potential correlations between primary constructs in this study (shown in Figure 2-2).

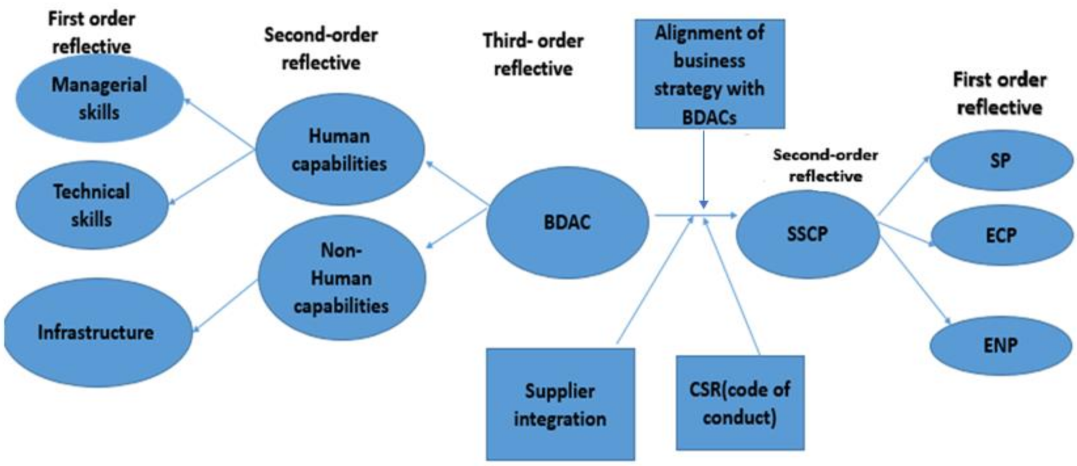

Figure 2-2 Research Model

According to Figure 2-2, our research model consists of nine latent constructs: technical skills (TS), managerial skills (MS), infrastructure (Inf), economic performance (EP), environmental performance (ENP), social performance (SP), corporate social responsibility (CSR), supplier integration (SI) and alignment of business strategy with BDACs. Every hypothesised relationship represented is theorised as being positive and direct in the research model. The BDACs are an antecedent in the theoretical model whilst environmental, economic, and social performance represent simultaneously. Also, corporate social responsibility, supplier integration and business strategy alignment with BDACs represent moderators in the relationship between BDACs and SSCP. We assume that the BDACs construct influences sustainability performance outcomes in SC. In light of this, we propose that BDACs have correlations with the primary SSCP constructs: social, economic, and environmental performance.

As depicted in Table 2-2, according to the systematic literature review, the two primary BDACs constructs considered include BDA human and non-human capabilities. Here, technical and managerial skills represent human capabilities whilst non-human capabilities encompass infrastructure. That is consistent with our literature review in Chapter 2, in Section 2.1.3. Moreover, social, economic, and environmental performance constructs represent sustainable performance outcomes in a supply chain that describes the social, ecological and economic consequences of adopting BDACs. That is consistent with our literature review in Chapter 2, Section 2.2.3. More details about all constructs are discussed later in Section 3.5 of Chapter 3. Construct definitions in the research model are displayed in Table 2-2.

Table 2-2 Definitions of Constructs and Related Literature.

Construct	Definition	Related Literature
Big Data analytics capability	Organisation 's ability to assemble, integrate, reconfigure and deploy its human and non-human BDA capabilities effectively, to address rapidly changing environments to achieve competitive advantage and improve firm performance.	Gupta and Georg(2016)
Technical skills of BD	"The know-how to use new technology to extract meaningful information from massive data volume"(1052).	Gupta and Georg(2016).
Managerial skills of BD	Ability to deeply understand how and where to apply the insights extracted from massive data volume drawing on having the current and predict the future needs of other business units, customers, and other partners.	Gupta and Georg(2016).
BDA infrastructure capability	"The ability of the BDA infrastructure (e.g., applications, hardware, data, and networks) to enable the BDA staff to quickly develop, deploy, and support necessary system components for a firm"pp 358.	Wamba et al. (2017)
Sustainable Supply Chain Performance	the extent to which an organisation improves sustainability performance by considering economic performance (profit-oriented and market-oriented outcomes), social performance (employee- and community-oriented outcomes), and environmental performance (pollution control and resource efficiency).	Cagno et al.(2019), Seuring and Müller (2008b)
Social performance	Organisation's ability to assess improving employee- and community-oriented outcomes.	Garriga and Mele(2004) ,Rao and Holt(2005).
Environmental performance	Organisation's ability to assess improving outcomes related to pollution control and resource utilisation.	Montabon et al.(2007),Pullman et al.,(2009)
Economic performance	Organisation's ability to assess achieving profit-oriented and market-oriented outcomes.	Flynn and Flynn (2004), Menor et al. (2007), Kristal et al(2010)
Supplier integration	"The extent of coordination between manufacturers and their suppliers in making decisions related to capacity planning, demand forecasting, inventory management, and replenishment as well as the flow of materials" pp 59	Piprani et al. (2020).
Corporate social responsibility	The extent to which an organisation commits to the adoption, determination of policies, decision-making, and following plans of social obligation that are beneficial to the values and aims of society.	Bowen (2013).
Alignment of business strategy with BDACs	"Extent to which BDA strategies are aligned with the overall of the organisation strategy" pp 120.	Akter et al.(2016)

2.5 Theoretical Perspective

This section provides the fundamental theoretical basis for the research model to be conceptualised. In light of this, the first subsection attempts to provide theoretical foundations drawing on the dynamic capabilities view (DCV). The second subsection aims to employ the TBL approach to build the theoretical foundation regarding sustainability performance outcomes.

2.5.1Dynamic Capabilities View For BDACs

Until now, the literature is inconclusive about how BDA can generate value for businesses (Sharma et al., 2014). Recent research has not provided sufficient empirical richness about data analytics from a capability's perspective, despite focusing on data analytics outcomes on different organisational issues in most prior studies. In such a context, organisations should be most interested in developing capabilities that create competitive advantage (Shuradze & Wagner, 2016).

Most of the studies are positioned under the resource-based view (RBV). According to Shdifat et al. (2019), 48% of research studies applied the RBV. In contrast, dynamic capability theory is employed by 16% of studies. This finding indicates that resources and capabilities vary among organisations, attaining outstanding performance and competitive advantage(Chae et al., 2014).To achieve those advantages, organisations should capture and improve 'unique', scarce, 'valuable' resources which involve skills, capabilities, know-how, and technologies (Barney, 1991). Although many studies have discussed the resources and processes required to utilise BD strategically, they have not described the BDACs concept clearly and a deep insight into how firms can build BDACs appears lacking (Gupta & George, 2016). According to the RBV, management, human, and infrastructure capabilities are considered the main capabilities that enable firms to develop BDACs.

With increasing uncertainties in a business environment, RBV theory fails to provide solutions or guidance about how a company's specific resources can be used or renewed in turbulent and dynamic environments. Businesses require an emphasis on capabilities development that can aid in adapting to uncertain environments.

That is why the dynamic capabilities (DC) concept emerged in the 1990s as an extension of the resource-based view to help firms understand how they could adapt under turbulent and dynamic environments (Ambrosini et al., 2009; Schilke, 2014). The RBV suggests that a firm's heterogeneous resources (valuable, rare, inimitable, and non-substitutable resources) determine its sustainable competitive advantages (Barney, 1991). On the other hand, the DC perspective aims to explain how organisations can continually acquire valuable, competitive resources that match or change the marketplace (Wheeler, 2002). Literature has several definitions of dynamic capabilities. DC is defined as "the ability to integrate, build, and reconfigure internal and external competencies to address rapidly changing environments" (Teece et al., 1997, p. 512). Winter (2003, p. 991) defines dynamic capabilities as "those that operate to extend, modify, or create ordinary capabilities." Also, Helfat et al. (2009, p. 1) offer a new definition of "the capacity of an organisation to purposefully create, extend or modify its resource base." Wang and Ahmed (2007) define dynamic capabilities as a "firm's behavioural orientation constantly to integrate, reconfigure, renew and recreate its resources and capabilities and, most importantly, upgrade and reconstruct its core capabilities in response to the changing environment to attain and sustain competitive advantage" (p. 35). Shanks and Sharma (2011) show the importance of using DCs by organisations to generate, extend, acquire, release, alter, and integrate their resources. That indicates that the role of common organisational processes is to modify the company's resource base, in line with other studies. In this research, BDACs are considered a special kind of organisational resource.

In the context of BD, scholars have frequently adopted dynamic capabilities as a theoretical perspective to understand how BD capabilities affect an organisation (Wamba et al., 2017). Scholars should focus simultaneously on three aspects to understand the impacts of BD: data as resources, processes to analyse BD and managing of knowledge which is extracted from BD (Ferraris et al., 2019). Firstly, researchers should recognise that BD represents much usability potential as an information resource. For example, BD may be used repeatedly to obtain different information to solve diverse problems (Erevelles et al., 2016). Secondly, the analysis of BD needs processes and capabilities to transform such data into meaningful information and insights (Côrte-Real et al., 2017). Human capabilities can improve the efficiency of BD analysis, such as technical skills and knowledge for analysts and managers (Zeng & Khan, 2018). Third, extensive generated knowledge from data analysis requires efficient tools and technology to manage it to create value (Ferraris et al., 2019).

For many organisations, the conceptualisation of BDACs depends on the organisational capabilities of managing the data set as well as the capabilities of applications that are used to process and analyse the data set in the various business domains. As such, we suppose that BDACs are an essential enterprise capability that organisations could leverage to create cutting-edge knowledge in a dynamic environment (Grant, 1996). From this perspective, the dynamic capabilities perspective is beneficial to understand BDACs' impact on an organisation. Building BDACs help organisations to establish knowledge creation routines, particularly when market dynamism is high. Also, BDACs can seem like an organisational information processing capability (GalbRaith, 2014) that reduces uncertainty by stimulating insights and knowledge-creation and increasing organisational capability for strategic decision-making.

Responding to increasing uncertainties and risks in the business environment (Adegbite et al., 2018), firms of the supply chain strive to exploit BDA to develop effective uncertainty management strategies (Sun et al., 2016). They prepare adequate contingency plans based on BDA, which help them to successfully address social and environmental changes (Sun & Strang, 2018). Mandal (2018) argues that BDA management capabilities are considered as dynamic capabilities that help firms in the tourism supply chain to respond to uncertainties and attain sustainable performance. In line with other studies (Wamba et al.,2017; MacAfee & Brynjolfsson, 2012b), we consider BDAC a strategic and organisational capability to help address social, environmental, and economic concerns in an uncertain environment. By doing so, BDACs can improve a company's sustainable performance in the supply chain.

2.5.2 The Triple Bottom Line for Sustainability Performance

Sustainability is becoming an essential element in successful companies. In general, sustainability indicates meeting the current generation's demands without overstepping future generations' needs (Aragon-Correa et al., 2017). However, corporate sustainability balances an organisation's environmental, economic, and social goals (Hansen & Schaltegger, 2016). Firm sustainability refers to a company's ability to meet the demands and requirements of current stakeholders whilst adopting long-term investment and management strategies to ensure social well-being, environmental protection, and future profitability (Pantelic et al., 2016).

Prior studies have been interested in social responsibility and its impact on business performance (Filios, 1983; Ullmann, 1985). Despite these early studies, the majority of studies on sustainability have included environmental sustainability, concentrating mainly on the influence of environmental aspects on the business's financial performance (Carson et al., 2001; Montabon et al., 2007). In 2000, this trend was upturned; new streams of studies are concerned with embracing a more comprehensive performance approach inspired by the TBL framework.

In the TBL framework, the primary dimensions of sustainable development have been employed, directing social, economic, and environmental aims within a business context (Blewitt, 2014). Successful business performance should be assessed not only in terms of its financial state but also in terms of environmental standards and social or ethical principles (Gimenez et al., 2012). Organisations will achieve success in the long run if they consider social, economic, and environmental issues (Elkington, 2004).

Profit, non-profit, and government sectors have paid more attention to the TBL. Therefore, the TBL is the most reported and cited framework for addressing an organisation's sustainability activities (Alhaddi, 2015). John Elkington produced the idea of TBL during the mid-1990s. Here, he tried to explore a method for evaluating the performance of organisations in corporate America (Elkington, 1994). The TBL concept has been presented through a framework that strives to concurrently concentrate on social, economic, and environmental issues and work cooperatively across these three pillars of sustainability performance to sustain long-term performance and produce more company value (Carter & Rogers, 2008). Slaper and Hall (2011) describe the TBL as a concept that operates beyond the traditional measurement of profit and returns on investments to include metrics for environmental and social impacts for assessing sustainability. In other words, it achieves an equal balance among the three dimensions of performance: social, environmental, and economic. Some studies refer to these three dimensions as the three P's: people, planet, and profit (Alhaddi, 2015; Elkington, 1998). Figure 2-3 displays TBL framework.

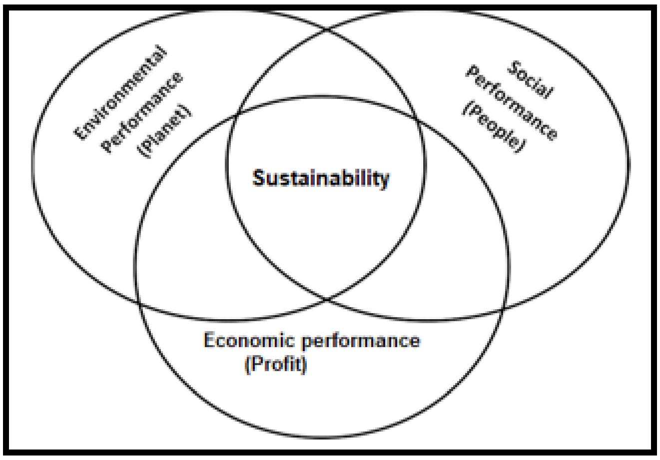

Figure 2-3 Triple Bottom Line Framework (derived from Carter and Rogers, 2008)

According to the TBL approach, the economic pillar (profit) refers to the influence of the organisation's business practices on the economic system (Elkington, 1997). The economic sphere ties business growth to economic growth and ultimately contributes to sustainability (Spangenberg, 2005). Organisations can achieve economic value and support the people in the future when they make serious attempts to merge environmental concerns into their strategic plans (Ross, 2015). It basically concerns the financial value that the firm generated after diminishing the cost of all inputs involving social criteria and environmental considerations.

The environmental pillar (planet) also demands endeavors for engaging in proactive practices that do not endanger the next-generation's environment by minimising ecological footprint. In essence, these practices focus on the efficient utilisation of natural recourses, waste management, and cutting of pollution, such as greenhouse gas emissions. The environmental line of assessment is related to the social and economic lines. Alhaddi (2015), for example, cited a study conducted by Kearney (2009). This study indicated that embracing eco-friendly practices assists organisations to achieve financial benefits by reducing operational costs (from decreasing energy and water usage) and growing revenues (from the improvement of innovative green products) (Kearney, 2009).

The social pillar (people) indicates an organisation's influences on the social systems in which it exists and operates. The organisation conducts social and ethical activities to protect, promote and preserve fairness, transparency, equality, health and safety values and welfare for current and future generations (Schaefer et al., 2015). These actions provide value to society and "give back" to the community, such as non-discrimination and avoiding employing forced and compulsory labour (Arowoshegbe & Emmanuel, 2016). Ignoring social responsibility can affect the business's performance and sustainability (Arowoshegbe & Emmanuel, 2016). On the other hand, Baral and Pokhare (2017) asserted that social sustainability would pave the way for corporate profit towards short-term and long-term growth.

The integration of sustainability into the supply chain is considered a growing area of research interest. Drawn on the TBL perspective, sustainability should be viewed as a holistic and interdisciplinary concept that encompasses environmental, economic, and social issues at different supply chain stages (Ahi & Searcy, 2015). In the same vein, the SSCP connects social, economic environmental criteria within activities related to the supply chain ((Chiappetta Jabbour et al., 2020)Carter and Easton, 2011). Consequently, it is argued that adopting SSCP is in line with the TBL framework, which leads to creating SSCP outcomes on the TBL performance pillars. According to previous theoretical reasoning, this research is based on the TBL approach to developing pillars of SSCP. Therefore, we form SSCP to develop theoretical relationships between the embedded constructs representing environmental, social and economic performance.

2.6 Hypothesis Development

This chapter aims to develop theoretical associations between variables by formulating hypotheses. This is accomplished using the theoretical foundation for BDACs, SSCP and the empirical evidence within the literature review.

In the development process of the hypotheses put forward in this thesis, the contingency perspective is taken into consideration. The contingency perspective assumes that the assumptions under any assessment may either be true or false, therefore either confirming or rejecting the theories (Layder, 1988). A series of hypotheses are developed to classify a relationship between BDACs and SSCP. The moderating effects of some variables (supplier integration(SI), corporate social responsibility(CSR) and alignment between business strategy and BDACs(ALG) in the relationship between BDACs and SSCP are also predicted. The proposed hypotheses are shown in Figure 2-4.

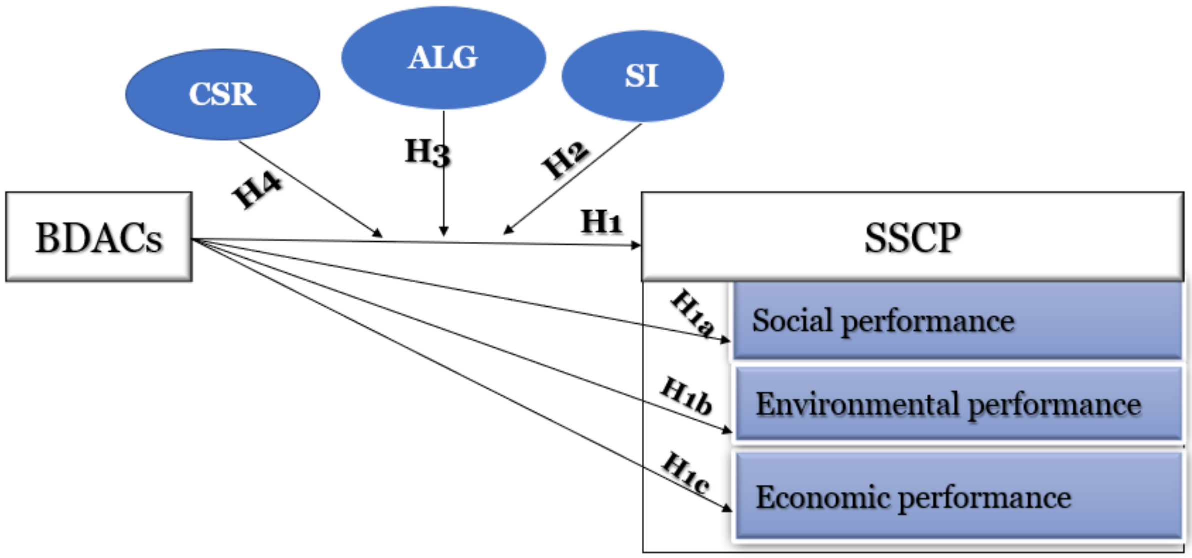

Figure 2-4 Hypotheses Model

2.6.1 The impact of BDACs on SSCP

Big data analytics capabilities refer to the competence to generate business insights by using data management, talent (personnel) capability and infrastructure (technology) to transform a business into a competitive force. According to Wamba et al.(2017), BDACs are considered higher-order organisational capabilities based on gathering strategic resources. Teece et al. (1997) contend that BDACs could be conceptualised as a substantial capability for an organisation. This capability depends on existing environmental conditions under which the organisation is functioning. The organisation can achieve sustained competitive advantage through the active exploitation of this organisational capability. Basically, BDACs are divided into two main subsets: human and non-human capabilities. It is important to note that this study grouped BDACs into the two major groupings in line with the previous research.

Big Data analytics highly depends on human capabilities (knowledge and skills) to employ BD techniques and tools (analytical methods and data mining tools). Human capability indicates the professional ability of BDA staff (e.g., knowledge and skills) to utilise analytical technologies and data analysis to generate valuable insights (Bharadwaj, 2000; Kim et al., 2012). In light of the study by Wamba et al. (2017), personnel expertise capability is considered a cornerstone of BDACs. Aligned with such a study, people with analytical experience and knowledge play an instrumental role in organisational maturity concerning BD (Coleman et al., 2016). Recent BD studies have noted the shortage of BDA specialists who possess all of the necessary knowledge and skills to conduct BDA (Dubey & Gunasekaran, 2015; Rialti et al., 2018). In this thesis, human capabilities refer to skills (technical skills and managerial skills), as mentioned in section 2.3.1.

On the other hand, non-human capabilities would be categorised into tangible and intangible capabilities. Tangible (basic resources, data, and infrastructure) and intangible resources (organisational learning and data-driven culture) may help organisations to achieve desired sustainability goals (Jeble et al., 2018). These capabilities are defined and discussed in the literature review. The prior studies call more attention to the resources (technology, human) that an organisation may need to leverage BD benefits. However, it does not yield insights into how firms can create BDACs. This study will focus on human (technical skills and managerial skills) and non-human capabilities (infrastructure), which will allow firms to create BDACs. Previous arguments, whilst providing conceptual evidence, observe little empirical testing of such benefits. Some scholars confirm a significant positive correlation between BDACs and economic performance (Dubey, Gunasekaran, Childe, Blome, et al., 2019; Mikalef et al., 2020; Yasmin et al., 2020). According to the work of Dubey et al. (2017), BD and predictive analytics have a significant impact on social and environmental performance in the supply chain. In fact, BD yields substantial benefits in society, such as legal, ethical, social, and political benefits in Europe. In light of such a study, these benefits can be applied to other places. Also, Jeble et al. (2018) find a positive relationship between predictive analytics capabilities and the sustainability performance of the supply chain. Considering the empirical evidence and theoretical arguments, we put forward the following hypothesis:

H1: Big Data analytics capabilities (BDACs) have a positive impact on sustainable supply chain performance (SSCP)

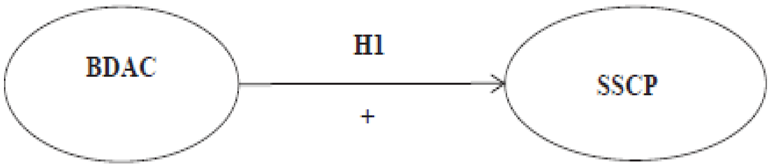

Figure 2-5 Hypothesis H1

2.6.1.1 Impact of BDACs on Social Performance

The social dimension has recently become the main concept in sustainable supply chains. While the standard of living has improved in many societies, other countries still strive to secure basic needs. Several studies have highlighted social problems in the supply chain, such as child labour, health and safety issues, equity problems, living conditions and sustainable working conditions. As a result, social sustainability in the supply chain has emerged.

Recent studies have shown the importance of social sustainability in the supply chain. For example, Klassen and Vereecke (2012) reported that big international companies, such as Apple and Nike, have embraced sustainable social supply chain practices such as monitoring suppliers' labour practices, improving product safety and developing interaction within local communities (Klassen & Vereecke, 2012). The gains from engaging social activities include both tangible and intangible benefits (DeSimone & Popoff, 2000), including reputational enhancement (Heikkurinen, 2010), an increase in sales (Dey et al., 2011), product differentiation (Mahler, 2007) and strong brand image (Shekari & Rajabzadeh Ghatari, 2013). Accordingly, companies need to adopt social sustainability in their supply chain to enhance their social performance. In contrast, a firm's poor social performance can negatively influence its reputation, drop its employee spirit and decline its sales (DeSimone & Popoff, 2000). Interestingly, ignoring social responsibility might result in economic costs (Dhiman, 2008). Furthermore, social responsibility extends beyond the borders of the firm to include its entire supply chain. Multinational corporations such as Nike (child labour) provide examples of companies hampered by unethical issues for their supply chain partners (Seuring & Müller, 2008b; Wolf, 2014).

The rapid growth of information technology and sensor technology has enabled large-scale data collection from each supply chain partner. Those data could be potentially valuable to reduce the lack of knowledge about social sustainability criteria and address social breaches in the supply chain. Consequently, BDA can find proper and accurate predictions and decisions, enhancing transparency and visibility in supply chains and mitigating social violations to achieve social sustainability (Keeso, 2014; Song et al., 2017; Wu et al., 2016). Mani et al. (2017) employed BDA to mitigate the social risk of the supply chain and demonstrate how such mitigation can help achieve sustainability. The results show that companies can predict various social problems, including workforce safety, fuel consumption monitoring, workforce health, security, the physical condition of vehicles, unethical behavior, theft, speeding and traffic violations through BDA. Thus, demonstrating how information management actions can decrease social breaches. Moreover, investment in advanced technologies for data gathering and analysing from suppliers will assist in monitoring the performance (Mamic, 2005), which will ultimately help managers decide how to reduce social violations in supply chains to achieve social sustainability.

While some studies suggested the importance of BDA in improving social sustainability in the supply chain (Dubey et al., 2017; Jeble et al., 2018; Song et al., 2017), there is still a lack of empirical studies which investigate the correlation between BDACs and social sustainability in the supply chain (Calic & Ghasemaghaei, 2021; Chiappetta Jabbour et al., 2020; Dubey, Gunasekaran, Childe, Papadopoulos, et al., 2019; Nandy & Lodh, 2012; Orlitzky et al., 2003). Consequently, this study investigates how organisations may utilise BDACs to solve social issues, such as health and safety and child labour. The next section will view how BDA can help mitigate social risks, such as child labour and health and safety. Hence, the following hypothesis:

H1a: BDACs have a positive impact on social performance.

2.6.1.2 Impact of BDACs on Environmental Performance

Environmental matters have been a topic of debate at varied levels from researchers and academics. The dramatically rising wastage of natural resources and the emission of CO_2 and other greenhouse gases make it essential to embrace an effective way to reduce and manage them sustainably. Carbon emissions arising from different resources, such as logistics and supply chain activities and manufacturing, are visible in the form of global warming leading to the melting of ice layers and rising sea levels (Jeble et al., 2018). One of the emerging challenges in the supply chain is inadequate and asymmetric knowledge about environmental matters (Dubey et al., 2017). Hence, businesses are constrained in responding to the growing environmental demands on business operations due to the lack of knowledge about environmental sustainability (Gunasekaran et al., 2014). To address this issue, Wolf (2011) recommended improving synthesis and transparency among supply chain partners and engaging themselves with the common goals of environmental sustainability. For this reason, BDA can be used to explore hidden patterns, unknown correlations and trends (Wu et al., 2016). Song et al. (2017) show that BDA can lead to sustainable natural resource management, such as enhanced environmental efficiency, protection and improved energy efficiency. Also, several studies have addressed environmental issues including pollution, waste, resource depletion and ecology disruptions with the aid of BDA (De Gennaro et al., 2016; Zheng et al., 2013; Zhu et al., 2017).

Even though some studies suggested the importance of BDA in improving environmental sustainability in the supply chain, empirical studies that understand how BDACs influences environmental performance in the supply chain are lacking. Consequently, this study investigates how organisations may utilise BDACs to solve environmental issues, emissions of CO_2 and gases, and depleting of environmental resources. Hence, we draw the hypothesis:

H1b.: BDACs have a positive impact on environmental performance.

2.6.1.3 Impact of BDACs on Economic Performance

Profit maximising for long-term survival is the primary goal for firms. To achieve this goal, firms strive to gain market share and build their competitive advantage in a highly competitive marketplace (Svensson & Wagner, 2015). The exponential growth in BD has provided valuable information about business markets, customers and the firm itself. As a result, some businesses are increasingly interested in understanding how they manage their business more effectively using BDA. According to several empirical studies, the business value of BDA solutions improves financial performance (Wamba et al., 2015; Akter et al., 2016). In addition, BDA increases customer satisfaction and loyalty by improving corporate ability to meet their preferences (Wamba et al., 2017). Further, BDA decreases customer acquisition costs (Wamba et al., 2015), which are critical factors for enhanced cash flows to enhance financial performance (Wamba et al., 2017). Big Data analytics can also increase profit (Schroeck et al., 2012) and market share, maximise sales and financial productivity (Manyika et al., 2011) as well as return on investment (Chen et al., 2015).

Other recent studies also indicate factors that contribute to a successful exploitation of BDA. For instance, Gupta and George (2016) demonstrate that investing in BDACs is associated with increased operation and market performance, and consequently superior firm performance. Similarly, scholars have acknowledged that organisations utilise BDACs to gain a competitive advantage (Akter et al., 2016; Wamba et al., 2017). According to a systematic literature review (Arunachalam et al., 2018), Studies show the role of BDACs in driving organisational decision making, which leads to driving positive firm performance. The results of the study by Gunasekaran et al. (2017) indicate the positive impact of BDACs assimilation as a capability on organisational and supply chain performance.

Although the impact of the BDA on the economic performance of organisations has attracted significant contributions (Akter et al., 2016; Gupta and George, 2016; Ji-fan Ren et al.,2017; Wamba et al., 2017; Gunasekaran et al., 2017), empirical studies are still limited with regards to investigating the impact of both dimensions of BDACs (human and non-human capabilities) on economic sustainability in the supply chain. Consequently, this study aims to investigate how organisations may utilise BDACs to achieve economic performance (profitability, sales growth). Hence, we hypothesise:

H1c: BDACs have a positive impact on economic performance.

2.6.2 The moderating Factors on The Relationship between BDACs and SSCP

2.6.2.1 Supplier Integration

Supply chains are very sophisticated, requiring companies to maintain contact and seek suppliers' cooperation to complement and improve their products and services.

In essence, both the strategies and the logistics of company requirements should be engaged by suppliers. This integration is essential for the success of the whole chain (Gavronski et al., 2011). Supply chain integration (SCI) indicates "the degree to which a manufacturer strategically collaborates with its supply chain partners and collaboratively manages Intra- and inter-organisation processes. The goal is to achieve the effective and efficient flows of products and services, information, money, and decisions, to provide maximum value to the customer at low cost and high speed" (Flynn et al., 2010, p. 59). Supply chain integration consists of internal and external integration. Internal integration is "the degree to which manufacturer structures its organisational strategies, practices, and processes into collaborative, synchronized processes, to fulfil its customers' requirements and efficiently interact with its suppliers" (Flynn et al., 2010, p. 59) whilst external integration is "the degree to which a company connects with its external partners to build inter-organisational strategies, processes, and practices into synergetic and synchronized processes "(Flynn et al.,2010, p.59). Internal integration concentrates on cross-functional collaboration within companies. In comparison, external integration concentrates on inter-organisational processes and strategies. It also involves supplier and customer integration. In this study, we are going to focus on supplier integration.

Supplier integration has been considered a significant functional activity in the supply chain (Zhang et al., 2016). Supplier integration is described as "the extent of coordination between manufacturers and their suppliers in making decisions related to capacity planning, demand forecasting, inventory management, and replenishment as well as the flow of materials" (Piprani et al., 2020, pp 59). Sharing essential information among suppliers, involving suppliers in product development and building supplier programs have an instrumental role in sustaining long-term quality and strategic connections (Li et al., 2005). Firms strive to organise strategic alliances with their leading suppliers and maintain long-term relations by sharing their information and building mutual trust and a harmonious culture (Kang et al., 2018). Cooperation with suppliers can also help firms identify multiple sustainability challenges (Huq et al., 2016). According to Elkington (1998), building powerful long-term supplier partnerships plays a key role in assisting firms' transition to sustainability.

Interestingly, SI affords the collaborative advantage that permits supply chain partners to create synergies and generate excellent operational performance (Cao & Zhang, 2011). In addition, SI can bring many benefits to social and environmental sustainability performance. Environmental cooperation activities with participants in the supply chain (such as setting common environmental goals, joint environmental planning and cooperation to reduce pollution or harmful effects on the environment) positively influence company performance (Vachon & Mao, 2008). In the firm's social performance, cooperative activities with supply chain members boost the social reputation (Gimenez et al., 2012). In addition, partnerships with suppliers on social issues (for example, providing social training or collaborating to address health and safety gaps in suppliers) will develop the company's skills and knowledge to improve social performance Supplier integration can provide updated information in turbulent environments and help managers reconfigure structures and processes to administer businesses flexibly and collaboratively to enhance sustainability performance (Huo, 2012). Therefore, SI is considered an essential enabler in facilitating SSCP by boosting the collaborative dimension that is essential for attaining sustainability goals(Di Maria et al., 2022). Supply chain integration has an impact on SSCP (Vanpoucke et al., 2017, Kang et al., 2018).

A moderator means the effect of interaction between an independent and dependent variable that assigns the appropriate conditions for its operation, the moderator affects the power of correlation between two variables. Some empirical studies consider varied moderators which examine the interaction between BDACs and SSCP like supply chain innovativeness (Bag et al., 2020), supply base complexity (Jeble et al. 2018), environmental dynamism (Wamba et al., 2020), organisational compatibility and resource complementarity (Dubey, Gunasekaran, Childe, Roubaud, et al., 2019), Flexible and control orientation(Dubey, Gunasekaran, Childe, Papadopoulos, et al., 2019). Gu et al.(2021) indicate that significant moderation between BDA capability and supplier development on firm performance. In this study, we argue that SI has presented an increasingly significant impact on the relationship between BDACs and SSCP acting as a moderator, thus the following hypothesis:

H2. SI has a positive moderating effect on the path connecting BDACs and SSCP.

2.6.2.2 Alignment of business strategy with BDACs

Business strategy is considered a primary concern of top management because it is crucial for a given business's survival in a competitive global environment. Alignment of business strategy with BDACs has defined as" the extent to which BDAC is align with the overall organisational strategy"(Akter et al., 2016, p. 120).

The business strategy highlights the resources and capabilities that should be allocated to achieve a competitive advantage. Therefore, an organisation, which possesses a distinct set of resources (tangible and intangible), will contribute decisively to strategic advantages. However, they are not sufficient to secure sustainability performance (López-Cabarcos et al., 2015). Generally, BDACs and business strategy alignment might be the key to improving SSCP.

Recently researchers and practitioners have paid more attention to business strategy alignment in the BD environment since synchronisation between BDACs and business strategies brings many advantages. For example, it increases synergy among different functional units. In contrast, non-synergy creates competing priorities, putting the various departments within an organisation at cross-purposes. In addition, non-synergy among different functional units negatively impacts financial performance; for example, an organisation will struggle to see investment returns of data analytics. Interestingly, aligning between BDACs and business strategy enables organisations to cope with changing environmental conditions by truly understanding their nature (van de Wetering et al., 2018). It also reduces the complexity of data across different company units by viewing the firm as a specific governance structure, a collection of interlinked resources (Peteraf, 1993). It can help firms match resources with changing market opportunities by truly understanding their nature (van de Wetering et al., 2018). Also, it helps to align resources with market dynamics aided by multidimensional capability (Akter et al., 2016).

Considering alignment between business strategy and BDACs as a strategic capability, it draws on a company's ability to apply and leverage capabilities of other resources (Bharadwaj, 2000). Firms with a high level of IT infrastructure, human (analytics skill or knowledge) and organisational (BDA management) resources could allow aligning their business plans to improve business performance (Akter et al., 2016). Therefore, aligning capabilitites with the strategic plan is the significant advantage of BDACs, which could assist businesses to achieve successful performance. BDACs can affect business performance via alignment as a moderator(Akter et al., 2016). Consequently, this thesis argues that the alignment between business strategy and BDACs is a critical moderating factor between BDACs and sustainable supply chain performance. Therefore, we hypothesise:

H3: A high level of alignment between business strategy and BDACs will result in a high level of BDACs impact on SSCP.

2.6.2.3 Corporate Social Responsibility

Corporate social responsibility (CSR) has received more interest from the government, industry and academia because it is considered a driving force towards supply chain sustainability. Effective CSR practices would enable companies to balance triple bottom line dimensions (social, environmental, and economic). Bowen (2013) defined CSR as a social obligation that encompasses the adoption, determination of these policies, decision-making, and following these plans that are beneficial to the values and aims of society.

Corporate social responsibility is gaining more interest as a keystone of essential decision-making criteria (Sharma & Vredenburg, 1998). In addition, CSR strives to strengthen the business by creating a common language among organisational actors to discuss social issues. Hence, CSR helps members share routines to develop and implement innovative solutions, such as environmentally friendly products (Shrivastava, 1995) and builds formal and informal relations among stakeholders (Howard-Grenville & Hoffman, 2003). Therefore, the adoption of CSR practices into business activities plays a vital role in improving collaborative relationships, innovation culture, and mutual trust among stakeholders (Surroca et al., 2010). When social and environmental awareness are embedded in the company's culture, economic performance will be improved (Howard-Grenville & Hoffman, 2003) as well as social and environmental performance. A socially responsible culture would bring beneficial outcomes, such as promoting organisational commitment and learning, increasing employee skills, integrating functions across the organisation, and building highly qualified employees. Accordingly, adopting a robust organisational culture with these characteristics will improve financial performance (Surroca et al., 2010). There are many academic efforts to find a positive correlation between CSR and economic performance. However, from a long-term perspective, there is a growing sense of CSR's influence on social and environmental performance (D'amato et al., 2009).

CSR has played instrumental role in achieving economic goals and wealth generation (Garriga & Mele, 2004). Consequently, many studies endeavored to find a correlation between CSR and firm performance (Hernández et al., 2020). These studies had mainly produced controversial results. Some researchers found a positive relationship between CSR and economic performance(Ali et al., 2020; Hernández et al., 2020; Long et al., 2020; Margolis et al., 2009). Contrastly, other researchers found a negative correlation (Crisóstomo et al., 2011). Some studies even reveal a neutral relationship between CSR and financial performance (Lu et al., 2014; McWilliams & Siegel, 2000). Interestingly, researchers paid more attention to investigating the influence of CSR on financial performance. However, there is still limited empirical evidence on the relationship between CSR and environmental and social performance. Orazalin (2020) demonstrates that effective organisational CSR strategies achieve better environmental and social performance, which positively impacts sustainability performance. According to the literature, results on the relationship between CSR and sustainability performance are mixed. In this regard, CSR has presented an increasingly significant impact upon the relationship between BDACs and SSCP acting as a moderator: Thus, we hypothesise:

H4. CSR has a positive moderating effect on the path connecting BDACs and SSCP.

Chapter 3. Research Methodology

This chapter describes this study's methodology to achieve the objectives and answer the research questions. Determining the research methodology that will be used before undertaking research is considered a crucial step in the study. As a result, the applicable methodology will help us effectively collect data and find a solution to the research problem (Rajasekar et al., 2013). There are two main sections in this chapter: the first section describes several methodological and philosophical considerations. This involves the research philosophy, research approach, research strategy, research method, and data collection technique. The second section discusses additional practical sub-aspects of this research including methodological concerns such as the measures of the constructs, questionnaire development and design, ethical considerations, population and sample size, and data collection process. Table 3.1 provides a summary of the thesis process.

Table 3-1 Summary of Thesis Process

Keywords	Research Questions	Research objectives	Hypotheses	Research Methods	Outputs of Research Methods
BDACs	RQ1: what capabilities have been required to build BDA?	To determine the capabilities which allow firms to create BDACs.		Systematic research literature reviews I. Extract the articles published from Scopus II. Standard Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)	I. Lay the groundwork about SSCP available in the literature to inform our and quantitative phases. II. Taxonomy of BDACS
SSCP	RQ2: what constitutes the dimensions of SSCP?	To determine the dimensions of SSCP.		Systematic research literature reviews: I. Extract the articles published from Scopus. II. Standard Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA)-	I. Lay the groundwork about SSCP available in the literature to inform our and quantitative phases. II. Taxonomy of SSCP
SSCP and BDACs	RQ3: To what extent can BDACs enhance SSCP?	To investigate the impact of BDACs on SSC.	H1: BDACs has a positive impact on SSCP. H1a: BDACs has a positive impact on social performance. H1b: BDACs has a positive impact on environmental performance H1c: BDACS has a positive impact on economic performance.	Quantitative method: - Online survey tool like Survey Monkey - Online survey questionnaire	Test the research model
SI (supplier integration)	RQ4.To what extent does SI influence the relationship between BDACs and SSCP?	To define the role of alignment of business strategy with BDACs, which influence the relationship between BDACs and SSCP.	H2: SI has a positive moderating effect on the path connecting BDACs and SSCP	Quantitative method - Online survey questionnaire. - Online survey tool like Survey Monkey.	Test H2
Alignment of business strategy with BDACs	RQ5.To what extent does alignment of business strategy with BDACS influence the relationship between BDACs and SSCP?	To define the role of CSR, which influences the relationship between BDACs and SSCP.	H3. High level of alignment between business strategy and BDACs will result in a high level of BDACs impact on SSCP.	Quantitative method: - Online survey questionnaire. - Online survey tool like Survey Monkey.	Test H3
CSR (corporate social responsibility)	RQ6. To what extent does CSR influence the relationship between BDACs and SSCP?	To define the role of SI, which influence the relationship between BDACs and SSCP.	H4: CSR has a positive moderating effect on the path connecting BDACs and SSCP	Quantitative method: - Online survey questionnaire - Online survey tool like Survey Monkey	Test H4

3.1 Research Philosophy

The research paradigm (philosophy) is defined as "a system of beliefs and assumptions about the development of knowledge in which researchers position their researches" (Saunders et al., 2019, p. 130). The research philosophy involves critical assumptions that affect the researchers' perceptions of the world and how they seek answers to research questions. These assumptions play a key role in selecting the proper research methodology, comprising research strategy and methods of data collection Saunders et al. (2019). Generally, a research philosophy embraces how researchers collect, analyse, and apply research data (Burrell & Morgan, 2006).

The two key research philosophies in social science studies are positivism and interpretivism(Collis & Hussey, 2014) . Positivism embraces an objective stance, using consistently rational and logical approaches to study a social phenomenon (Carson et al., 2001). Positivism depends on quantifiable observations that lead to statistical analyses. It has been concerned with information and positive facts (verified data) gained through observation (the senses) interpreted through logical and mathematical operations (Saunders et al., 2019). Research findings are usually observable and quantifiable.

A reality that is 'out there' is one of the philosophical principles of positivism. Therefore, the researcher should find the best and most impartial approach to collect positive information or facts about this reality. (Bell et al., 2018). The positivism paradigm involves developing research models and hypotheses, which counts on research questions where science quantitatively measures independent facts about reality, i.e., causal relation, to be tested (Bell et al., 2018).

On the contrary, an interpretative paradigm embraces an empathic (humanistic) attitude and uses a subjective viewpoint of the social reality that social actors meet (Saunders et al., 2019). Scholars contend that "subject matter of social sciences – people and their institutions – is fundamentally different from that of natural sciences" (Bryman & Bell, 2007, p. 31). This paradigm affirms that the social world is different from physical science as social science is very complicated to be studied exclusively through assumptions and scientific explanations (Saunders et al., 2019). The Interpretivism paradigm is based on the major belief that research is based on the interpretation of research materials by researchers and their beliefs and values (Saunders et al., 2019). Researchers also adopt a more personal and flexible research structure (Carson et al., 2001), which is responsive to capturing meanings in human interaction compared to positivist research based on rigid structural frameworks. One of the philosophical reflections of positivism is to understand and interpret the senses in human behaviour instead of generalising and predicting causes and effects (Neuman, 2006)

According to the previous review of philosophical positions in social research, this study was positioned within a positivist paradigm. We have seen the knowledge of research 'out there' and in the real world can be observed. The reality of this present study is depicted by objects regarded as 'real,' like social, economic, and environmental performance. Moreover, this thesis's principal objective is to undertake an empirical investigation utilising actual data consistent with a positivist paradigm. Consequently, this thesis adopts the positivism paradigm as a philosophical stance.

Interestingly, positivism is related to the targeted explanatory aims of research to comprehend causal relations (Saunders et al., 2019). In this study, positivism is adequate because it assists the research model development and links with the appropriate theories. In a brief sense, the study paradigm could be depicted as an overarching umbrella that directs and impacts the selection of the ideal study methodology, including research strategy and data collection methods. That is discussed in the following sections.

3.2 Research Approach

The standard research approaches employed in social science research can be categorised as deductive, inductive, or abductive. A deductive approach is a "top-down" structured technique that begins with a broad theory and proceeds to develop hypotheses that are empirically investigated. That is why; it is also indicated as "moving from the general to the particular" (Collis & Hussey, 2014, p. 7). Consequently, the deductive logic emphasises causality and follows 'the positivism paradigm' and 'quantitative research strategy' (David & Sutton, 2011). Conversely, an inductive approach comprises the process of building a theory, which starts with empirical observations towards generalisations about the phenomenon under consideration to build theory or develop a theoretical framework(Collis & Hussey, 2014). Inductive logic focuses on discovering novel phenomena through an in-depth investigation, which is harmonious with an interpretive paradigm and qualitative research strategy (Bell et al., 2018; Saunders et al., 2019). The abductive approach is a mix of inductive and deductive procedures that start with observing real-life and theoretical knowledge (move backward and forward) (Saunders et al., 2019).

Accordingly, this study has been supported by the deductive approach for theoretical testing of existing theories and knowledge of BDACs and SSCP. It involves providing empirical input to create a theoretical framework and then test hypotheses (DeCarlo, 2018). Many studies in BDA and supply chain performance employ a quantitative technique and use the deduction method as a research approach for testing theory (Bag et al., 2020; Dubey, Gunasekaran, Childe, Roubaud, et al., 2019; Edwin Cheng et al., 2021; Mandal, 2018; Mandal, 2019; Oncioiu et al., 2019; Pelliere & Da Cunha, 2018; Queiroz & Telles, 2018; Raut et al., 2021; Shokouhyar et al., 2020). Figure 3.1. displays the processes of deduction.

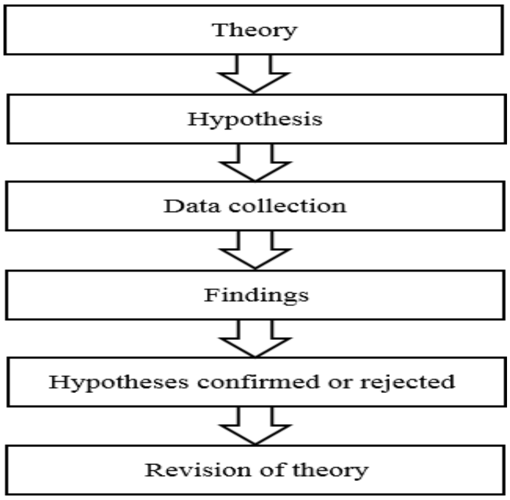

Figure 3-1 Deduction Process (source: (Bell et al., 2018, p. 21)

3.3 Research Strategy

In any social research, a research approach plays a vital role. It is a general orientation to conduct the research, which helps turn research questions into a research project (Bell et al., 2018; Saunders et al., 2019). Seven principal research strategies are broadly employed within management and business research i.e., survey, experiment, case study, archival and documentary research, ethnography, action research, grounded theory, and narrative inquiry (Saunders et al., 2019).

Interestingly, the research purpose (i.e., exploratory or explanatory) determines the type of strategy adopted in research (Yin, 2003). A research strategy refers to a plan of answering the research questions in a particular study. Therefore, the type of research question(s) influences the research strategy chosen. The following are some significant factors for selecting a research strategy which are recommended by Saunders et al. (2019) :

• the ability to answer the research questions
• the ability to achieve the research objectives
• consistency with philosophical considerations such as research philosophy and research approach
• the boundary of existing knowledge
• the availability of research resources (e.g., money, time).

This thesis adopts two research strategies based on the above criteria, i.e., systematic literature review (SLR) and survey, to answer the proposed research questions and meet the thesis's core objectives. Prior research is considered the backbone of this thesis. We conduct SLR to answer two main research questions RQ1: what capabilities have been required to build BDA? and RQ2: what constitutes the dimensions of SSCP? Also, the SLR was helped meet two primary objectives of this research: 1) determine the capabilities that allow firms to create BDACs and 2) determine the dimensions of SSCP. This research adopts the SLR to comprehensively cover relevant publications that lay the groundwork for BDACs and SSCP, presented in the following sub-section 3.3.1.

This study's third core objective is to develop a research model to investigate the influence of BDACs on SSCP. It involves empirical tests of causal relationships (recommended assumptions) between research variables, discussed in Chapter 5. Therefore, explanatory research is appropriate in answering the last four research questions, for example, RQ3. "to what extent can BDACs enhance SSC performance? “; RQ4. "to what extent does alignment of business strategy with BDACs influence the relationship between BDACs and sustainable supply chain performance?" and RQ5. “to what extent does CSR influence the relationship between BDACs and sustainable supply chain performance?”. The purpose of this (explanatory) study is consistent with the survey strategy. The survey strategy reflects the positivist approach from the philosophical standpoint because it targets the researchers' objectives within a specific theory or conceptual structure (Saunders et al., 2019). In the following Section 3.3.2, we will explain the nature of the survey strategy briefly.

3.3.1 Systematic Literature Review

Reviewing relevant historical literature is the first step for any academic research. Conducting 'cumulative research' is essential for a) facilitating new theories and frameworks, b) identifying well-studied research areas as well as discovering research gaps that were needed further (Webster & Watson, 2002), and c) collecting empirical findings linked to a narrow research question to support evidence-based practice (Paré et al., 2015).

To answer our research questions, we conduct the SLR and follow 'Standard Preferred Reporting Items for Systematic Reviews and Meta-Analyses' (PRISMA) (Moher et al., 2009). The literature search aims to achieve comprehensive coverage of relevant publications that lay the groundwork for BDACs and SSCP. A systematic review librarian was consulted to develop a literature search, including search database and keywords selection. An appropriate systematic approach was applied three times to cover the research questions. Table 3-2 summarises the SLR in this thesis. The following sections review the steps taken in this method.

Table 3-2. Summarize SLR Method

Feature	BDACs	SSCP	Impact of BDACs on SSCP
Research question	What capabilities have been required to build big data analytics?	What metrics have been required to measure or assess SSCP?	What is the impact of BDACS on SSCP?
Keywords	("big data analy*") and (skill* or capabilit* or competenc*)	(sustainab*) AND (supply AND chain) AND (metric OR indicator OR measure OR performance)	"big data analy*" AND (skill* or capabilit* or competenc*) AND ("supply chain") AND performance.
The number of studies retrieved with limit conditions: **- *Peer-reviewed*** **- *English language***	237	1,699	328
Criteria for eligibility	The subject category of research falls into Business, Management, and Accounting	• Articles published by the top journals on SSCP ((journals that have published more than five articles on SSCP). • The subject category of research falls into Business, Management, and Accounting.	The subject category of research falls into Business, Management, and Accounting.
Number of studies assessed for eligibility	61	160	38
Criteria for include	Focus on big data analytics capabilities' assessment	Focus on actionable assessment and/or metrics related to SSCP	Focus on studies investigating the impact of BDACS on SSCP
Studies included	25	19	20

3.3.1.1 Eligibility Criteria

When conducting a systematic review, clearly defining inclusion and exclusion criteria should be considered. They were applied to identify studies that provide the groundwork for the BDACs and SSCP. To reduce the probability of bias, we prepared inclusion and exclusion criteria for both portions of the literature review (BDACs and SSCP). We also determined selection criteria that drew on research questions, such as RQ1: "what capabilities have been required to build BDA?" and RQ2:" what constitutes the dimensions of SSCP?". The inclusion criteria include studies that are (i) published in peer-reviewed journals, (ii) written in English and (iii) related to the research questions.

3.3.1.2 Search Strategy

An essential phase in the research process is selecting the search keywords, yielding relevant articles for the topic of interest. The keywords were carefully selected based on the research question(s). Trial and error searches were performed to select appropriate search keywords. To answer the question "what capabilities have been required to build BDA?", we conducted a keyword search (("big data analy*") and (skill* or capabilit* or competenc*)) spanning the period between 2010 to 2018 in the SCOPUS database to find published studies related to BDACs. Our search period started in 2010 because significant BDACs were introduced after this date. To answer another research question, "what constitutes the dimensions of SSCP?" we conducted a keyword search ((sustainab*) and (supply AND chain) AND (indicator OR metric OR performance OR measure)) in Scopus from 2011 to 2018 to find published studies focused on the assessment of SSCP.

3.3.1.3 Study Selection

The filtering process was carried out to obtain high-quality scientific research for both Parts (A and B) of the literature review. In Part A of the literature review, the initial phase of the review process was to run a topic search (including title, keyword, and abstract) with the use of keywords (("big data analy*") and (skill* or capability* or competenc*)) in SCOPUS. The search was filtered to peer-reviewed articles in the English language published from 2010 to 2018. That gave us 185 studies. The evaluation was subsequently restricted to papers that fall within one of the following fields: Management, Business, and Accounting. The outcome was 61 studies that had their titles, abstracts, and keywords once more evaluated. We have observed that just 25 studies conformed with BDACs. This analysis encouraged us to define two key dimensions for assessing BDACs, namely human and non-human capacities. The literature search and selection technique are illustrated in Figure 3-2.

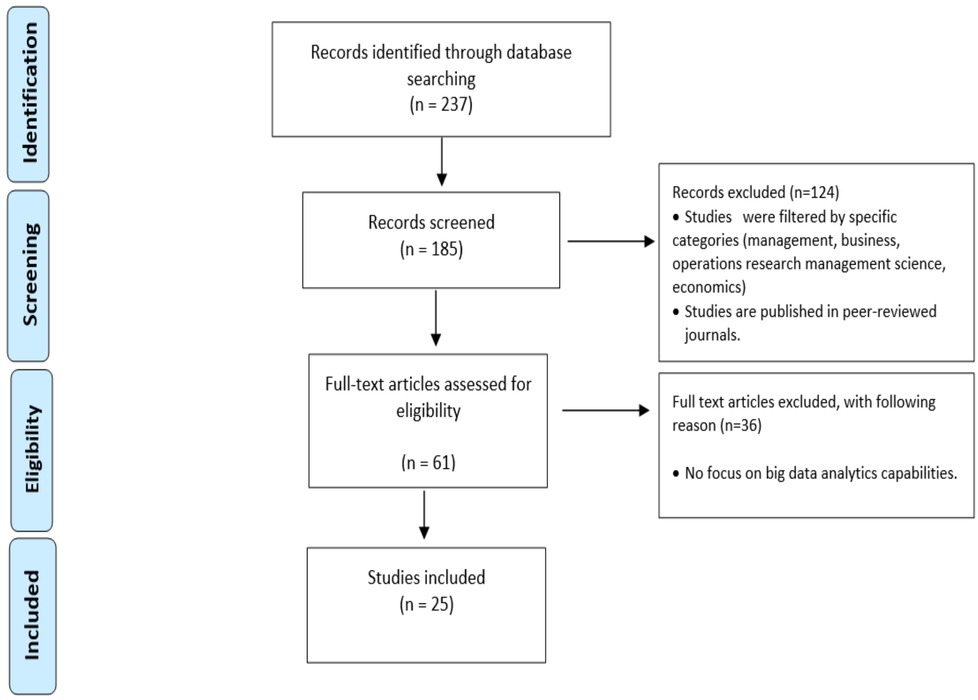

Figure 3-2 Systematic Literature Review of BDACs

In Part B of the literature review, the review process was commenced by searching abstract, keyword, and title in SCOPUS with keywords ((sustainable*) AND (supply AND chain) AND (indicator OR metric OR performance OR measure)). In addition, the results were filtered to peer-reviewed articles in the English language published from 2010 to 2018. We received 1699 papers in different categories of subjects. The next step included restricting the papers which were published in leading journals that have published more than five articles on SSCP: Journal of Business Ethics, International Journal of Production Economics, International Journal of Production Research, Business Strategy and the Environment, Production Planning and Control, Supply Chain Management, Journal of Manufacturing Technology Management, Technological Forecasting, and Social Change, Journal of Cleaner Production. Furthermore, we used an additional filter to limit papers according to their subject category that falls into Business, Management, and Accounting. This filtering resulted in 160 articles that examined their titles, abstracts and keywords to locate papers containing SSCP-related evaluations or metrics. Lastly, only 19 publications conformed with the assessment or metrics of SSCP. Figure 3-3 represents the search and selection procedure for the SSCP literature review.

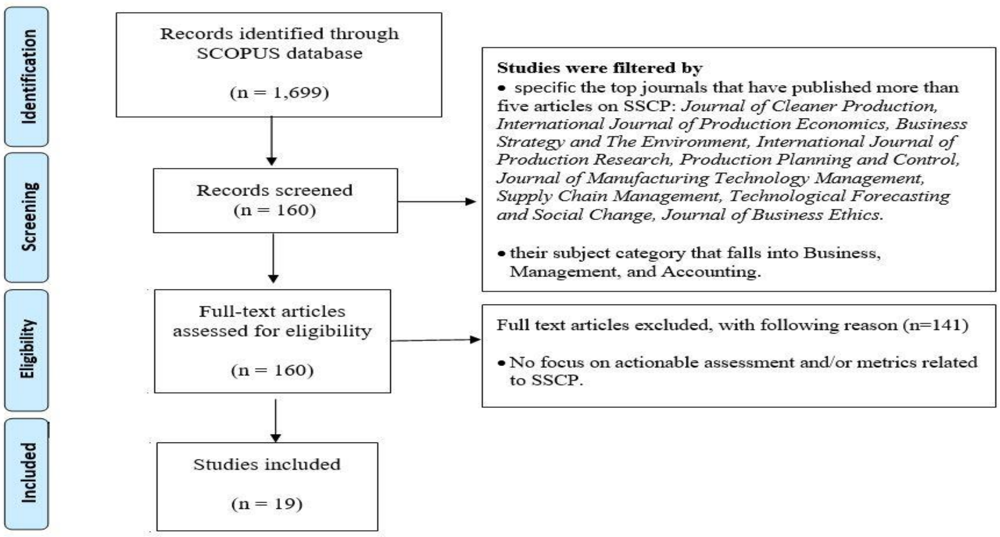

Figure 3-3 Systematic Literature Review of SSCP

3.3.1.4 Classification

An effective literature review should be 'concept-centric'. This approach recommends that the review should be partitioned into units of concept for further analysis (Webster & Watson, 2002). Therefore, in both sections of the SLR, we built a concept matrix with logical partitions to summarise the researched literature (the matrixes shown in tables A and B in Appendix B and C). Part A of the SLR highlighted the capabilities required to build BDA. To make the matrix, reviewed studies have suggested some classifications of BDACs. While some of the studies classified BDACs as human-based, management, and infrastructure-based capabilities, this study showed overlap between human-based and management capabilities as the attributes of management capabilities are similar to the attributes of human capability/managerial skills. Accordingly, we suggest that the BDACs can be categorised into two dimensions: human and non-human capabilities. In addition, this study introduced the attributes of each dimension (see Appendix B).

Part B of the literature review emphasised the assessment of SSCP. We looked to the TBL approach as a theoretical lens to classify these metrics. The TBL approach captures the intersection of environmental, social, and economic performance. Our literature review creates multi-dimensional measurement metrics for assessing each SSCP dimension (see Appendix C).

The overview of the SLR

According to Part A and B of the SLR, we found few studies related to BDACs and SSCP. Consequently, in March 2019, we conducted a keyword search in SCOPUS to find published studies about BDACs and SSCP. The keywords are used for literature search '(big data analy*" and (skill* or capabilit* or competenc*) AND (" supply chain ") AND performance)'. The search was narrowed into publications published between 2011 and 2018 published in English and peer reviewed. There were 328 publications at this point. The review was then reduced to papers falling within the topic category: Business, Management, and Accounting. This produced 38 study titles, abstracts, and keywords evaluated once again. We found that just 20 studies complied with BDAC and SSCP. Table C summarises the examinations of the existing literature on evaluation measurements of BDACs and SSCP (Appendix E). This overview encourages us to focus on gaps and investigate the correlation between BDACs and SSCP.

3.3.2 Survey

In business, management and information systems research, the survey strategy is the most common approach. It is extensively engaged to answer 'which', 'what' and 'where' questions (Saunders et al., 2019). A survey is defined as "gathering information about the characteristics, actions, or opinions of a large group of people, referred to as a population" (Ghani & Al-Meer, 1989, p. 191).

The survey strategy is based on deductive reasoning, aiming to test research inquiries through empirical observation (Bell et al., 2018). It is also widely employed in descriptive studies, which test causal relationships among variables in a real-life setting (Bell et al., 2018). The survey strategy has three principal data collection techniques: structured observations, questionnaires, and structured interviews (Saunders et al., 2019). The survey questionnaire is one of the most common data collection techniques in BDA studies. According to Shdifat et al. (2019), 84% of the empirical research in BDA studies used survey-based methodologies in their research. Recent BDA and SSCP studies also choose a questionnaire-based survey as a research method (Bag et al., 2020; Edwin Cheng et al., 2021; Jeble et al., 2018; Raut et al., 2021; Shokouhyar et al., 2020).

We employed the survey approach based on questionnaires to gather data and test the research model. The survey's purpose is to systematically acquire the same data type from a population sample, seeking statistical patterns and eventually generalising results for a larger population (Oates, 2006). There are many reasons for using this approach in this thesis. The survey strategy is based on deductive reasoning, aiming to test research inquiries through empirical observation (Bell et al., 2018). The survey could be applied to collect data from different unobservable contexts, such as participants' preferences and beliefs (Bloomfield et al., 2016). This method also meets limited budget requirements and allows for more effective and accurate data collection (Bougie & Sekaran, 2016).

Although the survey is one of the most common research strategies in the SCM field (Soni & Kodali, 2012), it has some challenges such as high non-response rates, non-response bias and lack of required knowledge. The ways in which respondents are motivated to get their answers and complete the questionnaire also lead to response bias (Saunders et al., 2019). However, these challenges can be mitigated by considering how questions are asked and designed to capture specific constructs (Bloomfield et al., 2016) and employing appropriate statistical techniques (Hair Jr et al., 2016).

3.3 Research Method

Selecting the research method should be appropriate to answer the research question and achieve the main purpose of the research. Qualitative, quantitative, and mixed methods are common methods of conducting research. The quantitative approach is selected to respond to research questions asking numerical data, the qualitative approach for research questions asking non-numerical (textural) data, and the mixed methods approach for research questions requiring numerical and non-numerical data (Williams, 2007). The quantitative method is primarily related to the questionnaire whilst interviews are fundamental to the qualitative technique. Interviews and questionnaires are connected with mixed methods (Creswell et al., 2003). Quantitative collection techniques include 'questionnaires' or 'structured interviews' or, probably, 'structured observation'. ‘Semi-structured’ and ‘in-depth interviews’ (telephone, group, and internet-mediated) are used in the qualitative collection technique. The mixed-method approach uses qualitative and quantitative data collection techniques (Saunders et al., 2019). Table 3-3 summarises the fundamental criteria of research methods in terms of philosophical assumptions, approach to theory development, the role of theory concerning research, analysis, and data collection techniques(Saunders et al., 2019).

Table 3-3 Key Quantitative and Qualitative Criteria (based off Saunders et al., 2019)

	Quantitative	Qualitative	Mixed-Method
Philosophical Assumptions	Positivism	Interpretivism	Pragmatism and critical realism.
Approach to Theory Development	Deductive	Inductive	Deductive, Inductive, or abductive
Role of Theory to Research	'Testing of theory'	'Generation of theory'	Development of theory
Analysis Techniques	Use of statistics and diagrams.	Use of conceptualization.	Multi-phase and single-phase analysis
Data Collection Techniques	'Questionnaires' or 'structured interviews' or, possibly, 'structured observation'.	semi-structured and in-depth interviews include (group, telephone, and Internet-mediated interviews)	Qualitative and quantitative data collection techniques

The quantitative method is employed in this study in line with the research philosophy (the positivist paradigm) and the research approach (deductive logic) (see Table 3.3). Consequently, the quantitative method is the most appropriate in this research because it allows conducting the empirical investigations to respond to the research questions and test the research model.

3.4 Data Collection Technique

3.4.1 The Questionnaire-Based Survey Method

The nature of the research objectives and questions determine what kind of information the study should collect. As previously discussed, there are three main data collection techniques in the survey strategy. One of the most dominant data collection techniques in the SCM context is the questionnaire (Kotzab et al., 2006). According to Shdifat et al. (2019), most empirical research (84%) in BDA studies used a questionnaire-based survey method. Recent BDA and SSCP studies choose a questionnaire-based survey as a research method (Bag et al., 2020; Edwin Cheng et al., 2021; Jeble et al., 2018; Raut et al., 2021; Shokouhyar et al., 2020; Mandal, 2018). It was widely implemented in the SCM field and BD research for many reasons. To begin, it is relatively inexpensive and easy to administer. It is also considered an effective instrument to collect an extensive volume of data from a sample (large number) of the population within a brief timeframe. Convenience on the part of the researcher concerning the research resources (e.g., time, money) and the researcher's existing knowledge about the topic (Brynard & Hanekom, 2006) also play a role.

Questionnaire is usually effective data collection instruments in analytical research and explanatory studies. Therefore, it allows researchers to investigate and explain cause-and-effect correlations among variables (Saunders et al., 2019). Consequently, consistent with the research aims, this thesis strives to answer the research questions and identify the causal relationships between BDACs and sustainable performance outcomes. The researcher considers the questionnaire technique to be the most appropriate research instrument for answering the research questions and assessing the proposed research hypotheses. For these reasons, the questionnaire helps understand the causal relationship between constructs and helps research outcomes become more generalisable (Pinsonneault & Kraemer, 1993). It can also collect valuable data from a large sample of participants' perspectives, attributes, and behaviours (Pinsonneault & Kraemer, 1993). To ensure higher confidence in the generalisability of the results, the questionnaire is a more appealing data gathering method for predictive theory and explanatory research (Wamba et al., 2017). It can also elicit latent variables and other information to quantify certain constructs, subsequently helping to achieve quantitative analysis (Bloomfield et al., 2016).

3.5 Measures of the Constructs

The measures for constructs used in this thesis were not developed from scratch. Rather, a set of validated measurement scales that had already been developed by antecedent research were adopted. This study involves five primary constructs BDACs, SSCP, supplier integration, corporate social responsibility, alignment of business strategy with BDACs

3.5.1 Big Data Analytics Capabilities

Big data analytics capabilities are defined as "a firm's ability to assemble, integrate, and deploy its Big Data-specific resources" (Gupta & George, 2016). Some studies

(Chae & Olson, 2013; Wamba et al., 2017) suggested classifying BDACs into three categories: infrastructure, data management, and talent. These are key capabilities for transforming the firm into a competitive force. Likewise, BDA's fundamental dimensions highlight management, infrastructure and staff skills capabilities (Akter et al., 2016).While some researchers have previously investigated and introduced some BDACs, a comprehensive picture of BDACs is lacking (Mikalef et al., 2018).

To shed light on the comprehensive picture of BDACs from the standpoint of measuring it in empirical contexts, we conducted a systematic literature review (SLR) to determine the capabilities that have been required to build BDA. According to the SLR, two core dimensions were identified when we assessed BDACs: human and non-human. Human BDACs encompass both skills (technical and managerial skills) and knowledge (technological management and relational knowledge). This thesis selected technical and managerial skills as human capabilities, as shown in Table 3-5. Non-human BDACs encompass data, basic resources, infrastructure, data-driven culture and organisational learning. We selected infrastructure as non-human capabilities, as shown in Table 3-6. The following subsections summarise each dimension.

3.5.1.1 Big Data Analytics Human Capability

Big data analytics human capability refers to “the BDA staff's professional ability (e.g., skills or knowledge) to undertake assigned tasks” (Wamba et al., 2017, p. 358). In this thesis, BDA human capabilities are a second-order construct and contain two first-order constructs: technical and managerial skills. Technical skills as a first-order construct have five indicators. The managerial skills construct has six indicators, as shown in Table 3.4.

Table 3-4 Measures for BDA Human Capabilities

Construct	Type	Code	Description of Measures	Relevant literature
Technical skills	Reflective	TS1	We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing.	Davenport(2014),Gupta & George (2016), Jeble et al.(2018)
		TS2	We have explored or adopted different data visualization tools.	
		TS3	We have explored or adopted cloud-based services for processing data and doing analytics.	
		TS4	We have explored or adopted open-source software for big data and analytics.	
		TS5	We have explored or adopted new forms of databases such as NoSQL (Not only SQL) for storing data.	
Managerial skills	Reflective	MS1	Our BDAC managers understand and appreciate the sustainable business development needs of other functional managers, suppliers and customers.	Ciampi et al.,(2021), Gupta &George(2016), Jeble et al.(2018),Mata et al.(1995), Mikalef et al.(2019)
		MS2	Our BDAC managers can coordinate BDAC related activities in ways to support other functional managers, suppliers and customers.	
		MS3	Our BDAC managers can work with functional managers, suppliers, and customers to determine opportunities that BD might bring to our business.	
		MS4	Our BDAC managers can understand and evaluate the output generated from big data.	
		MS5	Our big data analytics managers have a good sense of where to apply big data.	
		MS6	Our big data analytics managers are able to understand and evaluate the output extracted from big data.	

3.5.1.2 Big Data Analytics Non-Human Capability

In this thesis, BDA infrastructure capabilities are classified as non-human capabilities. It refers to the “BDA infrastructure's ability (e.g., applications, hardware, data, and networks) to enable the BDA staff to develop, deploy quickly, and support necessary system components for a firm “(Wamba et al., 2017, p. 358). Big data analytics non-human capability is set as a second-order construct and contain the first-order construct of BDA infrastructure capabilities. The first-order construct contains eight indicators, as presented in table 3-5.

Table 3-5 Measures For Non-Human BDACs

Construct	Type	Code	Description of Measures	Relevant literature
Infrastructure	Reflective	Inf1	Compared to rivals within our industry, our organisation has the foremost available analytics systems.	Akter et al.(2016), Kim et al. (2012), Terry Anthony Byrd(2000), Xiao et al. (2020)
		Inf2	All remote, branch and mobile offices are connected to the central office for analytics.	
		Inf3	Our organisation utilizes open systems network mechanisms to boost analytics connectivity.	
		Inf4	There are no identifiable communications bottlenecks within our organisation when sharing analytics insights.	
		Inf5	Software applications can be easily transported and used across multiple analytics platforms.	
		Inf6	Our user interfaces provide transparent access to all platforms and applications.	
		Inf7	Analytics-driven information is shared seamlessly across our organisation, regardless of the location.	
		Inf8	Our organisation provides multiple analytics interfaces or entry points for external end-users.	

3.5.2 Sustainable Supply Chain Performance

The 2030 agenda, which sets sustainable goals (SDGs) to protect our planet, has emphasised sustainability issues. That is why measuring sustainable performance outcomes has become more attractive to businesses. There are three essential dimensions to sustainability performance: social, environmental, and economic performance.

In this thesis, the key variables that were considered to investigate sustainability performance include economic performance (profit-oriented and market-oriented outcomes), social performance (employee- and community-oriented outcomes), and environmental performance (pollution control and resource efficiency. The following subsections summarise each variable.

3.5.2.1 Environmental performance

In this thesis, environmental performance (ENP) assesses the extent to which an organisation improves outcomes related to pollution control and resource utilisation. The items measuring the construct of ENP were created drawing on the recent discussions of ENP in business journals for practitioners, and academic business literature, especially the works of Green Jr et al. (2012), Dubey et al.(2017), Paulraj et al.(2017), Jeble et al.(2018), Belhadi et al.(2020). The intended respondents were IT decision-makers such as CIOs and IT managers because they were assumed to know enough to answer general environmental performance questions instead of being familiar with specific details. Respondents were asked to assess their supply chain using BDACs to achieve pollution control and resource efficiency outcomes. The survey included the two key performance indicators: reducing air emissions and reducing waste (water and solid), as shown in Table 3-6.

Table 3-6. Measures for environmental performance

Code	Description of Measures	Relevant literature
ENP1	Using big data analytics capabilities helps the supply chain to attain a reduction of air emissions.	Lin et al.(2013),Dubey et al.(2017),Paulraj et al.(2017),Singh & El-Kassar(2019), Green Jr et al.(2012), Jeble et al.(2018).
ENP2	Using big data analytics capabilities helps the supply chain to succeed in reducing waste (water and/or solid).	Dubey et al.(2017), Paulraj et al.(2017).

3.5.2.2 Economic performance

Businesses seek to contribute to profit maximisation at the firm level for the present day and future generations. Economic performance represents the ability of companies to offer returns to their shareholders. It is primarily correlated to reducing costs associated with purchased materials, energy consumption, waste treatment, discharge, and disposal (Green et al., 2012). Different indicators of economic performance can be measured from various perspectives, including a decrease in the cost of energy consumption, growth in profit, amount of goods delivered on time and reduction of fees for waste discharge (Esfahbodi et al., 2017; Feng et al., 2018; Kumar et al., 2018; Paulraj et al., 2017).

In this thesis, the economic performance indicates the extent to which a firm achieves profit-oriented and market-oriented outcomes. As the target respondents were senior IT managers and CIOs, they were expected to have enough knowledge to answer general economic performance aspects rather than be familiar with complex accounting numbers. Respondents were asked to assess their supply chain using BDACs to achieve profit-oriented and market-oriented outcomes. The survey included two main performance indicators: sales growth and profit growth, as shown in Table 3-7.

Table 3-7 Measures for Economic Performance

Code	Description of Measures	Relevant literature
ECP1	Our supply chain uses big data analytics capabilities to attain improving profit growth.	Gunasekaran et al.(2017), Lin et al.(2013),Singh & El-Kassar(2019).
ECP2	Our supply chain uses big data analytics capabilities to accomplish improving sales growth.	Gunasekaran et al.(2017), Lin et al.(2013),Singh & El-Kassar(2019).

3.5.2.3 Social performance

As pointed out in Chapter 2, social issues like poverty and gender discrimination inequality have received more attention from businesses in supply chains due to the growing pressures from customers, government, NGOs and other stakeholders (Mani et al., 2016). Measuring social performance focuses on the interaction between the organisation and the community and corresponds to issues related to community involvement, employee relations and fair wages (Goel, 2010).

In this thesis, social performance assesses the extent to which an organisation improves employee- and community-oriented outcomes. The items measuring the construct of social performance were generated based on the recent discussions of social performance in the popular business journals for practitioners and academic business literature, especially the works of (Green Jr et al., 2012; Jeble et al., 2018; Mani et al., 2018). As the target respondents were senior IT managers and CIOs, they were expected to have enough knowledge to answer general social performance aspects rather than be familiar with detailed information. Respondents were asked to assess their supply chain using BDACs to achieve employee- and community-oriented outcomes. The survey included three main performance indicators: gender equality, lowering health and safety accidents and increased buying from local suppliers, as shown in Table 3-8.

Table 3-8 Measures for Social Performance

Code	Description of Measures	Relevant literature
SP1	Our supply chain uses big data analytics capabilities to employ better practices, which lead to the improvement of gender equality.	Jeble et al. (2018)
SP2	Our supply chain uses big data analytics capabilities to achieve better practices lowering health and safety accidents.	Popovic et al.(2018); Huo (2019); Paulraj et al.(2017); chen (2017)
SP3	Our supply chain uses big data analytics capabilities to achieve better practices increasing buying from local suppliers	Mani et al. (2018)

3.5.3 Supplier Integration

Supplier integration is considered one of the key functional practices within the supply chain (Zhang et al., 2016). Supplier integration (SI) refers to “the extent of coordination between manufacturers and their suppliers in making decisions related to capacity planning, demand forecasting, inventory management, and replenishment as well as the flow of materials”(Piprani et al., 2020, pp 59). This information sharing brings many benefits, such as maintaining quality and long-term strategic relationships (Li et al., 2005). The firm strives to build strategic collaborations and keep a long-term successful relationship with premier suppliers by sharing their information and creating mutual trust and common culture (Kang et al., 2018). Cooperation with suppliers could also enable the company to discover different obstacles to sustainability (Huq et al., 2016). According to Elkington (1998), building powerful long-term corporations with suppliers plays a critical role in assisting firms' transition to sustainability.

To sum up, improving SSCP requires coordination across all supply chain partners. Supplier integration can provide updated information in turbulent environments and help managers reconfigure structures and processes to administer businesses flexibly and collaboratively to enhance sustainability performance (Huo, 2012). Therefore, SI is considered an essential enabler in facilitating SSCP by boosting the collaborative dimension that is essential for attaining sustainability goals(Di Maria et al., 2022).

In this thesis, supplier integration indicates embedding all focal firm requirements into operations, reflecting all conditions, training and collaboration amongst all supply chain members. This section asked respondents to assess their firm's embedding in the supply chain, as shown in Table 3-9.

Table 3-9 Measures for Supplier Integration

Code	Description of Measures	Relevant literature
SI1	Conducting joint planning with partners to anticipate/resolve potential supply chain problems.	Nelson(2015); achon and Klassen(2007)
SI2	Providing information to help our supply chain partners improve.	
SI3	Informing partners about industry/regulatory events/changes that may affect them and their products.	
SI4	Requiring partners to implement EMS programs to address our company policy.	
SI5	Requiring collaboration in design of new products with supply chain partners.	
SI6	Requiring partners to visit our facility for feedback to help improve our performance.	
SI7	Ensuring supply chain participants provide their employees with necessary training.	

3.5.4 Corporate Social Responsibility

Corporate social responsibility (CSR) has drawn extensive attention from the government, industry, and academia because it is considered a driving force toward supply chain sustainability. Effective CSR practices would enable companies to balance triple bottom line dimensions (social, environmental, and economic).

CSR is defined as a social responsibility of adopting policies, developing strategies, making decisions, and following beneficial and acceptable plans in the context of society's values and objectives (Bowen, 2013). The supply chain's CSR is measured in this thesis using a code of conduct, as shown in table 3-10.

Table 3-10 Measures for Corporate Social Responsibility

Code	Description of Measures	Relevant literature
COC1	Our supply chain organisations having a code of conduct	Ashkanasy et al. (2000)
COC2	Our organisation seeks to establish a code of conduct.	

3.5.6 Alignment of Business Strategy with BDACs

Top managers have paid more attention to business strategy because it is crucial for a given business's survival in a competitive global environment. A business strategy with an emphasis on resources and capabilities should be adopted to attain a competitive advantage. An organisation, which owns a distinct set of resources (tangible and intangible), will decisively engage in strategic advantages. However, they are not sufficient to secure sustainable performance.

BDACs and business strategy alignment refers to the extent to which BDA strategies align with the organisation strategy overall (Agarwal & Dhar, 2014; Akter et al., 2016; McAfee et al., 2012). Business strategy alignment in the BD environment has gained more interest from researchers and practitioners. Synchronisation between BDACs and business strategies brings many benefits. For example, it increases synergy among different functional units, in line with (Akter et al., 2016). This section asked respondents to assess the extent to which their organization's BDA strategies align with the overall organisation strategy, as shown in Table 3-11.

Table 3-11 Measures for Alignment of Business Strategy with BDACs

Code	Description of Measures	Relevant literature
Alg1	Big data analytics plan aligns with the company's mission, goals, objectives, and strategies.	Setia and Patel (2013); Akter et al.(2016)
Alg2	Big data analytics plan contains quantified goals and objectives.	
Alg3	Big data analytics plan contains detailed action plans/strategies that support company direction	
Alg4	We prioritize major big data analytics investments by the expected impact on business performance.	

3.6 Questionnaire Development

While questionnaires are usually effective data collection instruments in explanatory studies and analytical research (such as this), some factors affect an individual's ability to interpret and answer questionnaire questions. These factors, involving wording, measure design and placement and order of questions, play a vital role in mitigating any individual-level influences on the validity and reliability of the answers given (Forza, 2016). However, improving the visual design of questionnaires, such as the size and exact type of font, enables the respondent to answer the questionnaire questions conveniently.

According to the research model in this study, each latent variable is intangible and cannot directly observed or quantified. It could indirectly infer (directly measured) through association with other observable variables. A questionnaire was designed and built based on the latent variables captured from the research model, such as BDACs and SSCP. The constructs' operationalisation was based on prior literature, especially empirical studies (Borsboom et al., 2003) (see Section 4.7).

The questionnaire development process is considered one of the significant parts of this thesis. Thus, intensive efforts were made to avoid self-reporting bias in questionnaire design. Firstly, an online questionnaire development tool known as Survey Monkey was used to generate the questionnaire. This tool is provided with different options to design a practical presentation of the questionnaire through attractive colours, fonts, and a professional outlook. Secondly, consideration was taken to deliver the invitation letter in appealing appearance and demonstrated good research practice. Thirdly, potential respondents were greeted with a real-world problem that indicated significance to practice. Confidentiality was assured, and a research ethics approval number was also produced. In addition, incentives such as executive summary were offered to build credibility and facilitate better response rates.

A draft questionnaire was designed to be straightforward to increase the likelihood of participation. One professional expert in the industry and two academics were asked to review and comment on the suggested research instrument. Their comments were used to improve the survey's content and design. The questionnaire was subjected to an extra round of testing by a small sample group of 12 people. The reviewers' feedback was considered.

3.7 Questionnaire Design

The complete questionnaire (shown in Appendix F) was structured into four separate sections, discussed in the following summaries.

Section 1: Basic Organisational Characteristics

This section comprises nine questions in which the respondents were asked about their characteristics and those of their organisation. From an individual perspective, the respondents were asked for their education level, role, sex, and experience in the organisation. On the other hand, the respondents were asked for the organisational characteristics such as size, location, legal status, and primary activity.

Section 2: Big data Analytics Capabilities

BDACs are conceptualised as two-dimensional in this study, referring to both BDA human and non-human capabilities. The questionnaire contained eleven indicator statements for human BDACs (technical and managerial skills) and eight indicator statements for non-human BDACs (infrastructure). The scale used for all questions was a five-point Likert scale ranging from (1) strongly agree to (5) strongly disagree.

Section 3: Sustainable Supply Chain Performance

This section consisted of three sub-sections regarding sustainability performance. Sustainability performance was assessed based on perceptual measures (rather than objective measures) for three reasons. Firstly, perceptive measures can be just as effective as objective measures when they are effectively constructed and purposefully conducted, taking into account some principal practices (Dess & Robinson, 1984; Singh et al., 2016). Secondly, detailed financial and environmental information from companies is hard to come by. Finally, social sustainability is the most difficult sustainability dimension to assess due to the inability to determine which impacts should be considered (Hutchins & Sutherland, 2008) and quantify those impacts (Beske-Janssen et al., 2015). As such, the respondents were asked to assess their supply chain performance. This was done using a five-point Likert scale from (1) strongly agree to (5) strongly disagree.

Section 4: Supplier Integration

Supplier integration reflects embedding all of your firm's requirements for participation in the supply chain. This section asked respondents to assess their firm's incorporation of supplier integration using a five-point Likert scale from (1) strongly agree to (5) strongly disagree.

Section 5: Code of Conduct

Code of conduct is one of the most proper measures which is extensively used to achieve corporate social responsibility (Blome & Paulraj, 2013). These codes generally set minimum standards for businesses to reach the ‘do no harm’ form of CSR. Codes of Conduct are defined as "voluntary policy tools that set up social (and environmental) standards for multinationals in their supply chain operations around the world and tend to include generic clauses on child labour, forced labour, harassment, health and safety, freedom of association and discrimination” (Prieto-Carrón, 2008, p. 5) Code of conduct is used in this thesis to measure firms' CSR in the supply chain. This section asked respondents to assess their firms and supply chain compliance with the code of conduct using a five-point Likert scale from (1) strongly agree to (5) strongly disagree.

Section 6: Alignment of Business Strategy With BDACS

Business strategy is considered a primary concern of top management because it is crucial for a given business’s survival in a competitive global environment. Alignment of business strategy with BDACs is defined as how BDA strategies align with the overall organisation strategy (Agarwal & Dhar, 2014; Akter et al., 2016; McAfee, Brynjolfsson, Davenport, Patil, & Barton, 2012). The respondents were asked to assess the alignment of business strategy with BDACs. That was done using a five-point Likert scale from (1) strongly agree to (5) strongly disagree.

3.8 Ethical Consideration (Consideration of Ethics and Risks)

This thesis meets the ethics guidelines governed by "The Human Research Ethics Committee" at the University of Technology Sydney (UTS). The UTS Human Research Ethics Committee (HREC) on 11th May 2020 approved this research project. The approval number is UTS HREC REF NO. ETH20-4661 and is attached in Appendix A.

3.9 Selection of Target Population

This study strives to connect two research streams, namely BDACs and SSCP. The study samples were drawn from people who ought to have sufficient subject-matter knowledge to answer all questionnaire questions. The questionnaire asked about BDACs and sustainability performance. Consequently, it is considered the principal challenge.

There were two options to select the target population in this study. Firstly, ask multiple employees within the same organisation to complete different questionnaire parts and then join those parts for analysis. This technique may reduce any self-reporting bias, but it is likely to lower the response rate significantly. Secondly, asking specific employees within the same organisation to complete different parts of the questionnaire simultaneously. The main advantage of this is likely to increase the response rate.

There are two main criteria to select the population; this study discusses a brief overview of these criteria below.

1. IT decision-makers criteria

Respondents should have knowledge about: (a) the status of data analytics in their organisation, particularly the level of adopting BDACs (technical and managerial skills and infrastructure), and b) sustainable performance. Therefore, the ideal target respondents were IT-related managers, analytic professionals, or senior managers.

Analytic professionals can be assigned to many different organisational units, as they are challenging to locate in organisations. Senior managers have good knowledge of sustainable performance but may have shallow knowledge of technical aspects of BDA. Consequently, IT-related managers seemed a reachable and reasonable target. Moreover, the survey targeted only chief information officers (CIOs) and senior IT managers to ensure that respondents answered sustainable performance questions.

2. Organisation size criterion

Organisation size was employed as a criterion to control the population sample. According to the Australian Bureau of Statistics (2001), a classification scheme for SMEs was adopted; whereby 1-4 employees denotes a micro-business, 5-19 is classified as a small business, 19-199 is a medium business, and 200 employees and above is a large business. In particular, small organisations were excluded in this research because they have not adopted BDA and/or sustainable performance.

The researcher coordinated with a marketing research firm in Australia to determine potential respondents. The total of IT decision-makers in all Australian organisations regardless of size and industry is 9,237. In this study, the target respondents were IT decision-makers in medium and large organisations in Australia. According to these criteria, a list of 1,221 email contacts were received from the marketing provider (IMPACT LISTS), representing the sample size. This list contained the organisation's name, manager's name, position title, and email contacts.

3.9.1 Sample Size

Selecting an appropriate sample size is a critical issue to ensure research credibility and validity (Wolverton, 2009) and determine the extent to which statistical or analytic generalisations could be inferred (Onwuegbuzie & Collins, 2007).

According to Saunders et al. (2019), the following factors influence sample size selection:

1) data analysis technique,

2) a confidence that certainty level guarantees the features of collected samples are representative of the population,

3) the population size from which the researcher selects a sample,

4) margin of error that could be tolerated,

5) the number of research questions.

According to Hoyle (1995), sample size (from 100 to 200 individuals) is typically an appropriate point to start with path modelling. However, sample size selection is mainly correlated with the data analysis technique of the research and resources available, such as time and budget (Bryman and Bell, 2015; Saunders et al., 2019). In light of this, we draw on Partial Least Squares Structural Equation Modelling (PLS-SEM) as a data analysis approach to determine the sample size. PLS-SEM offers valid results in small samples (Hair, Hult, et al., 2017). Diverse PLS-SEM academics have recommended a rule of thumb for approximating sample size. The 10-times rule or the minimum R2 rule is recommended for the estimation of the minimum sample size. The 10-times rule indicates the minimum size of a sample is ten times the highest number of structural paths directed at a specific construct (Hair et al. 2016). In this case, the research model's highest number of structural paths is 3 (see Figure 3-4); thus, a minimum sample size of 30 is recommended. According to R2 rule, Hair et al. (2013) suggest that the following factors can drive the minimum sample size in a structural equation model design:

1. the significance level (1%, 5%, 10%,0.75)
2. the statistical power (commonly used 80%)

3. the minimum coefficient of determination (R^2 values) in structural model (0.10, 0.25, 0.50, 0.75)
4. complexity level of the PLS path model (the highest number of arrows pointing to a latent variable).

According to these factors, we need at least 22 observations to accomplish a statistical power of 80% for discovering R^2 values of at least 0.5 (at 1% significance levels). As a result, a sample size of 73 replies was regarded sufficient for this study.

3.10 Data Collection Process

We collected data within approximately 12 weeks, from July to September 2020. the survey was officially launched on Wednesday, 1st July 2020, via sending an email Invitation to the 1,221 target respondents. It was challenging to determine whether the respondents had already done the questionnaire. So, the researcher sent a follow-up email to all target respondents two weeks later to raise the response rate. However, in a follow-up email, we added a note stating, “If you have already completed and submitted the survey, thank you for your input. Please disregard this email”.

In September 2020, the final reminder email was delivered. A total of 1221 organisations were contacted by survey invitation email, with 98 responding. It's vital to notice that each response came from an individual organisation. Six organisations also said that they were unable to participate in the study. All responses were double-checked to guarantee that all responses satisfied the relevant standards. Some responses were excluded from further analysis for the following reasons. Firstly, respondents took significantly less time than expected to complete the survey (less than 5 minutes) (20 replies). Secondly, respondents have worked for an organisation with less than 20 people (2 answers). The final valid responses were 76, which represents an 8.03% response rate. Table 3-11 displays an analysis of the survey responses.

Table 3-12 Analysis of the Survey Responses

Target Sample	**1,221**
After the first invitation, responses had been received	10
After the first reminder, responses had been received	0
After the second reminder, responses had been received	26
After the final reminder, responses had been received	62
Total number of survey responses	**98**
Excepted responses:	
Response time (less than 5 minutes)	20
Size of organisation (less than 20 employees)	2
Final Sample	76
Response Rate (Total number of survey responses /Total Surveys Delivered)	8.03%

As seen in table 3-13, the response rate is low; this is the researcher's principal challenge when collecting data. It is critical to reaching a high response rate since it contributes to generalising the research results (Malhotra and Grover, 1998). That is a significant concern for researchers due to gradually decreasing response rates in academic studies in current decades (Baruch, 1999). These hurdles are more clearly noted in online internet surveys because of limited web access, personal hesitation to use the internet, and the challenge to collect valid email addresses (Klassen and Jacobs, 2001). Our target respondents are IT decision-makers in senior, medium, and mixed management levels in different Australian industries. They are well busy and do not have enough time to fill questionnaires. In addition, survey participation was voluntary, and data was collected during COVID-19. Therefore, the response rate is low (8.03 %). Despite this, the sample size is reliable and sufficient, considering the 10-times rule or the minimum R^2 rule.

Chapter 4. Data Analysis and Results

This chapter commences with the process of the data entry and administration in Section 4.1and then presents data screening in Section 4.2 to help ensure the integrity of the data for data analysis.In Section 4.3 the data quality issues are addressed including reliability, convergent and discriminant validity to verify the truthfulness and credibility of data. Thereafter, in Section 4.4, in order to determine whether the measurement items are representing their respective measures, factor analysis is conducted to confirm that they are indeed accounted for by the same underlying variable. In section 4.5, an overview of the participant's organisational and demographic characteristics is presented as well as a descriptive analysis of all study's constructs. To evaluate the PLS-SEM model, two key stages is contacted in section 4.6. Firstly, assessing the quality of the measurement model (outer model) and, secondly, evaluating the structural model (inner model) to test the research hypotheses constituting the theorised model and the hypotheses testing results in section 4.7. section4.8 reviews the summary of the research results.

4.1 Data preparation and Coding

We used an online survey development tool known as Survey Monkey to administer the online survey in this research. After finishing the data collection, the survey data were retrieved using the 'Survey Monkey online portal'. That portal was also used to upload data into an Excel file. Next, the dataset was refined by dropping data related to response time (less than five minutes) and firm size of fewer than 20 employees (22 responses in total). Finally, the dataset of 76 firms had been created. We coded each variable in the Excel file, i.e., technical skills ⇨ TS, managerial skill ⇨ MS, infrastructure ⇨ Inf, economic performance ⇨ ECP, social performance ⇨ SP, environmental performance ⇨ ENP, supplier integration ⇨ SI, Corporate social responsibility ⇨ CSR, Alignment of business strategy with BDACs ⇨ Alg. Then we used the IBM Statistics SPSS 25 to transfer 76 data set from Excel into an SPSS file.

4.2 Data Screening

Data screening is another effective procedure for checking missing values, data normality and assessing common method variance. These procedures are presented in the following sub-sections.

4.2.1 Missing Data

Missing data is considered a recurrent research problem, mainly when using the survey instrument. Missing data is defined as invalid responses associated with one or more constructs (Hair et al., 2014a). The missing data results from respondents' leaving or refusing to answer questions for several reasons, including the questionnaire's length and perceived sensitivity (Forza, 2016).

In this study, descriptive statistics, like frequencies, have been conducted for all constructs to check the dataset's missing values. Three responses failed to answer questions related to key constructs. Consequently, three complete observations were removed from the data set (76). Thus, 73 valid observations were eventually retained (see Appendix E).

4.2.2 Normality Testing

Evaluating the data normality is a significant prerequisite of many statistical analyses, particularly for parametric tests. Although PLS-SEM is a xcparametric method (free from normal distribution assumptions), excessive nonnormality will greatly affect the validity of parameter estimates. That is why it is critical to ensure the data is not steeply clustered around a single value (kurtosis) or overly biased in one direction (skewness) (Hair, Hult, et al., 2017). A general rule of thumb for skewness and kurtosis is that values of kurtosis exceeding ±10 and values of skewness exceeding ±3 are cause for concern and can be categorised as extremely non-normal (Kline,2015).

In this research, skewness and kurtosis values for each item were determined using IBM Statistics SPSS 25. The results (presented in Appendix E) indicate that all skewness and kurtosis values for all items are well under the thresholds suggested by Kline (2015). Consequently, excessive non-normality of data is not a critical matter in this thesis.

4.2.3 Common Method Bias Test

Common method bias occurs when a single questionnaire survey is used to measure all study scales simultaneously(Lee & Podsakoff, 2003). Such a bias can significantly influence measurement scale reliability and validity as well as co-variation between the constructs (Tehseen et al., 2017). The most recommended statistical tests for CMB include Harman's single-factor test, Partial Correlation procedures, Correlation Matrix procedure and the Measured Latent Marker Variable approach (Tehseen et al., 2017). Like many studies, this study uses the Correlation Matrix procedure to detect CMB. It was suggested by (Bagozzi et al., 1991). Correlations between the primary constructs over 0.9 indicate common method bias(Tehseen et al., 2020). In this study, according to the Correlation Matrix in Table 4-1. The values of latent construct correlations are less than 0.9. Thus, CMB is not a critical issue.

Table 4-1 Latent Variables Correlation

	BDACs	SSCP	SI	CSR	Alg
BDACs	1				
SSCP	0.822**	1			
SI	0.425**	0.467**	1		
CSR	0.633**	0.585**	0.391**	1	
Alg	0.696**	0.699**	0.365**	0.568**	1

**. Correlation is significant at the 0.01 level (2-tailed)

4.3 Data quality

Addressing data quality implications is beneficial before carrying out the statistical analysis. Validity and reliability concepts are commonly used to determine data quality (Saunders et al., 2009).

4.3.1 Validity

Validity refers to the extent of a measure's accuracy of measuring the concept (variable) (Bryman and Bell, 2015). It is principally linked to assessing the research results' precision, relevance, and integrity (Saunders et al., 2019). Consequently, validity is the most crucial criterion for the quality of research to determine the level of generalisation of research results. In quantitative studies, there are two critical types of validity tests i.e., content validity and construct validity (see Table 4-2).

Table 4-2. Types of Validity (derived from Bryman and Bell, 2015).

Validity type	Concept	This study's implications
Content validity	The extent to which a measure's items are fairly representative of the entire domain which latent concept strives to measure.	According to the extensive literature review conducted in Chapter 2, it is assumed that the scales adopted were drawn directly from existing published research.
Construct validity	The extent to which the study's measurement items actually measure intended constructs.	Confirming convergent and discriminant validity is used to achieve it, Drawing on Section 4.7.1. and 4.7.2.
Convergent validity (a subtype of construct validity)	The extent to which an indicator (instruments measuring) strongly associated with an alternative indicator of the identical construct.	The average variance extracted (AVE) is used to test it, Drawing on Section 4.7.1.
Discriminant validity (a subtype of construct validity)	The extent to which the indicators associated with a particular latent construct are connected to the same construct more than to another different construct (construct is different from other constructs).	The cross-loading and contemporary heterotrait-monotrait (HTMT) ratio is used to test it. Drawing on Section 4.7.2.

These validity types are aimed at evaluating every indicator's ability to measure its theoretical concept. Regarding content validity, the literature indicates that researchers should embrace validated instruments in prior research rather than improving new ones (Zohrabi, 2013). Therefore, most of the measurements in this study were adapted from the previous research directly, such as (Akter & Wamba, 2016; Dubey et al., 2017; Gupta & George, 2016) and they had also already been applied and validated in additional studies like (Ciampi et al., 2021; Jeble et al., 2018; Mikalef et al., 2020; Singh & El-Kassar, 2019) (see section 3.5 in chapter 3). Consequently, content validity was verified.

In addition, construct validity pertains to how measurement items measure an intended construct. It is commonly empirically tested through discriminant and convergent validity. Convergent validity can typically be attained through average variance extracted (AVE). On the other hand, cross-loading and the contemporary heterotrait-monotrait (HTMT) ratio are used to test discriminant validity. In section 5.7, we assessed the construct validity of all constructs.

4.3.2 Reliability

The second significant concept that identifies data quality is reliability. Reliability indicates "consistency of a measure of a concept "(Bell et al., 2018, p. 172). As per Saunders et al. (2019), all research measures must be consistent with being considered reliable. The measure is deemed to be reliable if it returns similar results under identical circumstances. It is commonly empirically tested through Cronbach's alpha coefficient. In Section 5.7, we assessed reliability of all constructs.

4.4 Factor Analysis

Factor Analysis (FA) is a statistical technique used to detect some variables' underlying structure in multivariate statistics. This technique aims to determine the primary relationships between determined constructs (Bandalos and Finney, 2018). Researchers mainly use it when developing a scale (a group of questions used to measure a particular construct) and state a group of latent constructs. Factor analysis is employed to obtain data summarising and filtering. Data summarising is usually applied to recognize the appropriate framework of the study variables under the accurate factors. In contrast, data reduction is a statistical method eliminating uncorrelated items and reducing the number of items found in each variable (Bougie & Sekaran, 2016).

Kaiser-Meyer-Olkin (KMO) is a sampling adequacy measure used to assess the appropriateness of data for factor analysis (Field, 2000). The KMO statistic varies between zero to one, but the generally acceptable index is over 0.6. As a minimum, the value of KMO should be at least 0.5, and a value between 0.5 and 0.7 is mediocre, and a value between 0.7 and 0.8 is excellent, between 0.8 and 0.9 is great, and above 0.9 is excellent (Hadi et al., 2016). Similarly, Hair et al. (2006) accepted the value of KMO greater than 0.5 and recommended value between 0.5 and 0.7 as mediocre and between 0.7 and 0.8 as good. The results illustrated in Table 4-5 demonstrate that all factors achieve values of more than 0.7. but three factors (corporate social responsibility, economic and environmental performance) contribute to small KMO due to having only two items. Moreover, they achieve a cut off of 0.5 as a minimum KMO value, and Cronbach's Alpha values for all of them are greater than 0.75, indicating data suitability for the factor analysis.

The Principal Component Analysis (PCA) with Varimax rotation is employed as an extraction method. The factors extracted are connected to all variables (see table 4-5), which provide sub-variables measuring main variables with their respective items to measure each sub-variable. The researcher renamed them based on the factor they described. The researcher, based on this result, reordered these items to stand together with its associated factor. Big Data analytics capabilities (BDACs) as an independent variable has two dimensions: human and non-human factors. The human factor has two dimensions (technical and managerial skills). In contrast, the non-human factor has one dimension (infrastructure). The dependent variable is the sustainable supply chain performance (SSCP), which comprises three factors (social, economic, and environmental performance). This study included three moderators (alignment of business strategy with BDACs, corporate social responsibility and supplier integration).

As per Hair et al. (2014), if factor loading for a measurement item is 0.5 or above, it will have practical significance for that factor. The results in the table indicate most measurement items demonstrate a factor loading of more than a cut off of 0.5 as a minimum recommended value which implies that at least half of the variance can be explained by all items in the respective construct. Consequently, all factors (variables) are suitable for further analysis.

Table 4-3 Factor Analysis and Reliability

Construct	Sub-construct	Second sub construct	Number of items	KMO	Cronbach's Alpha
BDACs	BDA Human capabilities	Management skills	5	0.83	0.84
		Technical skills	6	0.83	0.90
	BDA Non-human capabilities	Infrastructure	8	0.88	0.90
SSCP	Economic performance		2	0.50	0.90
	Environmental performance		2	0.50	0.74
	Social performance		3	0.71	0.84
Supplier integration			7	0.81	0.86
Corporate social responsibility			2	0.50	0.81
Alignment of business strategy with BDACs			4	0.80	0.89

Table 4-4 Rotated Component Matrix

Item	TS	MS	Inf	EP	EP	SP	SI	CSR	ALg
TS1	.869								
TS2	.797								
TS3	.796								
TS4	.788								
TS5	.711								
MS1		.874							
MS2		.873							
MS3		.860							
MS4		.815							
MS5		.779							
MS6		.765							
Inf1			.837						
Inf2			.833						
Inf3			.821						
Inf4			.749						
Inf5			.738						
Inf6			.734						
Inf7			.723						
Inf8			.709						
ENP1				.958					
ENP2				.958					
ECP1					.892				
ECP2					.892				
SP1						.908			
SP2						.863			
SP3						.858			
SI1							.892		
SI2							.884		
SI3							.867		
SI4							.851		
SI5							.529		
SI6							.509		
SI7							.500		
COC1								.918	
COC2								.918	
Alg1									.902
Alg2									.876
Alg3									.856
Alg4									.843

Extraction Method: Principal Component Analysis.

Rotation Method: Varimax with Kaiser Normalization.

4.5 Descriptive Statistics

4.5.1 Respondent Profile

The sample demographic was analysed using SPSS 25, and the results are shown in table 4-5. The 73 valid responses represent around (72.6%) male and (26%) female. In terms of respondent type, respondents hold varied management positions in their firms. Most respondents are chief information officers (23.3%), followed by IT directors (21.9%). The study targeted senior, medium, and mixed management levels to participate in this study.

Consequently, the gathered sample comprises managers with knowledge of their firm's sustainable performance and Big Data analytics. This sample of managers who work in different industries guaranteed the reliability of responses and, in turn, the robustness of the findings. Most of the respondents have held their positions for a relatively long time (see Table 4-5) i.e., 84.9% of the respondents have been in their organisations for more than three years, while only 15.1% have been in the position for less than three years but more than one year.

In essence, in this research, the job role of respondents is the main criterion determining to which extent respondents have experience and knowledge to answer the questionnaire based on their job position. This criterion reflects the respondent's sufficient knowledge and experience to answer the survey questionnaire. Consequently, the respondents were considered to be representative of the research sample. The received responses were consistent with the pre-determined respondent criterion (job role). The respondents consisted of IT decision-makers from several industries who have identical features to the target population. Thus, the research samples have all the desired traits of a representative sample of the target population, which guarantees a sufficient confidence level that the samples represent the population on statistical grounds.

Table 4-5 Respondent Profile

Respondent Descriptive Statistics	Number	% (rounded)
Gender		
Female	19	26.0
Male	53	72.6
Prefer not to say	1	1.4
Education status		
Secondary qualifications	6	8.2
College qualification (diploma/certificate)	9	12.3
Undergraduate degree	27	37.0
Postgraduate degree (Master's/PhD)	31	42.5
Experience		
1 - 3 years	11	15.1
More than 3 years	62	84.9
Position		
Chief Information Officer	17	23.3
IT Director	16	21.9
IT Services Manager	14	19.2
IT Infrastructure Manager	7	9.6
Systems/Network Administrator	3	4.1
General manager-IT manager	4	5.5
Chief Enterprise Architect	1	1.4
Other positions	9	12.3
Didn't mention	2	2.7

4.5.2 Organisational Profile

An overview of the participant's organisational characteristics is presented in this section. In terms of industry type characteristics, all samples were collected from different Australian industries. Here, hospitality and tourism, retail/supermarkets, research and development, mining, sales and marketing, and digital media have low participation. Each of these sectors achieved 1.4% of total responses. The high response industry is IT/IT consulting, with more than 30% responses.

Firm size can affect decision-making rationality and organisational performance (Garg, Walters, & Priem, 2003). The measurement of an organisation's size depends on the number of full-time employees collected through a demographic question in this study. As per the Australian Bureau of Statistics (2001), a classification scheme for SMEs was adopted; whereby 1-4 employees denote a micro-business, 5-19 is classified as a small business, 19-199 is a medium business, and 200 employees and above is a large business. In particular, small firms were excluded from this study. Table 4-6 shows that medium and large organisations were included in the survey where a total of 44 organisations were categorised as large firms (60.2%) and 29 organisations were medium-sized (39.7%). Moreover, half of organisations' legal status were private companies (37%), followed by publicly listed companies (25%). Victoria - Melbourne represented half of the participant's location ((38.3%)), followed by NSW-Sydney (24.7%).

Table 4-6 Organisational Profile

Organisational Descriptive Statistic	N	% (rounded)
Size (No. of employees)		
20- 199	29	39.7
200-1000	15	20.5
Over 1000 employees	29	39.7
The legal status of organization		
Publicly Listed Company	25	34.2
Private Company	37	50.7
Governmental organization	11	15.1
Industry(s)		
IT/IT Consulting	22	30.1
Engineering	3	4.1
Medical & Healthcare	4	5.5
Education & Training	8	11.0
Mining	1	1.4
Banking & Finance	5	6.8
Research & Development	1	1.4
Sales & Marketing	1	1.4
Commerce & Trade	3	4.1
Transport & Logistics	5	6.8
Hospitality & Tourism	1	1.4
Digital Media	1	1.4
Management & Consulting	5	6.8
Construction	4	5.5
Manufacturing	6	8.2
Wholesale, Distribution	1	1.4
Retail / supermarkets	1	1.4
Government	1	1.4

4.5.3 Study Constructs

Descriptive analysis is widely used in social science studies to illustrate the key features of collected data. Thus, each item's mean and standard deviation (SD) value were analysed through descriptive statistics. Standard deviation does not mean right or wrong, or even better or worse result; a lower SD is not necessarily more recommended. It is used merely as a descriptive statistic and describes the distribution to the mean. In this study, the survey items were based on a 5-point Likert-type scale. The research constructs are one primary independent variable and one dependent variable. Big Data analytics capabilities is an independent variable with two sub-constructs extracted from previous studies (human and non-human). Sustainable supply chain performance is a dependent variable with three sub-constructs (economic, environmental, and social performance). In addition, three moderators included supplier integration, corporate social responsibility and alignment of business strategy with BDACs.

4.5.3.1 Descriptive Analysis of BDACs

Big Data analytics capabilities is measured, as said earlier, with two dimensions. The first is related to a BDA human capabilities variable that includes technical skills, assessed by five items using a 5-point interval Likert Scale and management skills, measured by six items with the same scale. The second dimension, related to BDA non-human capabilities (infrastructure), is measured using eight items and shown in Table 4-7, which presents the statements' agreement levels.

Table 4-7 Mean and SD of Big Data Analytics Capabilities

Sub-construct	Item code	Statement	Mean	SD
Technical skills	TS1	We have explored or adopted parallel computing approaches (e.g., Hadoop) to big data processing	2.52	1.260
	TS2	We have explored or adopted different data visualization tools	1.93	.933
	TS3	We have explored or adopted cloud-based services for processing data and doing analytics	1.96	1.184
	TS4	We have explored or adopted open-source software for big data and analytics	2.38	1.162
	TS5	We have explored or adopted new forms of databases such as NoSQL (Not only SQL) for storing data.	2.49	1.168
Management skills	MS1	Our BDACs managers understand and appreciate the sustainable business development needs of other functional managers, suppliers, and customers.	2.26	1.118
	MS2	Our BDACs managers can coordinate BDACs related activities in ways to support other functional managers, suppliers, and customers.	2.41	1.141
	MS3	Our BDACs managers can work with functional managers, suppliers, and customers to determine opportunities that BD might bring to our business.	2.38	1.138
	MS4	Our BDACs managers can anticipate the future business needs of the other functional managers, suppliers, and customers	2.19	1.036
	MS5	Our big data analytics managers have a good sense of where to apply big data.	2.36	1.098
	MS6	Our big data analytics managers are able to understand and evaluate the output extracted from big data	2.48	1.107
Infrastructure	Inf1	Compared to rivals within our industry, our organisation has the foremost available analytics systems.	2.45	.987
	Inf2	All remote, branch and mobile offices are connected to the central office for analytics.	2.01	1.034
	Inf3	Our organisation utilizes open systems network mechanisms to boost analytics connectivity.	2.38	1.162
	Inf4	There are no identifiable communications bottlenecks within our organisation when sharing analytics insights.	2.48	1.029
	Inf5	Software applications can be easily transported and used across multiple analytics platforms.	2.40	.968
	Inf6	Our user interfaces provide transparent access to all platforms and applications.	2.47	1.068
	Inf7	Analytics-driven information is shared seamlessly across our organisation, regardless of the location.	2.34	1.083
	Inf8	Our organisation provides multiple analytics interfaces or entry points for external end-users.	2.25	1.038

Employee IT Skills were assessed by using four items. As shown in Table 4-7, the mean score for those indicators ranged from 1.93 to 2.52, reflecting the agreement level toward these items. For example, most of the responses revealed that TS1 (we have explored or adopted parallel computing approaches (e.g., Hadoop) to Big Data processing) was a common feature of technical skills dominating the organisations examined in Australia. That, in turn, reflected the organisations' importance in having various computing methods to deal with Big Data. The SD of this item was 2.52. On the other hand, a minor item that achieved the least mean was TS2 (we have explored or adopted different data visualisation tools), which also indicated the diversity of the tools used among the organisations to visualise the Big Data with a mean of 1.93.

4.5.3.2 Descriptive Analysis of Sustainable Supply Chain Performance

Sustainable supply chain performance is the dependent variable of this study, which is measured by three dimensions (social, environmental and economic performance), and each has sets of items (2, 2, and 3, respectively) also using a 5-point interval Likert Scale. Table 4-8 displays the levels of agreement as to the mean values of these items.

Table 4-8 Mean and SD of Sustainable Supply Chain Performance

Sub-construct	Item code	Statement	Mean	SD
Economic performance	ECP1	Attain improving profit growth.	2.12	1.092
	ECP2	Accomplish improving sales growth	2.19	1.036
Environmental performance	ENP2	Attain a reduction of air emissions.	2.73	1.272
	ENP3	Success in reducing waste (water and/or solid).	2.60	1.244
Social performance	SP1	Employ better practices, which lead to the improvement of gender equality.	2.37	1.184
	SP2	Achieve better practices lowering health and safety accidents.	2.22	1.133
	SP3	Achieve better practices through increased buying from local suppliers	2.38	1.075

Social, environmental, and economic performance were the three sub-constructs used to measure the SSCP construct, with two, two, and three items for each, respectively. Table 4-8 shows that these indicators' mean scores ranged from 2.12

to 2.73, reflecting the agreement level toward these items. For example, most of the responses revealed that ENP2 (attain reduction of air emissions) was a common environmental performance factor, reflecting the organisation's struggle to reduce air emissions, supporting its environmental responsibility towards society. On the other hand, the lowest mean was for the item of ECP1 (attain improving profit growth), which examines the organisation's intent to maximise their profit growth on behalf of other performance like social and environmental performance.

4.5.3.3 Descriptive Analysis of Supplier Integration

Supplier integration is the first moderator in this study, measured by seven items using a 5-point interval Likert Scale. Table 4-9 presents the agreement levels as to these items' mean and standard deviation values.

Table 4-9 Mean and SD of Supplier Integration

Construct	Item	Item	Mean	SD
Supplier Integration	SI1	Conducting joint planning with partners to anticipate/resolve potential supply chain problems.	2.30	.967
	SP2	Providing information to help our supply chain partners improve.	2.21	.999
	SP3	Informing partners about industry/regulatory events/changes that may affect them and their products.	2.29	.950
	SP4	Requiring partners to implement EMS programs to address our company policy.	3.12	1.471
	SP5	Requiring collaboration in the design of new products with supply chain partners.	2.92	1.507
	SP6	Requiring partners to visit our facility for feedback to help improve our performance	`	1.659
	SP7	Ensuring supply chain participants provide their employees with necessary training.	2.84	1.599

In table 4-9, the mean score for supplier integration indicators ranged from 2.21 to 3.12. The highest mean among this factor is 3.12 of SP4 (requiring partners to implement EMS programs to address our company policy), which indicates adopting particular approaches and patterns of EMS programs to achieve organisational policy successfully. It could also support the organisations' strategy due to integrating more advanced practices in implanting company operations. Though, SP2 items of the supplier integration construct showed the lowest mean with 2.21 and SD of 0.999.

4.5.3.4 Descriptive Analysis of Corporate Social Responsibility

This study's second moderator construct is corporate social responsibility, measured with two items using a 5-point interval Likert Scale. Table 4-10 presents the levels of agreement as to the mean and standard deviation values of these items. Statistical results show a high perception among the respondents with the significance of CSR. The mean of these items was ranged from 1.88 to 1.93 and SD of 0.816 and 0. 855. Statistical results.

Table 4-10 Mean and SD of Corporate Social Responsibility

Construct	Item	Item	Mean	SD
CSR	CSR1	Supply chain organisations have a corporate social responsibility	1.88	.816
	CSR2	Established a corporate social responsibility	1.93	.855

4.5.3.5 Descriptive Analysis of Alignment of Business Strategy with BDACs

Alignment of business strategy with BDACs is the third moderator construct of this study, measured with four items, using a 5-point interval Likert Scale. Table 4-11 presents the levels of agreement as to the mean and standard deviation values of these items. Statistical results display high perceptions among the respondents with the significance of this construct. The mean of these items ranged from 2.03 to 2.26 and SD of 0.957 to 1.155.

Table 4-11 Mean and SD of Alignment Of Business Strategy with BDACs

Sub-construct	Item code	Statement	Mean	SD
Alignment of business strategy with BDACs	Alg1	Big data analytics plan aligns with the company's mission, goals, objectives, and strategies	2.03	.957
	Alg2	Big data analytics plan contains quantified goals and objectives.	2.11	1.137
	Alg3	Big data analytics plan contains detaile action plans/strategies that support company direction	2.26	1.155
	Alg4	We prioritize significant big data analytics investments by the expected impact on business performance.	2.18	1.110

4.6 Evaluation of the PLS-SEM Model

In the PLS path model, PLS-SEM aims to maximise the variance explained by the endogenous latent variables. Consequently, the metrics reflecting the model's prediction capabilities are used to assess the PLS-SEM measurement and structural models (Hair et al., 2019). To evaluate the PLS-SEM model, there are two main approaches. Firstly, assessing the quality of the measurement model (outer model) and, secondly, evaluating the structural model (inner model). As displayed in Table 4-12, Smart PLS software Version 3 is used to conduct these two approaches.

Table 4-12 Evaluation of the PLS-SEM Model (derived from Hair et al., 2019; Hair Jr et al., 2016)

Evaluation of Reflective Measurement Model
Cross- loadings (≥ 0.6) • Internal consistency reliability Cronbach's alpha (α) composite reliability (CR) • Convergent Validity AVE (≥ 0.5) • Discriminant Validity HTMT (<0.9)
Evaluation of the Structural Model(s)
• Size and significance of path coefficients • Coefficients of determination (R^2) Predictive relevance (Q^2) • *f2* effect sizes

4.7 Measurement Model Analysis

The final study framework includes 39 reflective items for nine variables (latent constructs). Examining the measurements' goodness is the primary step to ensure that the indicators or measures are reliable and valid before analysing the structured model and testing the suggested hypotheses. The literature relevant to this field has shown two methods of testing the dataset's goodness. The first step is called the exploratory factor analysis (EFA). The second method is the confirmatory factor analysis (CFA) (Hair et al., 2010). Although the two approaches have similar features, some studies showed some differences between them.

Although the EFA method is more common and widely used in social studies, this method is not perfect and has some limitations (Watkins, 2018). One key end of this approach appears in how a particular indicator is associated with a certain construct. Under this issue, the analysis to determine the validity of the measurement model examines the higher factor loading regardless of the chance of cross-loading the item on other factors. The main justification for using the CFA is that this method could provide a clear picture of the concept of unidimensional (Orcan, 2018). Consequently, this study runs CFA to test the measurement model, or sometimes called the outer model, by analysing the correlation between the items and its respective construct.

We used SmartPLS Version 3 to assess the measurement model's reliability and different types of validity. Two main criteria were applied to test the measurement models i.e., reliability and validity. Reliability indicates the extent to which instrument measures are free from bias across different times. As per Bougie and Sekaran (2016), reliability is also referred to as an instrument's ability to measure what is to be measured, whereas validity evaluates how well the developed items could measure an intended construct.

4.7.1 Outer Loadings

Examining the outer loading is the first stage in measurement model (outer model) evaluation. It is an essential test of reliability to examine each indicator's load on its respective factor. The outer loadings indicate how the same variable's items are consistent and measure the same concept. Hair et al. (2014a) suggested that outer loading should meet the standard value of 0.70.

Researchers commonly find lower outer loadings less than 0.70 in social science research, especially when recently established measures are used (Hair Jr et al.,2016). As displayed in Table 4-13, only one item (SI4) was dropped due to its low outer loading (0.56) and AVE (0.48). The AVE also improved to (0.5) after dropping SI4. The outer loading indicators between 0.40 and 0.70 should only be taken into consideration for scale removal when eliminating the indicator causes an increase in the AVE, or composite reliability or above the recommended cut-off value (Hair Jr et al.,2016). We eliminate SI4 and maintain and accept the outer loading with fewer than 0.70 but not fewer than 0.40 (Hair Jr et al.,2016).

Table 4-13 Results of Measurement Model

Construct	Item code	Outer loading	CR	AVE
Technical skills	TS1	0.80	0.89	0.63
	TS2	0.78		
	TS3	0.70		
	TS4	0.79		
	TS5	0.87		
Management skills	MS1	0.81	0.92	0.68
	MS2	0.87		
	MS3	0.87		
	MS4	0.78		
	MS5	0.86		
	MS6	0.76		
Infrastructure	Inf1	0.73	0.92	0.59
	Inf2	0.74		
	Inf3	0.82		
	Inf4	0.70		
	Inf5	0.73		
	Inf6	0.83		
	Inf7	0.83		
	Inf8	0.72		
Environmental performance	ENP1	0.95	0.95	0.91
	ENP2	0.96		
Economic performance	ECP1	0.91	0.88	0.79
	ECP2	0.87		
Social performance	SP1	0.91	0.90	0.76
	SP2	0.85		
	SP3	0.86		
Supplier integration*	SI1	0.81	0.86	0.50
	SI2	0.80		
	SI3	0.77		
	SI5	0.60		
	SI6	0.62		
	SI7	0.63		
Corporate social responsibility	CSR1	0.91	0.91	0.84
	CSR2	0.92		
Business strategy alignment	Alg1	0.84	0.92	0.75
	Alg2	0.89		
	Alg3	0.87		
	Alg4	0.85		

***SI4 removed due to validity and reliability concerns.**

4.7.2 Internal Consistency Reliability

4.7.2.1 Cronbach's Alpha Coefficient

One of the most common methods employed as an assessment of reliability is Cronbach's alpha. This study uses Cronbach's alpha internal consistency analysis to assess all survey constructs' reliability for two main reasons. Firstly, one standard form of the questionnaire was sent to all participants simultaneously, and secondly, the survey was conducted only once.

Cronbach's alpha coefficient ranges from 0.00 to 1.00. Acceptable Cronbach's alpha coefficient values should not be 0.60 or less than 0.60 (Malhotra & Birks, 2007). However, Zikmund and Babin (2007, p. 322) provide range reliability of Cronbach's alpha coefficient evaluations which is represented in Table 4-14. They also suggested that 0.60 values could be accepted but offer fair reliability. The reliability coefficients (Cronbach's alpha values) are shown in table 4-15 for all constructs (BDACS, SSCP, SI, CSR, ALG) exceeding the 0.80 level, indicating excellent reliability. This suggests that internal consistency exists among the research variables, confirming a strong correlation among the questionnaire's measurement items.

Table 4-14. Range Reliability of Cronbach's Alpha Coefficient Evaluations(Source: Zikmund and Babin (2007, p. 322)

Range	Evaluation
0.80 –0.95	Excellent reliability
0.70 – 0.80	Good reliability
0.60 – 0.70	Fair reliability
Less than 0.60	Poor reliability

Table 4-15 The Reliability Coefficients (Cronbach's Alpha Values)

Construct	Cronbach's Alpha
BDACs	0.86
SSCP	0.86
SI	0.86
CSR	0.81
ALG	0.89

4.7.2.2 Composite Reliability

Composite reliability (CR) is the most robust evaluation of internal consistency of a construct due to prioritising items by their reliability in evaluating the measurement model (Hair et al., 2011). Composite reliability is a measure of the complete reliability of a set of heterogeneous indicators. The recommended CR value should be equal to or more than 0.70 to confirm that the construct measurements reflect the latent variable (Henseler, 2017). Values between 0.70 and 0.90 can be regarded as satisfactory. Composite reliability values below 0.60 indicate a lack of internal consistency reliability. In this study, all values of CR have met the suggested threshold of 0.70 and ranged from 0.86 to 0.95, as shown in Table 4-13.

4.7.3 Convergent Validity

Convergent validity is the degree to which one measure of a construct correlates with other measurements of the same construct (Hair Jr et al., 2016). It also shows any conflict between measurements of a construct (Cheah et al., 2018). Researchers use different approaches to assess the convergent validity of reflective constructs such as the AVE and the outer loadings of the indicators (Hair Jr et al., 2016) and CR, as discussed in the following subsections.

4.7.3.1 Average Variance Extracted

The AVE is a standard measure of convergent validity. It is the degree to which a latent construct explains the variance of its indicators. It also indicates “the grand mean value of the squared loadings of the indicators associated with the construct (i.e., the sum of the squared loadings divided by the number of indicators)” (Hair Jr et al.,2016, p.138).

In general, a construct with an AVE value of 0.50 or larger explains at least half of its underlying indicators' variance (Hair Jr et al.,2016). In this study, AVE values of all latent constructs have met the suggested threshold value of 0.50, as presented in Table 4-13.

4.7.4 Discriminant Validity

Discriminant validity is a primary approach to assess the uniqueness of constructs in research models. It is used to evaluate the extent to which the latent construct is differentiated from other constructs within the empirical measurements and standards (Hair Jr et al., 2016). Based on this definition, a high value of discriminant validity means that a particular construct is unique in examining a concept, which cannot be imitated by another construct (Hair et al., 2014a). Two different approaches to assessing the discriminant validity of reflective constructs include the Heterotrait-Monotrait Ratio (HTMT) and cross-loading (Hair Jr et al., 2016).

4.7.4.1 Cross-loadings

Cross-loadings are commonly applied to evaluate the discriminant validity of indicators. In this approach, an indicator's outer loading on the associated construct should be greater than any of its cross-loadings (i.e., its correlation) on other constructs (Ab Hamid et al., 2017). Hence, this cross-loading matrix could help examine and interpret the discriminant validity.

As illustrated in Table 4-16, the findings of the cross-loadings indicate that the values of latent construct loadings of each construct, which is in the bold number to its respective latent construct, have exceeded the correlation with other different constructs suggested.

Table 4-16 Cross-Loading Matrix

	CSR	MS	TS	Alg	ECP	ENP	Inf	SP	SI
CSR	**0.91**								
MS	0.55	**0.82**							
TS	0.57	0.78	**0.79**						
Alg	0.57	0.79	0.60	**0.86**					
ECP	0.39	0.45	0.37	0.55	**0.89**				
ENP	0.48	0.65	0.55	0.58	0.34	**0.95**			
Inf	0.58	0.68	0.71	0.55	0.46	0.70	**0.76**		
SP	0.56	0.74	0.64	0.60	0.38	0.78	0.74	**0.87**	
SI	0.58	0.44	0.43	0.44	0.42	0.58	0.46	0.57	**0.69**

4.7.4.2 Heterotrait-Monotrait Ratio

Heterotrait-Monotrait Ratio HTMT is another assessment of the measurement model. The HTMT is considered a novel and more robust method for measuring discriminant validity (Henseler et al., 2015). The HTMT measures the average correlations of indicators across different constructs, in which they measure other concepts and phenomena (Henseler et al., 2015). A measurement of a construct is related to the average of correlations among indicators in the same construct (Henseler et al., 2015). The criterion for HTMT is to have a value below 0.90. Table 4-17 shows that all values of the HTMT test are less than 0.90.

Table 4-17 Heterotrait-Monotrait Ratio (HTMT)

	CSR	MS	TS	Alg	ECP	ENP	Inf	SP	SI
CSR									
MS	0.639								
TS	0.695	0.884							
Alg	0.661	0.879	0.687						
ECP	0.503	0.540	0.469	0.666					
ENP	0.564	0.723	0.625	0.638	0.405				
Inf	0.675	0.751	0.811	0.613	0.565	0.777			
SP	0.678	0.844	0.756	0.688	0.482	0.884	0.885		
SI	0.621	0.462	0.474	0.485	0.508	0.606	0.654	0.607	

Accordingly, most results have been tested successfully, demonstrating the validity and reliability of the measurement model. That enables the researcher to proceed to analyse the structural model and test the current study's hypotheses. Figure 4-1 shows the final resulted measurement model by using Smart PLS software Version 3.

Running the PLS algorithm provided the outer loadings, path coefficients, and the R^2 value for the dependent variable SSCP (see figure 4-1). Figure 4-1 shows the latent endogenous construct of SSCP has an R^2 value of 0.708. The path coefficient and R^2 values can provide a causal relationship when significant or supported by additional data analysis. The primary path is on BDCA with a positive effect value of 0.599. Path coefficients above 0.20 are considered significant, and a value below 0.10 is usually not significant (Hair et al., 2014).

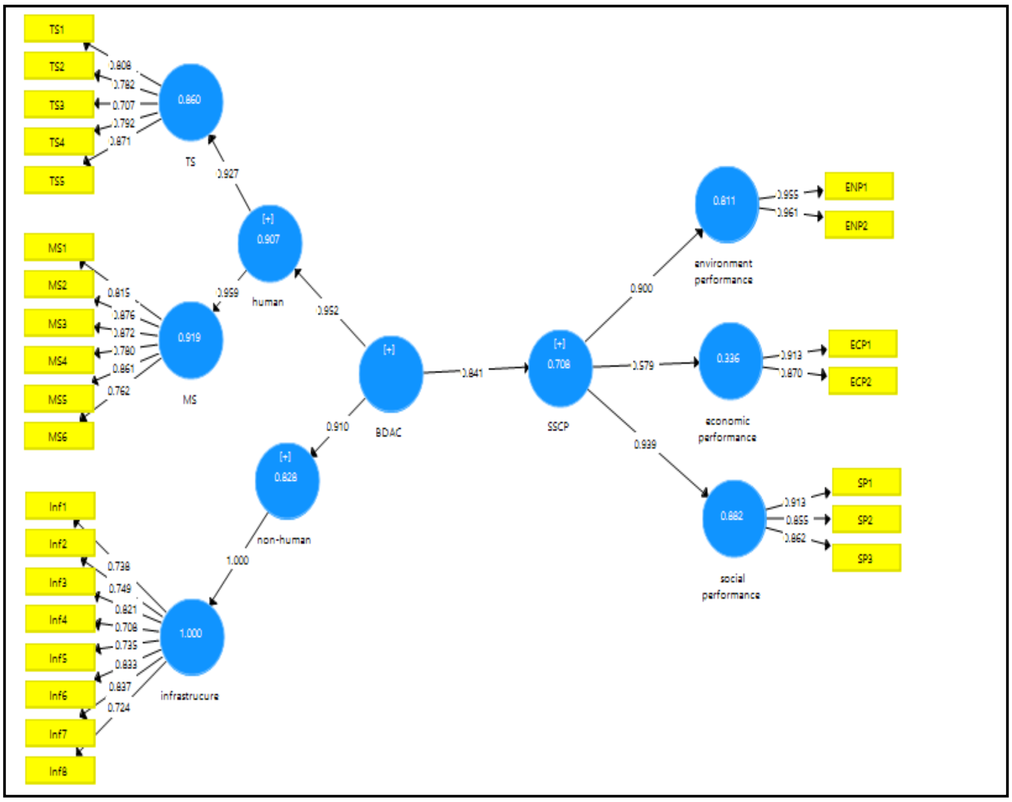

Figure 4-1 Measurement Model Using Smart PLS

4.8 Structural Model Analysis

Having observed the reliability and validity of the measurement model, it was conceivable to test the causal associations in the research model. Accordingly, this section examines whether data and reporting hypothesis testing results evaluate the proposed hypotheses of this research.

Some different tests are suggested to assess the inner model, which focuses on the latent construct. These tests include an assessment of the coefficient of determination (R^2), predictive relevance (Q2), the goodness of fit (GoF), effect size (f^2), and the path coefficient. All these tests will be discussed individually in the following sub-sections. Through a PLS-SEM bootstrapping procedure, the significance of coefficients was determined, as illustrated in Figure 4-2, which presents the PLS model as built with Smart PLS software. This figure shows the results with great significant paths: BDACS to SSCP (.841) with a significant p-value (0.000).

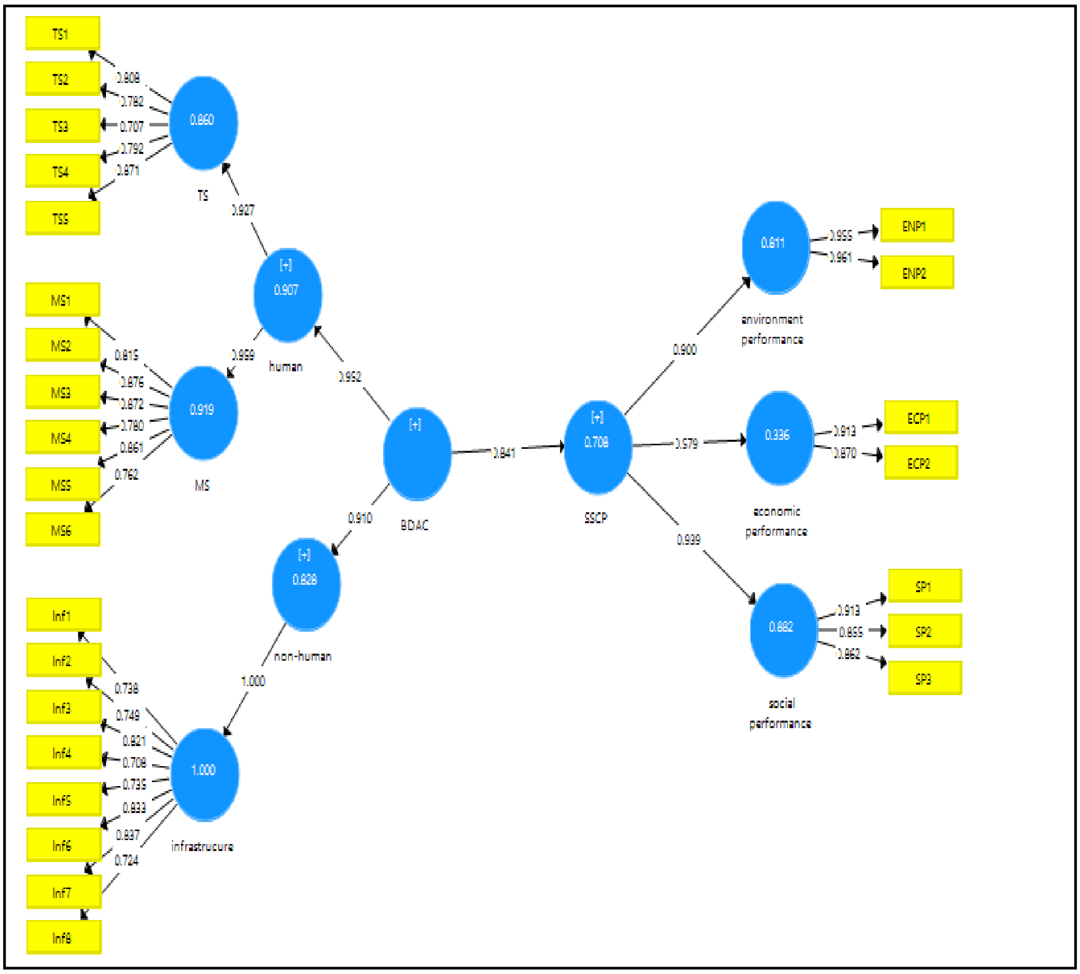

Figure 4-2 Structural Model Path

4.8.1 Coefficient of Determination

One popular method to evaluate the structural model is the coefficient of determination (R^2) which measures the predictive power of the model. The value of R^2 represents the amount of variance in the dependent (endogenous) variables, which can be interpreted by one or more independent (exogenous) variables (Hair Jr et al., 2016). It is calculated by the squared correlation between actual and expected values of a particular endogenous construct. R^2 values of 0.75, 0.50, or 0.25 for the endogenous variable can be defined as substantial, moderate, and weak (Hair Jr et al., 2016). Thus, according to the obtained results in this study, the value of R^2 has fulfilled the suggested criteria. Table 4-18 presents the R^2 value of the endogenous variable and constructs. Based on the results, the power of independent (exogenous) variables of BDACs in explaining SSCP was substantial. That value indicated that this exogenous construct could account for 70.8% of the variance in the SSCP. The R^2 for ENP, SP and ECOP are 0.811, 0.882 and 0.336, respectively, which are substantial, except ECP is weak.

Table 4-18 Coefficient of Determination Scores

Dependent variable	Endogenous construct	R^2	Result
SSCP		0.708	Substantial
	EVP	0.811	Substantial
	SP	0.882	Substantial
	ECOP	0.336	Weak

4.8.2 Predictive Relevance of the Model

Predictive relevance (Q^2) is another statistical criterion used to evaluate the quality of the structural model being studied and predicted. The key assumption of predictive relevance is that the structural model should adequately predict the endogenous variable and its measurements (Ramayah et al., 2018). For that purpose, the blindfolding process has been used to obtain the Q^2 by conducting a Smart PLS software calculation between the cross-validity redundancy and cross validity communality. This procedure will skip the data from the dataset based on a stated distance value called D. This value could be any number between 5 to 10 (Chin, 2010). The only necessary condition is that the sample size divided by D should be a round number.

However, the procedure of blindfolding should only be used if the dependent variable has reflective measurements (Henseler et al., 2017), which are used in this current study. Predictive relevance (Q^2) has two types 1) cross-validity communality and 2) cross-validity redundancy. Hair et al. (2017) suggested using cross-validated redundancy to evaluate both measurement and the structural model for data prediction, which is a good fit with the PLS-SEM procedure. Therefore, if the value of cross-validity redundancy is larger than zero ($Q^2 > 0$), this means predictive relevance is achieved. While a value of Q^2 lower than zero indicates that the model lacks predictive relevance. Table 4-19 shows the predictive relevance result of the endogenous (dependent) variable. Q^2 of an endogenous construct (SSCP) was above zero, which supports the claim that the current study model has a valuable ability to predict.

Table 4-19 Predictive Relevance of Endogenous Construct

Construct	Validated redundancy	Result
SSCP	0.398	Q2 > 0 Explanatory variable provides predictive relevance

4.8.3 Goodness of Fit

Goodness-of-Fit (GoF) is defined as the approved fit measures, which is the geometric mean of both the AVE and the average R^2 of the dependent variable. The main aim of GoF is to estimate the study model at both levels, measurement, and structural models, with more focus on the overall performance of the model (Henseler, 2017). Equation1 shows the formula for calculation of GoF, which includes the square root of R^2 of the endogenous construct times the average of all AVEs. Table 4-20 presents the GoF criteria. According to the obtained results and provided equation, the calculated value of the GoF is 0.711, which is large enough to provide sufficient model validity.

Equation 4-1 Goodness of Fit Formula

$$\boxed{\text{GoF} = \sqrt{R^2 * AVE}}$$

Table 4-20 GoF Baseline Criteria

GoF small	0.10
GoF medium	0.25
GoF large	0.36

4.8.4 Effect Size

Effect size (f^2) is used to check whether the independent (exogenous) variable affects the dependent (endogenous) variable by the difference in the R^2 value when that exogenous variable is excluded from the model vs. when it is included (Hair Jr et al.,2016). Equation 4-1 shows the f^2 calculation. In this case, f^2 calculations were conducted within Smart PLS 3. Based on the assumption made by Cohen (1988) for assessing f^2, the value greater than 0.35 is considered a large effect size in this setting. In contrast, the value between 0.15 to 0.35 is considered medium, between 0.02 to 0.15 is considered small, and a value lower than 0.02 is not affected (Hair Jr et al., 2016). Table 4-21 presents the f^2 for the study variable, which indicates that the effect size of BDACs on SSCP was a large effect. However, the effect size means a strong effect of the BDACs towards SSCP represented in the regression weight value around 0.708, indicating a very strong effect.

Equation 4-2 Effect size (f^2)

$$f^2 = \frac{R^2_{included} - R^2_{excluded}}{1 - R^2_{included}}$$

Table 4-21. Effect Size (f^2) of the Independent Construct

Construct	R2	Effect size F2	Result
BDACS ⟶ SSCP	0.708	0.841	Large effect

4.9 Hypotheses Testing

The final important step of analysing the structural model is testing the research hypotheses by evaluating the path coefficients. The hypotheses were tested by running the bootstrapping procedure. This procedure is a process that resamples a single dataset to create many simulated samples. It allows the researcher to calculate the standard errors, construct confidence intervals and test hypotheses. Generally, PLS-SEM does not require a normally distributed dataset.

4.9.1 Testing Direct Hypotheses

There is a criterion used to determine whether the relationships are significant according to the t-value. Widely, the critical values used are 1.65 at the significance level of 10%, 1.96 at the significance level of 5%, and 2.57 at the significance level of 1%. In explanatory studies, the researchers usually assume a significance level of 10%. Selecting the significance levels depends on the study field and its objective (Morrison and Henkel, 2017). The lower value means the stronger significance of the relationships in the model. Table 4- 22 shows the results of the path coefficient used to test the direct research hypotheses.

Table 4-22 Path Coefficient of Research Hypotheses

Hypothesis	Constructs Path	Path coefficient (β)	Standard deviation	T-value	P-value	Results
H1	BDACS → SSCP	0.841	0.037	22.773	0.000	Supported**
H1a	BDACS → SP	0.729	0.054	13.597	0.000	Supported**
H1b	BDACS → ENP	0.818	0.040	20.241	0.000	Supported**
H1c	BDACS → ECP	0.484	0.108	4.493	0.000	Supported**

****Significant level at P<0.01 and * Significant level at P<0.05.**

BDACS =big data analytical capabilities; SSCP =sustainable supply chain performance; ENP =environmental performance; ECP =economic performance; SP =social performance.

The study model has one main hypothesis with three sub-hypotheses. As displayed in Table 4-22, the beta values for four identified relationships were supported with positive scores. In addition, these path coefficients were significant as the T-values were greater than the significant critical values (>1.96, for significance at 95% level and >2.65 for significance at 99% level). Therefore, all direct hypotheses were significant at 99% and supported.

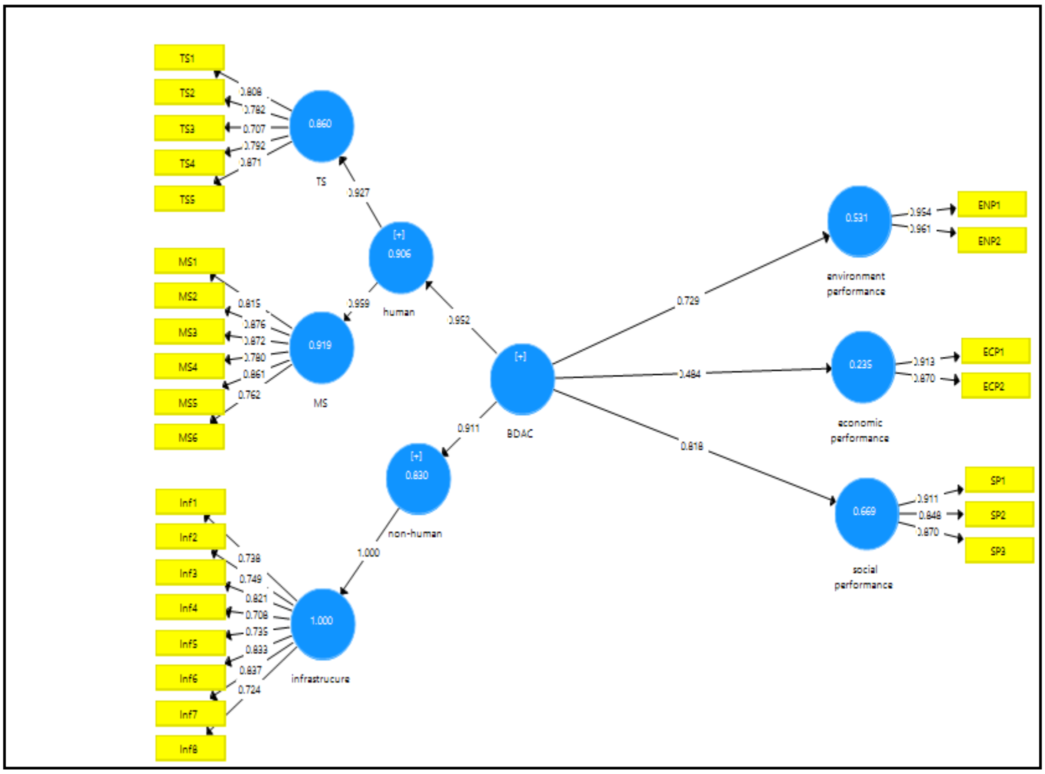

Figure 4-3 Bootstrapping Direct Effect Results

4.9.2 Testing Moderation Hypotheses

Moderation occurs when the moderator variable changes the relationship between the independent and dependent variables (Memon et al., 2019) by either developing, strengthening, or weakening this relationship. This study contains three moderators i.e., alignment of business strategy with BDACs (Alg), corporate social responsibility (CSR), and supplier integration (SI).

The results are shown in Table 4-23, the moderated path of alignment * BDACs → SSCP (t= 0.704, p= 0.482) is not significant. Therefore, the alignment of business strategy with BDACs does not moderate the relationship between BDACS to SSCP. The second moderator path of CSR * BDACs → SSCP (t= 0.798, p= 0.425) is not significant. Thus, CSR does not moderate the relationship between BDACs to SSCP. The third moderator path of supplier integration * BDACs → SSCP (t= 0.720, p= 0.472) is not significant. Consequently, supplier integration does not affect the relationship between BDACs to SSCP.

Table 4-23 Test of Moderating Role

			Bootstrapped Betas			
Hypothesis	**Moderation path**	**Path coefficient (β)**	**Standard deviation**	**T statistics**	**P-values**	**Results**
H2	Alignment*BDACs→ SSCP	-0.033	0.048	0.704	0.482	Not supported
H3	CSR* BDACs→ SSCP	-0.054	0.068	0.798	0.425	Not supported
H4	Supplier integration* BDACs→ SSCP	-0.036	0.050	0.720	0.472	Not supported

4.10 Summary of Results

Based on the target population's results, this study has conducted a set of analyses using SPSS 25 and Smart PLS 3. We used SPSS to extract the descriptive analyses like mean and standard deviation and normal distribution. On the other hand, SmartPLS was used to examine the reliability and the different types of validity, like convergent and discriminant validity. Two main approaches were used to evaluate the PLS-SEM model. The first was the measurement model (outer model), which examined both convergent and discriminant validity. The second approach was performed using the bootstrapping procedure on the structural model (inner model) to test the relationships among the model's constructs and examine the hypothesised relationships. As predicted, a significant positive relationship was found between BDACs and SSCP in the studied sample of organisations from Australia. However, all the moderators showed no interaction effect in the relationship between BDACs and SSCP.

Chapter 5. Discussion

We strive to answer the research questions by effectively achieving the abovementioned research objectives. This study's results were attained by analysing and assessing the research model, effectively answering the research questions. Based on the validated and reliable measurement model and the relative statistical significance support for some hypotheses, the proposed model is considered a good representation of the theoretical relationships among presumed constructs, able to answer the research questions.

5.1 What Capabilities Have Been Required to Build BDACs?

This study conducted a systematic literature review (SLR) of relevant Big Data analytics capability (BDACs) literature to answer this question. Peer-reviewed articles in the English language published from 2010 to 2018 were considered to explore and identify essential BDACs. As a result, we conceptualised BD as a dynamic capability and considered this concept as Big Data analytics capability, drawn on the theoretical lens of the dynamic capabilities view (DCV) (Teece et al., 1997). In addition, the findings of the SLR indicate that most studies have concentrated on resources (organisational and technological) and processes for strategically utilising BD. Yet, actual capabilities to build effective BDACs have been overlooked. There is also neglect of a comprehensive picture of BDACs, although some research has previously investigated and introduced some BDACs (Mikalef et al., 2018).

Consequently, this SLR fills the gap in the literature by depicting a holistic view of BDACs, which involves BDA human and non-human capabilities. The earlier comprises knowledge (relational knowledge and technological management) and skills (technical and managerial skills). The latter has five key components i.e., primary resources, data, infrastructure, organisational learning and data-driven culture. Following this, some well-established measurement scales from previous and contemporary studies were directly adopted to construct the scales for measuring BDACs. Table A illustrates BDAC dimensions with the related attributes for each dimension (see Appendix B). Different statistical tests were conducted to verify that the employed measurements were truly reflective scales and confirmed validity.

Interestingly, considering the critical dimensions of BDACs (human and non-human) is essential for many organisations to acquire the full benefit from BDACs. This result broadly relates to the findings concerning talent, management and infrastructure outlined by Akter et al. (2016) and tangible, intangible and human resources described by Jeble et al. (2018). In that regard, the theoretical contribution of the BDACs SLR is a conceptualisation of BDACs as a technology-based organisational dynamic capability. This conceptualisation lays the groundwork for future research to investigate other organisational processes and BD outcomes. For practitioners, these findings recommend that reaping the benefits of Big Data depends not only on the technologies that enable it but also on human and non human capabilities. Therefore, organisations should strengthen BDACs by enhancing their IT infrastructure and encouraging their human capital to develop Big Data analytical skills (Wamba et al., 2017; Akter et al.,2016). For instance, LaValle et al. (2011) indicate that IT infrastructure is one reason Big Data projects are frequently fruitful.

5.2 What Constitutes the Dimensions of SSCP?

An extensive literature review of relevant SSCP literature was conducted to answer this question. For doing this, the SLR approach was employed across peer-reviewed articles in the English language published from 2010 to 2019 to explore and identify measurement metrics for assessing three main dimensions of sustainability in the supply chain.

Drawing on the triple bottom line (TBL) approach as a theoretical lens to classify sustainability metrics, capturing the intersection of social, economic, and environmental performance. Our literature review creates multi-dimensional measurement metrics for assessing each SSCP dimension.

According to the SLR of SSCP, the findings indicate that social performance is the most challenging aspect of sustainability to assess, due to difficulty determining which influences should be considered (Hutchins & Sutherland, 2008) and how to quantify those influences (Beske-Janssen et al.,2015). Table B illustrates the multi-dimensional measurement metrics for assessing SSCP dimensions (see Appendix C). Consequently, this research has made a valuable contribution to the current literature by providing a multi-dimensional measurement of SSCP comprising social, environmental, and economic performances. These metrics offer a measurement basis for future empirical studies to investigate sustainable performance in the supply chain.

5.3 To What Extent Can BDACs Enhance SSCP?

The effective execution of the first two research questions has enabled the third research question aiming at investigating the impact of BDACs on SSCP. In an attempt to empirically assess the theorised model, this research adopted a quantitative method through web-based survey questionnaires. Consequently, this research collected 73 valid data sets from Australian IT decision-makers (senior IT managers and CIOs) operating in different sectors. Finally, the hypothesised causal relationships in the research model were examined using partial least squares structural equation modelling (PLS-SEM). Research findings stemming from the empirical results were then presented. This study's results were attained by analysing and assessing the impact of BDACs on sustainable supply chain performance. Drawing on statistical significance support for some hypotheses, this study demonstrates that BDACs have positively influenced an organisations' sustainability performance in the supply chain. However, this impact is direct without a moderated effect.

The current results presented significant support to our theoretical reasoning, as explained in Section 2.4.1, that building of BDACs leads to attaining environmental (ENP), social (SP), and economic performance (ECP), achieving the firm's sustainable performance and contributing to sustainable development goals. In this case, BDACs have a positive and significant relationship with SSCP (H1)(β = 0.841, t = 22.773, p< 0.01) and BDACs are a significant predictor of SSCP (explaining 70.8% of the variance). Indeed, the results showed that BDACs positively and strongly influence SP and ENP (0.818, 0.729), respectively. BDACs also have a positive yet weak influence on ECP (0.484), according to the effect sizes of R^2 set by Hair et al. (2016).

Interestingly, the theoretical relationship between BDACs and social performance (SP) is substantial and significant(H1a) (β = 0.818, t = 20.241, p< 0.01). This result indicates a significant contribution of BDACs in attaining SP. In light of this, SP appears to be the mainstay in the proposed TBL model to achieve sustainable performance, particularly in Australia. In this regard, Australian organisations have employed BDACs to find accurate predictions, leading to better social responsibility practices by enhancing transparency in supply chains and mitigating social violations (Wu et al., 2016; Song et al., 2017). Such practices can include improving gender equality, reducing health and safety accidents and increasing buying from local suppliers, leading to social sustainability. This study's findings also support earlier empirical studies, which confirm a positive association between BDACs and SP (Dubey et al., 2017; Jeble et al., 2018).

Furthermore, BDACs strongly and positively impact envirnomental performance (ENP)(H1b) (β = 0.729, t = 13.597, p< 0.01). It appears that ENP of Australian organisations has experienced larger improvements, as measured by reducing water waste, solid waste, and air emissions. These enhancements have been achieved by employing BDACs to explore hidden patterns, unknown correlations and trends for dealing with environmental matters, such as pollution, waste, ecology disruptions and resource depletion (Wu et al., 2016). Thus, leading to minimising negative environmental impacts and achieving environmental sustainability. This finding conforms to previous studies by demonstrating that BDACs significantly contribute to addressing previously mentioned environmental issues (De Gennaro et al., 2016; Zheng et al., 2013; Zhu, Wu, Li, & Xiong, 2017). The findings of this study extend the prior arguments of researchers who argued that BDACs significantly impact ENP (Dubey et al., 2017; Nisar et al.,2020; Jeble et al., 2018).

Lastly, the research findings interestingly reveal that BDACs have a weak yet positive influence on economic performance(H1c) (β=0.484, t = 4.493, p< 0.01). This observation indicates a salient theoretical point of view on how organisations may utilise BDACs to improve profit growth and sales growth to relatively enhance economic performance. This study's findings also support the conclusions of earlier empirical studies, which support a positive association between BDACs and EP (Akter et al., 2016; Yasmin et al.,2020; Gupta and George, 2016; Mikalef et al., 2020; Ji-fan Ren et al.,2017; Wamba et al., 2017; Gunasekaran et al., 2017).

5.4 To What Extent Does Supplier Integration Influence the Relationship between BDACs and SSCP?

Surprisingly, supplier integration (SI) has no moderating effect regarding the moderating construct's role(H2). We can interpret this result as an absence of an effective information-sharing system among the supply chain members. Thus, the respondents did not have enough information about their supply chain partners' situation. Therefore, this does not seem to be particularly important to relationships between BDACs and SSCP. Our research model can remove this construct, mapping the relationships between BDACs and SSCP and the moderating effects.

Another issue is that firms may require further efforts to find suitable suppliers to achieve SI. The right suppliers should have the ability to build and sustain long-term healthy relationships by sharing their information and building mutual trust and a culture of cooperation (Kang et al., 2018). The non-significant result of SI may lie because, even though SI has received growing attention, Australian supply chains seem to neglect it. In this respect, SI's influence on the path connecting BDACs and SSCP remains an interesting question for further research.

Moreover, this non-significant result may be related to the target respondents. The survey targeted IT-related managers such as chief information officers and IT managers. Survey administration requirements excluded supply chain managers from taking this survey who provide information about supply chain integration. Although the survey respondents completed SI measurement items, their responses displayed a biased view of SI because they did not have complete knowledge about this area in their organisations. It was one of the main limitations of this study. Researchers can further investigate SI's potential impact on the BDACs-SSCP relationship in future research that targets supply chain managers as potential informants. We anticipate this direction will be taken by future research.

5.5 To What Extent Does Alignment of Business Strategy with BDACs Influence the Relationship between BDACs and SSCP?

Consistent with our hypothesis (H3), alignment between business strategy and BDACs has a moderating effect on the association between BDACs and SSCP. Nevertheless, we are puzzled by the result since it indicates that such a moderating effect is not significant. Taking a step back and reflecting, it seems that such an outcome result makes theoretical sense. This result might indicate that a BDAC strategy is implicitly embedded in business strategy. When a firm has a business strategy, it strongly focuses on utilising cutting-edge technology and improving human resource skills orientation. The business has lower motivation to seek alignment with the BDACs strategy. Moreover, this finding suggests that the alignment between BDACs and business strategy has not yet been acknowledged as a primary significant factor in the organisation. That explains the misconception that investment in BDAC building is an expense rather than a long-term investment with larger benefits. On the other hand, managers have limited experience in Big Data and analytics skills.

Another reason can include that BDAC strategy is a dynamic strategy that is difficult to align with business strategy, itself considered a long-term plan. In light of this, the nonsignificant result of alignment between business strategy and BDACs remains inconclusive. Consequently, this perplexing phenomenon should receive more interest from future empirical studies.

5.6 To What Extent Does Corporate Social Responsibility Influence the Relationship between BDACs and SSCP?

Contrary to our expectations, corporate social responsibility (CSR) does not significantly influence the paths connecting BDACs and SSCP (H4). According to CSR, this result may be related to the following principal reasons: firstly, having a positive impact on sustainability issues such as reducing greenhouse gas emissions is not a "quick fix" project. Therefore, the companies require a long-term mindset backed up by measurable commitments, actions, and solid promises. The CSR initiatives must also be demonstrated to both shareholders and stakeholders over time. Another reason involves the difficulty of finding the right shareholders who support CSR initiatives. Obviously, leaders of corporate organisations understand that businesses play a crucial role in tackling sustainability matters such as climate change. However, many believe that proceeding with a sustainability agenda runs counter to their shareholders' desires. Although shareholders have been voicing concerns about sustainability, they rarely engage in environmental and social practices. In light of this, the nonsignificant result of CSR also remains inconclusive. Thus, this result motivates additional empirical studies.

Chapter 6. Conclusion

The conclusion chapter discusses key theoretical contributions stemming from the research findings. In addition, practical implications are outlined. Finally, the limitations of the research are mentioned, and recommendations for future research are drawn.

6.1 Summary

Analysing big data (BD) has received more interest from academics and practitioners due to its ability to boost visibility, mitigate risk and improve competitiveness (Raut et al., 2021) achieve superior organizational performance (Gupta et al., 2020) and co-innovation (Lozada et al., 2019). However, Big data analytics (BDA) have focused on processes and tools applied to extract valuable and meaningful insights (Ghasemaghaei & Hassanein, 2015), while the significance of organisational resources was neglected. Thus, the primary aim of this study is to contribute to BDA literature by addressing a gap by depicting a comprehensive picture of Big data analytics capabilities (BDACs), which involves BDA human and non-human capabilities.

In light of emerged debates concerning whether BDACs can mitigate social breaches, develop environmental protection, maximize profitability and ultimately translate into attaining sustainability performance.That is why it is essential to attempt to understand these complexities and uncertainties from an academic as well as a practical perspective. Consequently, to improve general understanding of this topic, a comprehensive BDACs-SSCP model was developed and empirically tested in this study.

We implemented two research strategies to meet the thesis's core objectives and answer the research questions. Firstly, we conducted a systemic literature review (SLR) to set the foundations for BDACs and sustainable supply chain performance (SSCP). Based on this SLR, we create multi-dimensional measurement metrics for assessing each SSCP dimension as well as BDACs. Secondly, we carried out a deductive-based survey methodology to investigate the influence of BDACs in improving the sustainability performance of Australian organisations in different industries. A relatively small sample size resulted from this survey effort (73 valid responses). After that, this study conducted a set of analyses using SPSS 25 and Smart PLS 3. We used SPSS to extract the descriptive analyses like a normal distribution. On the other hand, SmartPLS was used for the evaluation of all constructs used in the research model as well as hypotheses testing based on two main approaches. The first approach was a measurement model (outer model), which confirms sufficient reliability and validity of all measurements. The second approach was the structural model (inner model) which was used to test the relationships among the model's constructs and examine the hypothesised relationships. Revisiting the main research question,as predicted, a significant positive relationship was found between BDACs and SSCP in Australian organisations. Indeed, this result indicates a significant contribution of BDACs in attaining social and economic and environmental performance. However, all the moderators showed no interaction effect in the relationship between BDACs and SSCP.

6.2 Theoretical Contribution

This study mainly contributes to sustainable supply chain literature as well as BD literature. Interestingly, there is a well-defined gap in existing knowledge concerning building Big Data analytics capabilities (BDACs) in firms and measuring multi-dimensional sustainable supply chain performance (SSCP) comprising environmental, social, and economic performance. Additionally, a gap remains in understanding and investigating the relationship between BDACs and SSCP.

From the BDACs point of view, even though BDA literature is a growing stream, theoretically driven research is still limited in the IT-business context (Mikalef et al., 2018). Thus, based on the dynamic capabilities view (DCV) (Teece et al., 1997), we conceptualised BDACs as an organisational technology-based dynamic capability. According to previous studies, some dimensions of BDACs have been emphasised as being fundamental for organisations. For example, data management, infrastructure and personnel are three critical capabilities to help companies gain a competitive advantage (Wamba et al., 2017). In some studies, in the healthcare context, analytical and predictive analytics capabilities are considered core capabilities for BDACs (Wang & Hajli, 2017; Wang et al., 2018). However, many prior studies focus on technical capabilities and do not provide a comprehensive picture of BDACs (Mikalef et al., 2018, Gupta & Georg, 2016). We addressed the gap in the literature by depicting a holistic view of BDACs, which involves BDA human and non-human capabilities. Consequently, our capability-based measurement of BDACs joins the existing studies trying to expand the understanding of BDACs and yield empirical support (Gupta & George 2016; Grover et al. 2018; Mikalef et al. 2018; Arunachalam, Kumar & Kawalek 2018, Akter et al., 2016). Additionally, this study argues that BDA human and non-human capabilities are essential for harnessing BD value. We provide a conceptual basis for future research to pay more attention towards investigating how organisations can harvest the maximum benefit from BDA by adopting and reconfiguring appropriate BDA human and non-human capabilities.

Considering SSCP, the triple bottom line (TBL) approach has gained popularity as a valuable lens to assess sustainability, capturing the intersection of social, economic, and environmental performance. Consequently, TBL has received more attention from previous studies, yet empirical evidence of TBL is relatively neglected (Hassini et al., 2012; Yang, 2013). Drawing on the triple bottom line (TBL), this research establishes the theoretical foundation concerning a comprehensive picture of SSCP comprising social, environmental, and economic performance. Consequently, our multi-dimensional measurement of SSCP joins the existing studies trying to expand the understanding of the sustainability performance (Das 2018; Dubey et al. 2017; Huo, Gu & Wang 2019, Ahi & Searcy 2015; Mani, Gunasekaran & Delgado 2018; Popovic et al. 2018; Tajbakhsh & Hassini 2015).

Regarding the relationship between BDACs and SSCP, the novelty of this research is that it provides an empirically validated BDACs-SSCP model. This model further extends the previous claim of scholars who argue that BDACs have a positive impact on economic performance (Dubey, Gunasekaran, Childe, Blome, et al., 2019; Yasmin et al., 2020; Mikalef et al., 2020) and environmental performance (Nisar et al., 2020) by looking at the research phenomenon from a holistic and integrated perspective, integrating two dimensions of BDACs (human and non-human capabilities) and the three main dimensions of SSCP into one comprehensive model. Consequently, we fill a gap regarding scarce empirical studies by investigating the impact of BDACs on SSCP (Song et al., 2017; Waller & Fawcett, 2013). This model also successfully assesses the positive impact of BDACs on sustainability performance in the supply chain as a guiding mechanism for organisations.

6.3 Practical Implications

In light of emerged debates (Song et al. 2017, Waller & Fawcett 2013) concerning whether BDACs can enhance sustainability performance. This study's findings support how BDACs can positively impact sustainability performance. Our study yields some interesting practical implications for policymakers and practitioners in different industries such as manufacturing, retail, public sector administration, and healthcare. The following are some of the implications:

I. Providing a framework for practitioners and government policymakers of the importance of investing in BDACs to achieve sustainability performance via adopting BDACs. In this regard, this framework helps managers design and carry out policies, practices, and strategies that assist organisations in meeting social, economic, and environmental goals simultaneously (Song et al., 2017). Consequently, we see a window of opportunity for Australian consumers, businesses, and governments alike to profit from BDACs

II. Guiding human resource and training departments to acquire managerial and technical skills or recruiting these specific skills to strengthen BDA human capabilities. In this regard, the survey instrument in this study can serve as an audit tool to assess the extent to which organisations have management and technical skills related to BD. Admittedly, employees are considered the backbone of any organisation that may provide a sustainable competitive advantage. However, collecting a massive amount of data and acquiring robust IT infrastructure for building successful BDACs will be in vain with lacking managerial and technical skills. For instance, hiring the wrong employee can be destructive for businesses. The U.S. Department of Labour claims "a bad hiring decision" could cost a company up to 30% of the first-year earnings of its employee (Tatman, 2020).

III. Recommending managers invest in more advanced IT infrastructures to collect, assimilate and analyse big high-quality data to extract valuable insights. Additionally, developing the flexibility of the BDA infrastructure assists organisations in dealing with uncertain business situations and making alignment between resources and short-term and long-term business strategies, such as strategic alliances (Akter et al., 2016).

IV. Capturing the full potential of BDACs will require practitioners not only to commit to hiring and developing BDA human capabilities but also to invest in BDA infrastructure capabilities. Building successful BDACs may eliminate the supply chain complexity caused by information asymmetry due to poor visibility among supply chain participants.

V. Valuable insights and decisions supported by BDACs assist in improving coordination among supply chain participants, which empower supply chain managers to manage their supply chains more effectively by considering social, economic, and environmental performances.

6.4 Contributions to Current Thinking in the BDACs and SSCP Fields

First, investigating the impact of BDACs on SSCP with a focus on all sustainability performance outcomes is a relatively neglected research area (Song et al., 2017), especially in the Australian context. Therefore, this research has painted a picture of an increasing trend of empirical investigation concerning an investigation on how organisations can harvest the maximum benefit from BDA to achieve sustainability performance by adopting and reconfiguring appropriate BDA human and non-human capabilities.

Second, emphasising how the influence of BDACs extends from the traditional realms of the supply chain to sustainable supply chains. BDACs play a valuable role in exploring hidden patterns, unknown correlations, and trends and finding proper and accurate predictions (Song et al., 2017; Wu et al., 2016). This enhances supply chain transparency which helps detect unethical and unsustainable practices that may negatively impact communities and the ecosystem. Better real-time tracking and forecasting, supply chain visibility, resilience and cost savings are all benefits of BDACs (Dubey et al., 2018). Consequently, there is an excellent opportunity for consumers, businesses and governments in Australia to benefit from the wave of BD.

6.5 Limitations and Recommendations for Future Research

This research model is theoretically well-founded and tested with standard questionnaires and reliable data. However, the current study has some limitations, as with any research, paving the way for several future research directions.

The first limitation is the sample size; we used the PLS-SEM technique to evaluate the whole model fit with 73 samples. Thus, using a larger sample by expanding the geographical limits to conduct the same research model in various contexts (developed, underdeveloped, and emerging economies) would pave the way for another research direction, strengthening the generalisability of the conclusions.

The second limitation, related to methodological perspective, concerns the fact that a cross-sectional approach was adopted to gather data from a single data source at a single point in time to test this research model. This may not confirm causality and may not be a specific valid estimate. Consequently, forthcoming studies may conduct a longitudinal method to further develop our understanding by investigating a causal association between dependent and independent constructs (Guide & Ketokivi, 2015). Such a method also allows for tracking moderators' roles, such as supplier integration in the relationships between BDACs and SSCP. Further, this study collects data from a single respondent (IT-related managers such as information officers, senior IT managers, etc.) in different Australian sectors to investigate the impact of BDACs on SSCP in a single firm. That is a reason for potential method bias in single respondents. However, it is often ideal, although difficult, to collect data from multiple respondents (supply chain managers and IT-related managers) or by various methods. Therefore, future research which adopts multiple methods (qualitative and quantitative methods) or multiple respondents will be fruitful.

From the theoretical perspective, the third limitation concerns the fact that this study emphasises the influence of BDA human and non-human capabilities on SSCP. Hence, it may also be interesting to integrate more intangible capabilities in future research, for instance, data-driven culture and organisational learning. Other BDA human capabilities, such as knowledge capabilities (technological and relational knowledge), could help build more comprehensive scales for BDACs and their actual impact on SSCP measures. Additionally, it is beneficial to check if the years of work experience of respondents, industry and the firm's size impact data quality and compare the results with this study.

Finally, we did not explore the impact of other moderators such as organisational culture, supply chain agility and top management commitment on implementing BDACs at a firm, which could extend knowledge in BD literature.

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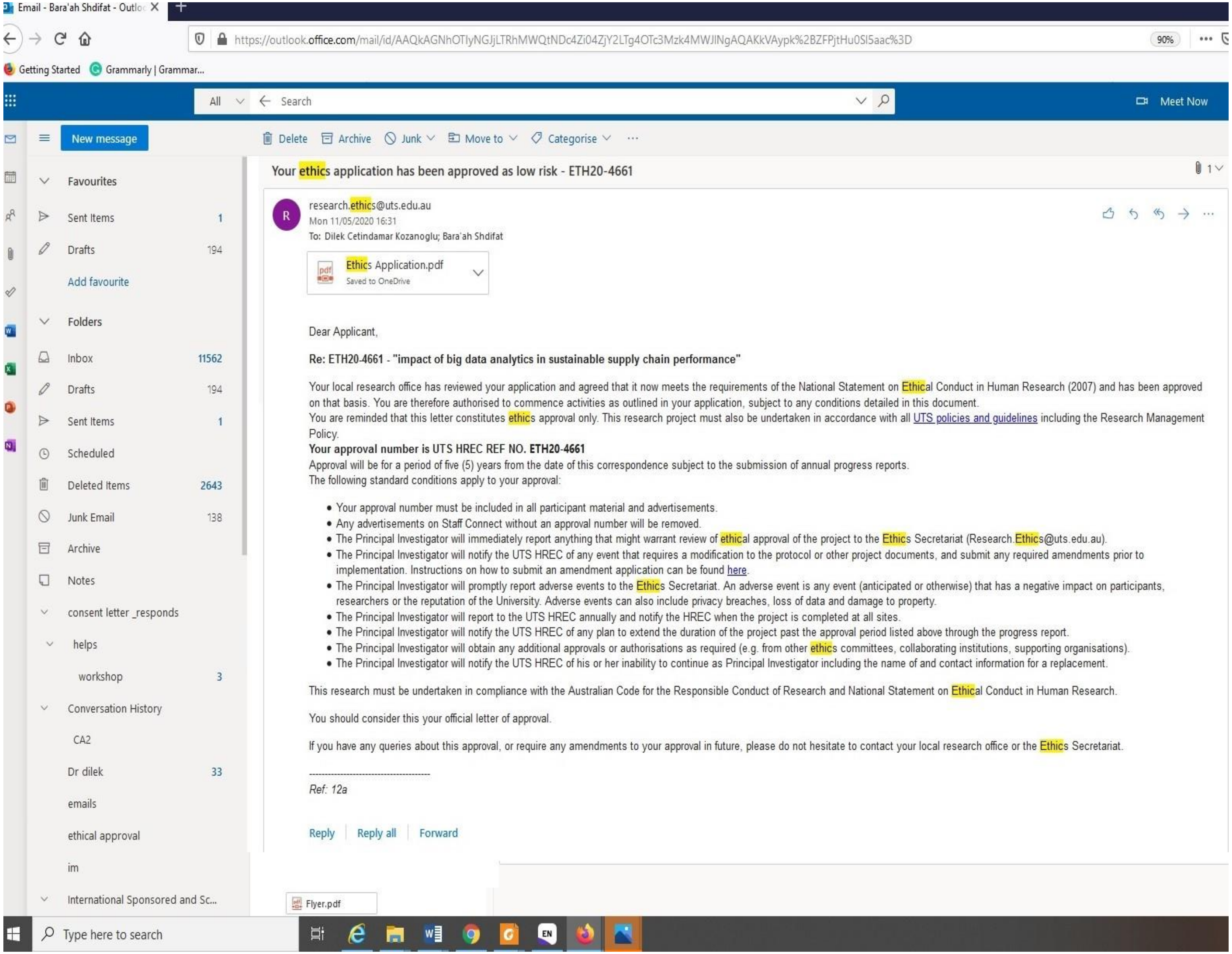
Appendix A: Ethics Approval



Your ethics application has been approved as low risk - ETH20-4661

research.ethics@uts.edu.au
Mon 11/05/2020 16:31
To: Dilek Cetindamar Kozanoglu; Bara'ah Shdifat

Ethics Application.pdf
Saved to OneDrive

Dear Applicant,

Re: ETH20-4661 - "impact of big data analytics in sustainable supply chain performance"

Your local research office has reviewed your application and agreed that it now meets the requirements of the National Statement on Ethical Conduct in Human Research (2007) and has been approved on that basis. You are therefore authorised to commence activities as outlined in your application, subject to any conditions detailed in this document.
You are reminded that this letter constitutes ethics approval only. This research project must also be undertaken in accordance with all UTS policies and guidelines including the Research Management Policy.
Your approval number is UTS HREC REF NO. ETH20-4661
Approval will be for a period of five (5) years from the date of this correspondence subject to the submission of annual progress reports.
The following standard conditions apply to your approval:

- Your approval number must be included in all participant material and advertisements.
- Any advertisements on Staff Connect without an approval number will be removed.
- The Principal Investigator will immediately report anything that might warrant review of ethical approval of the project to the Ethics Secretariat (Research.Ethics@uts.edu.au).
- The Principal Investigator will notify the UTS HREC of any event that requires a modification to the protocol or other project documents, and submit any required amendments prior to implementation. Instructions on how to submit an amendment application can be found here.
- The Principal Investigator will promptly report adverse events to the Ethics Secretariat. An adverse event is any event (anticipated or otherwise) that has a negative impact on participants, researchers or the reputation of the University. Adverse events can also include privacy breaches, loss of data and damage to property.
- The Principal Investigator will report to the UTS HREC annually and notify the HREC when the project is completed at all sites.
- The Principal Investigator will notify the UTS HREC of any plan to extend the duration of the project past the approval period listed above through the progress report.
- The Principal Investigator will obtain any additional approvals or authorisations as required (e.g. from other ethics committees, collaborating institutions, supporting organisations).
- The Principal Investigator will notify the UTS HREC of his or her inability to continue as Principal Investigator including the name of and contact information for a replacement.

This research must be undertaken in compliance with the Australian Code for the Responsible Conduct of Research and National Statement on Ethical Conduct in Human Research.

You should consider this your official letter of approval.

If you have any queries about this approval, or require any amendments to your approval in future, please do not hesitate to contact your local research office or the Ethics Secretariat.

Ref: 12a

Reply | Reply all | Forward

Appendix B: Results of Systematic Literature Review on BDACs

Table A. BDACs dimensions with related attributes for each dimension.

Dimension	Sub Dimension	Attributes	References
BDA Human Capability	Skills	Technical skills	(Akhtar et al. 2018; Akter et al. 2016; Arunachalam, Kumar & Kawalek 2018; Barbosa et al. 2018; Caesarius & Hohenthal 2018; Chaurasia & Rosin 2017; Coleman et al. 2016; Dremel et al. 2017; Ghasemaghaei, Ebrahimi & Hassanein 2018; Grover et al. 2018; Gupta & George 2016; Mikalef et al. 2018; Rialti et al. 2018; Sedkaoui 2018; Thirathon, Wieder & Ossimitz 2018; Wamba et al. 2017; Wang & Byrd 2017; Wang & Hajli 2017; Wang, Kung & Byrd 2018; Wang et al. 2018)
		Managerial skills	
	Knowledge		(Akhtar et al. 2018; Barbosa et al. 2018; Caesarius & Hohenthal 2018; Grover et al. 2018; Mandal 2018)
BDA Non-human Capability metrics	Data		(Barbosa et al. 2018; Gupta & George 2016; Mikalef et al. 2018; Sedkaoui 2018)
	Basic resources		(Barbosa et al. 2018; Gupta & George 2016)
	Infrastructure		(Akter et al. 2016; Chen, Chiang & Storey 2012; Coleman et al. 2016; Giannakis & Louis 2016; Grover et al. 2018; Gupta & George 2016; Lai, Sun & Ren 2018; Mikalef et al. 2018; Ren et al. 2017; Thirathon, Wieder & Ossimitz 2018; Wamba et al. 2017)
	Data Driven Culture		(Arunachalam, Kumar & Kawalek 2018; Barbosa et al. 2018; Gupta & George 2016; Mikalef et al. 2018)
	Organisational learning		(Barbosa et al. 2018; Gupta & George 2016)

Appendix C: Results of Systematic Literature Review on SSCP

Table B. Multi-dimensional measurement metrics for assessing SSCP dimensions.

Performance metrics	References
Social performance metrics	
Health and safety	(Huo, Gu & Wang 2019; Khan et al. 2018; Kumar, Subramanian & Maria Arputham 2018; Rashidi & Saen 2018; Silva, Gomes & Sarkis 2019; Yildiz Çankaya & Sezen 2019)
Employment benefits	(Huo, Gu & Wang 2019; Rashidi & Saen 2018; Silva, Gomes & Sarkis 2019)
Labour rights	(Das 2018; Dubey et al. 2017; Huo, Gu & Wang 2019; Khan et al. 2018; Kumar, Subramanian & Maria Arputham 2018; Popovic et al. 2018; Rashidi & Saen 2018; Silva, Gomes & Sarkis 2019; Yildiz Çankaya & Sezen 2019)
Community	(Kumar, Subramanian & Maria Arputham 2018; Rashidi & Saen 2018; Yildiz Çankaya & Sezen 2019)
Human rights implementation and integration	(Mani, Gunasekaran & Delgado 2018; Popovic et al. 2018; Tajbakhsh & Hassini 2015)
Training, education, and personal skills	(Popovic et al. 2018; Rashidi & Saen 2018; Tajbakhsh & Hassini 2015)
Diversity	(Dubey et al. 2017; Popovic et al. 2018)
Economic performance metrics	
Quality	(Ahi & Searcy 2015; Das 2018; Esfahbodi, Zhang & Watson 2016; Esfahbodi et al. 2017; Feng et al. 2018; Hassini, Surti & Searcy 2012; Huo, Gu & Wang 2019; Kumar & Rahman 2016; Kumar, Subramanian & Maria Arputham 2018; Luthra, Garg & Haleem 2016; Paulraj, Chen & Blome 2017; Silva, Gomes & Sarkis 2019)
Profit	(Ahi & Searcy 2015; Feng et al. 2018; Huo, Gu & Wang 2019; Singh & El-Kassar 2019; Yildiz Çankaya & Sezen 2019)
Cost	(Esfahbodi, Zhang & Watson 2016; Esfahbodi et al. 2017; Khan et al. 2018; Yildiz Çankaya & Sezen 2019; Miemczyk & Luzzini, 2019)
Time	(Feng et al. 2018; Khan et al. 2018; Kumar & Rahman 2016; Qorri, Mujkić & Kraslawski 2018; Rashidi & Saen 2018; Tajbakhsh & Hassini 2015)

Performance metrics	References
Environment performance metrics	
Pollution control	(Ahi & Searcy 2015; Burki, Ersoy & Dahlstrom 2018; Das 2018; Esfahbodi, Zhang & Watson 2016; Esfahbodi et al. 2017; Feng et al. 2018; Hassini, Surti & Searcy 2012; Huo, Gu & Wang 2019; Kumar & Rahman 2016; Kumar, Subramanian & Maria Arputham 2018; Luthra, Garg & Haleem 2016; Paulraj, Chen & Blome 2017; Silva, Gomes & Sarkis 2019)
Resource utilized	(Ahi & Searcy 2015; Hassini, Surti & Searcy 2012; Huo, Gu & Wang 2019; Kumar, Subramanian & Maria Arputham 2018; Paulraj, Chen & Blome 2017; Qorri, Mujkić & Kraslawski 2018; Rashidi & Saen 2018)

Appendix D: The Research Problem and Gaps in The Literature

Table C Research Problem and Gaps in the Literature

Keywords Authors	**BDAC**							**SSCP**			**Moderators**		
	Human		**Non-Human**										
	skills	Knowledge	Data	BR	Inf	OL	DDC	EP	ENP	SP	SI	CSR	Alg
Jeble et al. (2018)j	✓		✓			✓	✓	✓	✓	✓			
Santanu Mandal (2018)	✓							✓	✓	✓			
Mandal (2019)	✓												
Mandal (2018)		✓											
Dubey et al. (2017)	✓					✓	✓		✓	✓			
Song et al.(2017)									✓	✓			
Wolfert et al.(2017)					✓				✓				
Roman Pais Seles et al. (2018); Zhang et al. (2017); De Gennaro et al.(2016); Koseleva & Ropaite(2017); Liu & Wu(2017); Zhao et al. (2017).									✓				
Akter et al.(2016) ; Wamba et al.(2017)	✓	✓			✓			✓					
Gupta and George (2016)	✓		✓	✓	✓	✓	✓	✓					
Fosso Wamba et al. (2017); Gunasekaran et al. (2016)								✓					
Arunachalam et al. (2017)	✓							✓					
Arunachalam et al. (2017)	✓												
Dubey et al. (2018)	✓		✓	✓	✓	✓	✓						
The present study draws on the above literature to explore the impact of BDAC in SSCP	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓			

Basic resources (BR), organisational learning (OL),data-driven culture (DDC), infrastructure (Inf), economic performance (EP), environmental performance (ENP), social performance (SP), corporate social responsibility (CSR), supplier integration (SI), alignment of business strategy with BDACs (Alg)

Appendix E: Questionnaire

Role Of Big Data Analytic capabilities On Sustainable Supply Chain Performance

Introduction

This survey is part of a broader PhD research project being conducted at the University of Technology in Sydney. The overall aim of this research project is to:

1. **Better understand to what extent big data analytics capabilities (BDACs) can enhance sustainable supply chain performance.**

2. **Investigate the impact of building human (managerial and technical skills) and non-human big data analytics capabilities (infrastructure) on enhancing social, economic, environmental performance.**

3. **Better understand the vital role of Supplier Integration and Alignment of business strategy with BDACs.**

Your involvement would be highly useful to shed light on the relationship between BDACs and sustainability performance of companies, motivating companies to take into account the use of BDACs for the benefit of sustainability. Our research hopes to contribute to this critical agenda for climate change.

All information gathered here will be used for this research project. In addition to this (and by UTS policies and good research practice) all data collected, as part of this survey will be treated with absolute confidentiality (see the Participant Information Sheet on how we achieve this). No identifiable unit-level company data (including names and other company-specific comments) will appear on any reports stemming from this research. The survey participation is voluntary, and you may withdraw at any time.

The survey is divided into six sections (1-6) and should take between 10-15 minutes to complete. All respondents who provide contact information will receive an executive summary of the results which you can then use to benchmark your organization's' performance relative to others in your industry.

You may also ask for a brief summary of findings upon the completion of this research.

If you need further information or clarification, please don't hesitate to contact with the Researcher – Principal Supervisor – **Prof Dilek Cetindamar Kozanoglulu** (Dilek.CetindamarKozanoglu@uts.edu.au)

Co-supervisor – Dr. Eila.Erfani (Dr. Eila.Erfani@uts.edu.au)

Besides, If you have any questions relating to your participation that can't be resolved by the researcher or supervisory panel, please contact UTS Research Ethics Officer at (+61295149772; research.ethics@uts.edu.au).

Thank you in advance for your time and participation in this research project

Sincerely,
Bara'ah Shdifat
PhD Candidate (Researcher)
School of Information, Systems and Modeling
University of Technology, Sydney, Australia
Email: Baraah.Shdifat@student.uts.edu.au.

Role Of Big Data Analytic capabilities On Sustainable Supply Chain Performance

PARTICIPANT CONSENT FORM

1. I hereby agree to participate in the online research survey being conducted as a part of doctoral research entitled – 'Impact of Big Data Analytics capabilities On Sustainable Supply Chain Performance'. I am aware that:

- My participation in this online survey is completely voluntary.
- I can withdraw my participation in this research at any time and in such an instance, my responses would be removed from this research.
- My responses would be anonymously used in this research.
- All collected data-sets would be protected and secured by the researcher in both electronic and printed format and be made available only the supervisory panel and concerned research ethics office at UTS (if required).
- All collected data relating to this research would be only used for academic and research purposes.
- I have an opportunity to seek additional information including use of data relating to this research.

0

- Yes, I agree to participate in this survey.
- No, I don't agree to participate in this survey

Section 1: Background Information

This section focusses on generic background information about your organisation.

* 1. What industry/primary activity is your organization in?

Other (please specify)

* 2. What is the legal status of your organization?

- Publicly Listed Company
- Private Company
- Governmenal organization

* 3. 3. How many people are employed (full-time equivalent) by your organization?

- 1-4
- 5-19
- 20-99
- 100-199
- 200-1000
- Over 1000 employees

* 4. What is your gender?

- Female
- Male
- Prefer not to say

* 5. What is the name/title of your position?

- Chief Information Officer
- IT Director
- IT Services Manager
- IT Infrastructure Manager
- Systems/Network Administrator
- Other (please specify)

* 6. What is your education status?

- Secondary qualifications
- College qualification (diploma/certificate)
- Undergraduate degree
- Postgraduate degree (Master's/PhD)

* 7. For how long have you been working for your organization?

- Less than 1 year.
- 1 - 3 years
- More than 3 year.

* 8. Where is your organization located?

Section 2: Big data analytics capabilities

Big data analytics capabilities: firm's ability to assemble, integrate, reconfigure and deploy its big data capabilities(**Human and Non-Human**) to address rapidly changing environments.

2.1: Human big data analytics capabilities

This section asks which of these human big data analytics capabilities (**technical and managerial skills**) your organisation currently adopts and the importance your organisation places on their adoption. Using the scale provided, please indicate your preference by selecting a relevant option.

* 10. We have explored or adopted parallel computing approaches (e.g. Hadoop) to big data processing

- Strongly agree
- Agree
- Netural
- Disagree
- Strongly disagree

* 11. We have explored or adopted different data visualization tools

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 12. We have explored or adopted cloud based services for processing data and doing analytics

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 13. We have explored or adopted open-source software for big data and analytics

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 14. We have explored or adopted new forms of databases such as NoSQL (Not only SQL) for storing data

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 15. Our big data analytics managers understand and appreciate sustainable business development needs of other functional managers, suppliers and customers.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 16. Our big data analytics managers can coordinate BDAC related activities in ways to support other functional managers, suppliers and customers

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 17. Our big data analytics managers can work with functional managers, suppliers, and customers to determine opportunities that BD might bring to our business.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 18. Our big data analytics managers can understand and evaluate the output generated from big data.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 19. Our big data analytics managers have a good sense of where to apply big data.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 20. Our big data analytics managers can anticipate the future business needs of the other functional managers, suppliers and customers.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 21. Our analytics personnel create very capable decision support systems driven by analytics.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 22. Our analytics personnel are very capable in terms of programming skills.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 23. Our analytics personnel are very capable in the areas of data and network management and maintenance.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

2.2 :Non-human big data analytics capabilities

This section asks which of these Non-human big data analytics capabilities **(Infrastructure)** your organization currently adopts and the importance your organisation places on their adoption. Using the scale provided, please indicate your preference by selecting a relevant option.

* 24. Compared to rivals within our industry, our organization has the foremost available analytics systems.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 25. All remote, branch and mobile offices are connected to the central office for analytics.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 26. Our organization utilizes open systems network mechanisms to boost analytics connectivity.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 27. There are no identifiable communications bottlenecks within our organization when sharing analytics insights.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 28. Software applications can be easily transported and used across multiple analytics platforms.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 29. Our user interfaces provide trans-parent access to all platforms and applications.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 30. Analytics-driven information is shared seamlessly across our organization, regardless of the location.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 31. Our organization provides multiple analytics interfaces or entry points for external end-users.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

Section 3: Sustainable supply chain performance

This section focuses on (environmental and social and economic) performance of your organisation

3.1: Environmental performance

This section focuses on environmental performance of your organisation. Using the scale provided, please indicate your preference by selecting a relevant option.

Our supply chain uses big data analytics capabilities to :

* 32. Attain reduction of air emissions.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 33. Success in reducing waste (water and/or solid).

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

3.2 : Economic performance

This section focuses on Economic performance of your organisation. Using the scale provided, please indicate your preference by selecting a relevant option.

Our supply chain uses big data analytics capabilities to :

* 34. Attain improving profit growth.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 35. Accomplish improving sales growth

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

3.3: Social performance

This section focuses on social performance of your organisation. Using the scale provided, please indicate your preference by selecting a relevant option.

Our supply chain uses big data analytics capabilities to :

* 36. Employ better practices, which lead to improvement of gender equality.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 37. Achieve better practices in lowering health and safety accidents.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 38. Achieve better practices through increased buying from local suppliers

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

Section 4: Supplier Integration

Supplier Integration reflects embedding all of your firm's requirements for participation in the supply chain. Using the scale provided, please indicate your preference by selecting a relevant option.

Our organisation seeks to incorporate supplier integration by

* 39. Conducting joint planning with partners to anticipate/resolve potential supply chain problems.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 40. Providing information to help our supply chain partners improve.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 41. Informing partners about industry/regulatory events/changes that may affect them and their products.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 42. Requiring partners to implement EMS programs to address our company policy.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 43. Requiring collaboration in design of new products with supply chain partners.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 44. Requiring partners to visit our facility for feedback to help improve our performance.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

* 45. Ensuring supply chain participants provide their employees with necessary training.

Strongly agree | Agree | Neutral | Disagree | Strongly disagree

Section 5: Sustainability code of conduct

This section focuses Sustainability code of conduct. Using the scale provided, please indicate your preference by selecting a relevant option.

Our organization seeks to work with

* 46. supply chain organizations having a code of conduct.

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 47. established a code of conduct

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Section 6: Alignment of business strategy with big data analytics stratregy

This section focuses on alignment of business strategy with big data analyticsstrategy of your organisation **(Extent to which BDA strategies are aligned with the overall of the organisation strategy)**. Using the scale provided, please indicate your preference by selecting a relevant option.

Our organisation seeks to align business strategy with BDACs: 0

* 48. Big data analytics plan aligns with the company's mission, goals, objectives, and strategies. 0

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 49. Big data analytics plan contains quantified goals and objectives. 0

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 50. Big data analytics plan contains detailed action plans/strategies that support company direction. 0

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

* 51. We prioritize major big data analytics investments by the expected impact on business performance. 0

- Strongly agree
- Agree
- Neutral
- Disagree
- Strongly disagree

Role Of Big Data Analytic capabilities On Sustainable Supply Chain Performance

Finished

We thank you for your time and valuable contubition to this survey.

Appendix F: Missing Data and Data Distribution

Construct	Item	N	Mean	Std. Deviation	Missing		Skewness	Kurtosis
					Count	Percent		
Technical skills	TS1	73	2.52	1.260	0	.0	.638	-.556
	TS2	73	1.93	.933	0	.0	1.511	3.105
	TS3	73	1.96	1.184	0	.0	1.425	1.356
	TS4	73	2.38	1.162	0	.0	.891	.066
	TS5	73	2.49	1.168	0	.0	.608	-.483
Managerial skills	MS1	73	2.26	1.118	0	.0	.933	.450
	MS2	73	2.41	1.141	0	.0	.745	.097
	MS3	73	2.38	1.138	0	.0	.935	.469
	MS4	73	2.19	1.036	0	.0	1.142	1.199
	MS5	73	2.36	1.098	0	.0	.994	.675
	MS6	73	2.48	1.107	0	.0	.843	.430
Infrastructure	Inf1	73	2.45	.987	0	.0	.672	.285
	Inf2	73	2.01	1.034	0	.0	1.134	1.150
	Inf3	73	2.38	1.162	0	.0	.509	-.493
	Inf4	73	2.48	1.029	0	.0	.332	-.766
	Inf5	73	2.40	.968	0	.0	.724	.174
	Inf6	73	2.47	1.068	0	.0	.443	-.612
	Inf7	73	2.34	1.083	0	.0	.757	-.096
	Inf8	73	2.25	1.038	0	.0	.939	.525
Enviromnetal Performance	EP1	73	2.73	1.272	0	.0	.328	-.841
	EP2	73	2.60	1.244	0	.0	.359	-.733
Economic Performance	ECP1	73	2.12	1.092	0	.0	1.196	1.213
	ECP2	73	2.19	1.036	0	.0	1.296	1.706
Social Performance	SP1	73	2.37	1.184	0	.0	.629	-.350
	SP2	73	2.22	1.133	0	.0	.848	.104
	SP3	73	2.38	1.075	0	.0	.828	.171
Supplier Integration	SI1	73	2.30	.967	0	.0	.775	.414
	SI2	73	2.21	.999	0	.0	.773	.324
	SI3	73	2.29	.950	0	.0	.787	1.024
	SI4	73	3.12	1.471	0	.0	.884	-.162
	SI5	73	2.92	1.507	0	.0	1.070	.142
	SI6	73	2.74	1.659	0	.0	.954	-.241
	SI7	73	2.84	1.599	0	.0	1.010	-.139
Corporate social responsibility	COC1	73	1.88	.816	0	.0	1.023	1.913
	COC2	73	1.93	.855	0	.0	.818	.973
Alignment of business strategy with BDACs	Alg1	73	2.03	.957	0	.0	1.704	4.757
	Alg2	73	2.11	1.137	0	.0	1.527	2.234
	Alg3	73	2.26	1.155	0	.0	1.193	1.244
	Alg4	73	2.18	1.110	0	.0	1.203	1.687