KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI

Effects of Big Data Analytics Capability on Supply Chain Innovation among Manufacturing Multinational firms in Ghana: The mediating role of Knowledge Creation

By

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DECLARATION

I hereby declare that this submission is my own work towards Masters of Science in Logistics and Supply Chain Management and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

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(Head of Department, SCIS)	**Signature**	**Date**

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DEDICATION

I dedicate this work to my mother, Lydia Gyebi for her profound support that empowers me to overcome different challenges and to Rev. Dr. (Mrs.) Grace Sintim-Adasi for encouraging me to pursue this master's programme.

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ABSTRACT

Although Supply Chain Innovation and Big Data Analytics Capability have drawn a lot of attention in the literature on supply chains, there is still a scarcity of research regarding the knowledge contents that play a mediating role between Supply Chain Innovation and Big Data Analytics Capability. This study postulates that manufacturing companies that are able to apply new ideas in the face of knowledge creation tend to develop a strong supply chain that might help them to resist the effects of firm innovations as well as build a stronger hedge against future issues. The study was conducted to understand how big data analytics capability affect supply chain innovation with the mediating role of knowledge creation among multinational manufacturing companies in Ghana. Based on the gaps identified in literature, a framework of four (4) hypotheses were developed. To achieve this, 250 owners and managers of manufacturing companies in Ghana were sampled. A self-administered instrument was used to gather data from the 250 participants. The analyses were done using SPSS and Smart PL-SEM. The result showed that Big data analytics capability has a positive significant influence on supply chain innovation and knowledge creation. The result further showed that the relationship between supply chain innovation and big data analytics capability is mediated through knowledge creation. The practical implication is that the relationship among BDA, SCI and KC is not a single directional relationship.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

The global economy is now within the supply chain (SC) era, where competition have moved from just firm level to industries, sectors and recently SC (Weihua et al., 2021). The increasing competition in the global market make the SC especially among multinational firms very dynamic. Due to the dynamic nature of SC of multinational firms, they face multiple challenges in keeping up with the changing or the dynamic nature of the industry they operate within (Ayman et al., 2022). Firms therefore in their quest to achieve higher performance levels and remain competitive, strive to improve their SC. To remain competitive as a firm, it remains imperative to be innovative, such that firms are able to timely adjust to the dynamics. Innovation is increasingly receiving attention as a strategy to remain competitive in a dynamic business environment. However, with the level of competition and the fact that firms are now competing at the SC level, just firm level innovation may not be enough. Thus there is the need for firms to timely redesign their SC to deliver new product and services that meet the changing needs of clients as well as enhance output levels *** the entire SC. Although supply chain innovation (SCI) may be achieved via diverse routes, two perspectives have received minimal attention in supply chain management literature. These include BDAC and knowledge creation (KC). Managers of firms are under intense pressure in today's data driven markets to device innovative strategies, create and deliver value to consumers via SCM. The ability to meet this expectation hinges on the ability to generate knowledge or insight from the large volumes of data generated from daily operational activities. Bahrami et al. (2022) indicated that developing a better understanding of Big Data Analytics (BDA) would be essential in achieving SCI. The authors also believe that understanding BDAC may not just result in supply chain innovation but may also aid in creating new knowledge which could facilitate the achievement of superior innovation in the SC. This study is therefore conducted to examine how BDAC and KC may be useful in achieving SCI in the context of multinational firms in the emerging economies like Ghana.

1.2 Problem Statement

In terms of how they link corporate partners, encourage teamwork, disseminate innovation, allow data-driven decision making, and track movements in real time, supply chains are becoming more and more sophisticated. As a means of producing and distributing massive amounts of data, BDA is one of the essential elements for fostering operational and supply chain innovation (Bahrami et al., 2022), which stimulates increased value creation throughout the supply chain (Kache and Seuring, 2017; LaValle et al., 2011). If multinational firms are to keep up with the growing demands of today's customers, who want everything cheaper, faster, and more personalized (Deloitte, 2018; GSCI, 2017; Montgomery, 2018), supply chain managers must become increasingly aware of the relevance of BDA capabilities in achieving supply chain value. The disruption they cause can quickly leave behind those who do not adapt their data-driven strategies accordingly (Waller and Fawcett, 2013). In a world where there is an abundance of data, an organization's ability to handle aggregate data to produce and extract crucial knowledge and information will determine how successful they are in the long run (Kaplan and Haenlein, 2019). It has never been more crucial than it is the post covid-19 pandemic period, as supply chain companies work to recover from the COVID-19 disruption and increasingly turn to big data analytics as a means of enhancing supply chain innovation (Bahrami et al., 2022). Organizations can increase their dynamic capabilities through the use of BDA capabilities, which also have favorable implications on their capacity for incremental and radical innovation (Mikalef et al., 2019; 2021; Awan et al., 2022; Bahrami et al., 2022). According to Lozada et al. (2019), BDA capabilities have a direct and significant impact on co-innovation. Furthermore, Fernando et al. (2018) demonstrated that BDA significantly affects service supply chain's capacity for innovation. Though the growth of literature on the phenomena appears to have increased significantly in the last decade, the actual theoretical and practical understanding of how firms could leverage BDAC to achieve supply chain innovation is limited (Bahrami et al., 2022). It is therefore unclear if SC managers could rely on BDAC as a strategic way of achieving supply chain innovation. Additionally, while some scholars (Mikalef et al., 2019; 2021; Awan et al., 2022; Bahrami et al., 2022) hold positive view of BDAC, Gupta and George (2016) hold contradictory view that investing in BDA does not always pay off. The above concerns necessitate the need for more empirical studies how supply chain innovation may be achieved via BDAC (Mikalef and Krogstie, 2018; Lozada et al., 2019; Bahrami et al., 2022). Apart from the limited knowledge on the relationship between BDAC and supply chain innovation, recent studies (Mikalef et al., 2020; Gunther et al., 2017) have advanced the need to investigate other organizational capacities that may play indirect role in the BDAC and supply chain innovation relationship. This study argues that BDAC alone may not be enough to achieve the desire innovation outcome, however, the readiness of players along the supply chain to create and share tacit and explicit knowledge remain essential to achieving supply chain innovation. Knowledge creation reflects the act of making knowledge created by individuals available, amplifying it in social contexts, and selectively connecting it to the existing knowledge in the organization (Nonaka and von Krogh, 2009). Despite the growth of discourse on BDAC and KC, to the best of the researchers' knowledge no studies so far has been conducted to examine how KC may play an indirect role in the relationship between BDAC and SCI. Philip (2018) also indicated that though knowledge creation has received considerable recognition in literature, combining it with emerging concepts like BDAC remains scanty. Finally, Bahrami et al (2022) indicated that existing studies have relied solely on DCT and hence recommended future studies combine DCT with other theories including OIPT. Hence closing this gap provides interesting contributions both to theory, practice and managerial implications that could guide managerial decisions. This study therefore affords a twofold contribution in the context of developing economies, especially Sub-Saharan African continent; the first fold provides contemporary insight of the relationship between BDAC and SCI while it also examines the mediating role of KC in the relationship between BDAC and SCI which has not yet missing in academic discourses.

1.3 Objectives of the study

The key objective of this study is to examine how supply chain innovation could be achieved through BDAC and the mediating role of Knowledge Creation in the direct relationship. Three specific objectives were put forward based on the gaps identified. These objectives include

i. To examine the effect of big data analytics capability on supply chain innovation.
ii. To evaluate the relationship between data analytics capability on knowledge creation.
iii. To investigate the mediating role of knowledge creation on the relationship between data analytics capability on supply chain innovation.

1.4 Research Questions

i. What is the effect of big data analytics capability on supply chain innovation?
ii. What is the relationship between data analytics capability on knowledge creation?
iii. What is the mediating role of knowledge creation on the relationship between data analytics capability on supply chain innovation?

1.5 Significance of the Study

Based on the multiple unanswered questions in literature regarding the phenomena under enquiry. This study has multiple contribution to theory, practices and managerial guidance. Theoretically, this study is among the few attempt to combine Organizational Information Processing Theory and Dynamic Capability Theory to understand how Knowledge Creation may play an indirect role in the relationship between big data analytics capability and supply chain innovation. Bahrami et al (2022) indicated that existing studies have relied solely on DCT and hence recommended future studies combine DCT with other theories including OIPT. Practically, one of the unique contributions of the study is the researcher's novelty of the combination of big data analytics capability and knowledge creation to investigate their impact on supply chain innovation in the context of multinational firms in Ghana, first of its kind in the setting and a paradigm for scholars to direct their research focus. This study therefore provides better understanding to managers regarding the unique nature of big data analytics capability and knowledge creation as drivers of supply chain innovation.

1.6 Scope of the Study

The scope circles the context and limitations of the research. This study contextually focused on multinational firms in developing economy, specifically in Ghana. Even though multinational firms include both service and manufacturing, this study uniquely focused both industries. The study contextually examines how supply chain innovation could be achieved through BDAC and the mediating role of Knowledge Creation in the direct relationship Theoretically, the study will employ the OIPT and DCT to understand the relationship explored in the study.

1.7 Research Methodology

This study adopted a survey research design approach as the main methodology for the study. This approach will enable an in-depth exploration of data pertaining to the subject matter of how supply chain innovation could be achieved through BDAC and the mediating role of Knowledge Creation in the direct relationship. This approach will allow the relevant data to be collected from the purported respondents after the appropriate sampling technique, and the sample size has been determined out of the study population of manufacturing firms. A structured questionnaire adapted and modified from previous studies was used to collect the relevant data for the study, analysis of the data will then be employed by the application of both descriptive and inferential statistical tools. With regard to the descriptive statistic, tables, charts and graphs shall be employed to pictorially display the data, whilst summary measures such as means, median, modes, etc shall be employed in addition. The inferential statistical tools including partial least squares regression and correlation analytical method. However, prior to the use of the data collection and analysis, both the instrument and data shall be validated for the test of reliability and validity.

1.8 Limitations

The researcher envisages some challenges during the study. Among the challenges are the active participation of the interviewees and time limitation. The first challenge encountered in this study was access to the interviewees and their willingness to share relevant and appropriate information amidst the corona virus pandemic.

1.9 Organization of the study

The study shall be organized into five main chapters which are chapter one, chapter two, chapter three, chapter four and chapter five. Chapter one which is the first contains the introduction as the main heading with its content being the background to the study, the statement of the problem, the research questions, the general and specific objectives of the study, the relevance, among others.

The second chapter will examine relevant related literature review, where relevant theories, concepts, and empirical issues will be examined to support the study. Chapter three on the other hand shall deal with the study methodology by describing study design employed, the study population, sampling and sample size determination, methods of data collection, the sources of data, methods of data analysis.

The fourth chapter will also consider the analysis and discussion of result from the analysis, whilst the final chapter will present a summary of the major findings, conclusion, and recommendations for the consideration by stakeholders.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter is organized into four sections. These sections are conceptual review, theoretical review, and theoretical underpinnings in this study, empirical review, conceptual framework, hypotheses and literature gap.

2.2 Conceptual Review

The conceptual review section contains the definitions, operationalization and how the variables have been used in this study. Under this section, there are three main variables (big data analytic capability, supply chain innovation and knowledge creation) to be operationalized.

2.2.1 Big Data Analytics Capability

Big data analytics capability (BDAC) is the capacity to process aggregate data to generate and take out important and needed knowledge and information (Ferraris et al., 2018), for effective and efficient management, which is done through arrangement and interpretation (Kaplan and Haenlein, 2019). BDAC is the ability of an organization to extract compound data for visualization and analysis of the data to gain valuable insights for evidence-driven strategic planning and decision making. Again, Mikalef, et al., 2020 describes BDAC as the capacity to generate meaning from large amount of data through categorization and interpretation for use by organizations to increase performance. BDAC is the process whereby an organization uses its tools, techniques and procedures to enable big data to be extracted for analysis and utilised for the benefit of the organization. Big data is defined by Senthilkumar et al. (2018) as large number of structured and unstructured data available in real-time. This study will define BDAC as the ability to process aggregate data to generate and take out important concept and information (Ferraris et al., 2018), for effective management through arrangement and interpretation of the data (Kaplan and Haenlein, 2019).

2.2.2 Supply Chain Innovation

Many organizations are striving to enhance their supply chains (SCs) to ensure their organization achieve higher performance and sustainability in this competitive market (Abdallah, Alfar and Alhyari, 2021) hence they are investing into creating innovations in SCs to tackle with recent demands (Mate, 2022). SCs are systems for producing and delivering of goods and services (Büyüközkan and Göçer, 2018). Supply Chain Innovation (SCI) describes the integration of new ideas into organizations to reduce cost and achieve high efficiency (Remko, 2020). SCI is defined as a change in SCs within an organization to boost the creation of new value for stakeholders (Giacomarra et al., 2019). Also, SCI is an approach utilized by organizations to ensure the attainment of quality and boost value given to customers (Chen, 2018). Luomaranta and Martinsuo (2020), stated that the notion behind SCI focuses on innovative efforts by organizations to attain advantage in competitive market for their SCs by creating efficiency in service and operations to increase the revenue of the firm. This study will employ the definition of SCI by Luomaranta and Martinsuo (2020); it is change to enhance the performance of organizational SCs through formation of collaborative relations and interaction to bring about novel technologies which will benefit customers, suppliers and other organizations

2.2.3 Knowledge Creation

Knowledge is a key and viewed as a vital factor to achieve good outcome within organizations (Baia, Ferreira and Rodrigues, 2020). Salunke, Weerawardena and McColl-Kennedy (2019) defines knowledge creation (KC) as the ability to develop new ideas which can impact the performance of an organization. KC is defined by Ode and Ayavoo (2020) as a procedure which involves the formation of new ideas or replacing existing ideas with new ones within organizations. Frank (2019) stated that KC is the ability to combine information and concepts into new knowledge. Papa et al. (2018) identified KC into modes which are socialization, combination, externalization and internalization. Socialization is regarded as the transformation of old knowledge to new knowledge by members of an organization through social experiences and gatherings (Olaisen and Revang, 2018). Chotimah and Jannah (2020), defines combination as the classification, reclassification and integration of existing tacit knowledge into the development of new tacit knowledge. Externalization is explained as the transformation of tacit knowledge into explicit knowledge and internalization is defined as transforming explicit knowledge into tacit knowledge (Papa et al., 2018). The capability to create new knowledge is a unique skill for organizational growth and performance (Dagnino, Picone and Ferrigno, 2022). The capability to generate new knowledge is described by Salunke, Weerawardena and McColl-Kennedy (2019) as the capacity of an organization to exchange and combine knowledge to form new knowledge. Also, KC capability is explained as the extent to which members of an organization collectively combine knowledge and information into new concepts and values the exchange and combination process by having access to one another and other stakeholders (Grants, 2022). A study conducted by Dagnino, Picone and Ferrigno in 2021 noted the importance of KC capability as a distinctive competence for profit and competitive advantage. This study will employ the definition of KC by Ode and Ayavoo (2020) as a process to form new ideas or replace existing ideas with new ideas within an organization.

2.3 Theoretical Review

2.3.1 Dynamic Capability Theory

Big data differs from regular data in five ways. The huge data quantities that exponentially grow are referred to as "volume." The term "velocity" refers to how quickly data is gathered, processed, and analyzed in the present. The range of data types gathered in big data scenarios is referred to as "variety." "Veracity" refers to the dependability of the data sources. The strategic, informational, and transactional advantages of big data are referred to as its "value" (Akter et al., 2016). Virtually all firms now have access to big data, but utilizing standard techniques to analyze and gain useful insights from this type of data is challenging or even impossible (Jha et al., 2020). So, even though it's crucial to comprehend the "Vs" of big data, a crucial query in modern research is how big data creates value (Gupta and George, 2016). The value of big data has increased dramatically in recent years, and BDA now plays a strategic role. BDA is a method for locating important possibilities as well as for finding and resolving business issues. The crucial insights provided by the BDA can be incredibly helpful to businesses in helping them understand the changes taking place in the modern workplace. Big data projects must take into account factors other than data, tools, and analytical methodologies in order to gain these crucial insights and guarantee project success. In order to widen the definition of big data to include all organizational resources, the concept of BDA capabilities was developed (Mikalef et al., 2020). BDA capabilities allow the organization to process, analyze, and visualize data by mobilizing and rearranging organizational resources. This ultimately results in the provision of relevant insights to improve decision-making, planning, and execution of the company's missions (Srinivasan and Swink, 2018; Dubey et al., 2019; Mikalef et al., 2020). This perspective on BDA capabilities suggests that they can be seen as a dynamic capability for the company, as dynamic capabilities involve identifying and shaping opportunities, investing in already-existing opportunities, and maintaining a competitive advantage through mobilization, promotion, and resource reallocation (Teece, 2007). It is essential to understand that while dynamic capabilities are a requirement for gaining a competitive edge in today's dynamic and unpredictable situations, they are insufficient; success necessitates extra resources and capabilities produced through dynamic capabilities (Teece et al., 1997; Eisenhardt and Martin, 2000). As a result, the organizational communication network, business processes, and strategic orientations are changed as a result of the insights gained through BDA capabilities. This helps other organizational capabilities strengthen these intermediate capabilities, which in turn increases the organization's value creation (Mikalef et al., 2018; Warner and Wager, 2019). The author argues that this relationship can be strengthened among firms that have more KC capability. The study, therefore, argues that KC mediates the relationship between BDAC and SCI.

2.3.2 Organizational Information Processing Theory (OIPT)

Galbraith established the Organizational Information Processing Theory (OIPT) in 1973. The theory is based on a trinity of ideas: the importance of information processing, the limitations of IT, and how to strike a good balance between the two. In order to make sound decisions and deal with environmental uncertainty, collaborative groups of organizations need access to reliable data. As a general matter, businesses can either build buffers to absorb shocks and lessen the impact of uncertainty, or they can employ structural mechanisms and information processing capability to improve information flow and mitigate risk (Premkumar et al.,2005). Srinivasan and Swink (2018) argue that, in order to carry out complicated tasks, organizations need to effectively organize and export information. This is especially true in the context of relief operations. According to Fairbark et al. (2006), OIPT takes into account the connection between the height (i.e., the effective use of information) and the value (i.e., competitive advantage) of information as a resource. The author contends that in OIPT, humanitarian workers must process data with rising levels of uncertainty if they are to achieve their desired level of performance. As uncertainty is defined as the gap between the quality of information needed to complete a task and the degree of information already available to the organization, it is clear that uncertainty is a key factor in the importance of information processing (Galbraith,1973; Dubey et al., 2019). Long-term collaboration or affiliation is one technique Galbraith (1974) proposed for exerting influence over the workplace. The research also found that an organization's innovations improved when its information processing needs were matched with its processing capabilities (Premkumar et al., 2005; Srinvasan and Swink, 2015, 2018; Fan et al., 2016; 2017; Dubey et al., 2019). Based on the above the author combines BDAC, knowledge creation as drivers of supply chain innovation. The author believes that building strong analytics capability will help firms organizations to gain new insight from existing data available, this will also be facilitating KC through effective information sharing, based on the OIPT enhanced SCI could be shaped through KC and BDAC. The author argues that this relationship can be strengthened among firms that have more KC culture. The study, therefore, argues that KC mediates the relationship between BDAC and SCI.

2.4 Empirical Review

2.4.1 Effect of Big Data Analytic Capability on Supply Chain Innovation

Rodriguez and Da Cunha conducted a study in 2018 to identify characteristics of BDAC used to maintain SCI. Their study reviewed several literatures to examine the purpose of the research. Their study utilized a comprehensive analysis methodology to assess literatures on BDAC, SCI and absorptive capacity. They developed a conceptual framework that enabled them to identify key characteristics and explored the definitions and operationalization of the variables used in the study. The study revealed that absorptive capacity enables BDAC to influence SCI sustainability. The authors recommend that future studies should focus on investigating and forming an action oriented research approach to validate the conceptual framework developed in their study within organizations.

Bag et al., 2022 carried out a study with the aim of assessing the role BDAC plays in enhancing sustainability for supply chain performance (SCP). The researchers employed statistical survey to determine the goal of the study by sampling executives from five mining industries in South Africa. Data gathered was analyzed using Partial Least Squares Structural Equation Modelling (PLS-SEM). The study shows that BDAC management has a significant impact on innovation of SCs and sustainability. The researchers recommend that future research should investigate the connection between workers learning performance and workers strength. Also, the authors emphasized the need to conduct this study in other developing African countries.

Bahrami, Shokouhyar and Seifian (2021) carried out a study with aim of examining how BDAC has an effect on supply chain performance (SCP) through supply chain resilience (SCR) and SCI. the researchers employed a cross-sectional design to gather responses from 367 companies. The research targeted participants who were senior managers with honours degree and a background field in business analytics. The findings of the research revealed that BDAC enhance SCP through SCI and SCR. The authors recommend that future studies should look at sociocultural factors and employ other models.

Dubey, Gunasekaran and Childe (2019) conducted a study on big data analytics capability in supply chain agility: The moderating effect of organizational flexibility. The goal of the study was to evaluate the time and approach firms use to develop BDAC to enhance supply chain agility (SCA) and innovation. The authors employed cross-sectional survey design for the study. A sample size of 745 supply chain managers were used and data from 2015 was analyzed with 173 responses. The findings of the study revealed that BDAC has a positive influence on innovation and SCA. The researchers suggested that future studies should focus on conducting studies from various backgrounds in firms, industries and nations over a period of time.

Shokouhvar, Seddigh and Panahifar (2020) conducted a study to assess the effect of BDAC on SCs sustainability in companies and also to develop a theory. The study also evaluated different dimensions such as technological innovations and management that influence supply chain management and BDAC of companies. The authors applied a quantitative survey approach to achieve the purpose of their study. Questionnaires were administered to 234 pharmaceutical industries and 188 responses from participants who are managers were used in the study. The findings from the study Shokouhvar, Seddigh and Panahifar conducted showed that BDAC strongly affect SCs sustainability in the pharmaceutical industries and there was no significant effect on some dimensions such as technology innovations and management.

2.4.2 Effect of Big Data Analytic Capability on Knowledge Creation

Ferraris et al. (2018) conducted a research with the aim of assessing BDAC and knowledge management on the performance of firms. The authors sampled 159 firms for the study. The sampled firms used in the study were Small and Medium-sized Enterprises (SMEs). Questionnaires were administered to participants to gather responses. The findings of the research revealed that BDAC within firms increases the performance of the firms through knowledge creation management. The research was limited to India hence the researchers recommend that future studies should focus on extending this study into other geographic location and should also gather data from other industries and companies since their data was gathered only in SMEs.

Pauleen and Wang (2017), conducted a study to emphasize that knowledge creation and knowledge management must responsed to key changes that BDAC brings to organizational data and information operations. Their paper presented several perspectives on knowledge management. The authors analyzed works from other authors to make their case on the relationship between big data and big knowledge. The authors employed Big Data/Analytics-Knowledge

Management (BDA-KM) theory to make their case. The findings from their study shows that knowledge is a central principle when using BDAC in organizations. The authors suggest that future studies should investigate how the integration of knowledge management and BDAC can be used in organizations for decision making and strategic planning.

Faroukhi, et al. (2020) conducted a study with the purpose of making a comprehensive review of big data value, value creation and data value. The researchers employed a systematic review approach to evaluate literatures for their study. Systematic review is an approach for evidence-driven practice. The authors reviewed relevant literatures to be able to achieve the aim of the study. They found that recent market demands have made it crucial to use BDAC to inform organizational decisions based on knowledge creation. BDAC influence organizational decisions based on knowledge creation. The researchers recommend that future studies should be geared towards forming a suitable Big Data Value Chain approach for global use.

Sumbal et al. (2019) carried out a study to examine the role of big data in organizations and knowledge, and value creation. They used qualitative research design to ascertain the aim of the study. They applied an inductive approach by using semi-structured questions for their interviews with senior organizational managers and analysts in oil and gas enterprises. The findings of the study shows that value and knowledge creation through BDAC is an important aspect that influence and increase performance of members of an organization. The authors developed a framework for the study to show the aspects that influence performance at the organization. The authors recommend future studies to carry out the study using quantitative research design.

Dahiya, et al. (2021) conducted a study with the aim of investigating BDAC related with knowledge management in organizations. The authors applied resource-based view to review literatures for their study. They used informal cases to support their arguments. The findings show that BDAC solutions and public derived data will not create organization specific knowledge and will not provide competitive advantage. They recommend that future studies should investigate in-depth into big data analytic solutions carried out by organizations and examine big data analytics knowledge along with knowledge management.

2.5.3 Effect of Knowledge Creation on Supply Chain Innovation

Jimenez-Jimenez, Martínez-Costa and Rodriguez (2018) conducted a study aimed at analyzing the direct effect of innovations such as information technology and supply chain. The authors sampled firms that are solely into manufacturing. A sample size of 200 manufacturing firms were used for the study. Data was collected over two months in 2016 with 200 questionnaires used for collecting responses from these firms. The authors employed structural equation modeling to test the research hypothesis. The findings shows that supply chain influence technological innovations. The impact has to do with knowledge creation to ensure technology innovations. Future research should focus on using quantitative design for this study.

Grimsdottir and Edvardsson carried out a study in 2018 to investigate and present results on knowledge management, knowledge creation and innovations in SMEs. Qualitative research design was used for the case study. Two companies were used for the study where interviews were done to collect responses from SMEs managers from these companies. The findings from the study states that both companies use innovation but only one company uses knowledge from consumers and suppliers in their operations. The authors recommend that future studies should increase sample size and focus on cultural factors for the study.

Ordieres-Meré, Prieto Remon and Rubio (2020) conducted a study which aimed at investigating sustainable innovations such as transformation in digitalisation which can be used to render services and produce goods. The study also aimed at investigating the effects of knowledge creation and its influence on innovation such as digitalization. Qualitative research design was employed in the study to be able to gain in-depth understanding of the study. The authors found that within the past fifteen years, air industry transportation through knowledge creation has developed strategic innovation in aircraft technologies and has enhanced their operations. The authors suggest to other researchers to use quantification in future studies when investigating sustainable innovations in digital transformation.

2.5.4 The Mediating Role of Knowledge Creation

Saide and Sheng conducted a study in 2020 which aimed at identifying big data and knowledge management which can be used in recent issues. Quantitative approach was used for the survey. Questionnaires were used to collect responses from several companies and firm. A sample size of 155 firms were used for the survey. The findings shows a relation between knowledge exploration-exploitation capabilities and business process innovation. The authors recommend that studies should be conducted in the future to investigate the survey in different geographic locations.

Mehralian, Nazari and Ghasemzadeh (2018) conducted a study which evaluated how knowledge creation and intellectual capital influence indicators of organizational performance. A cross-sectional survey was used. Study population were Iranian pharmaceutical companies with a sample size of 100 companies in pharmaceutics. Questionnaires were administered to collect responses from companies participating in the research. They completed 470 questionnaires used for data collection. The balanced scorecard approach was utilized to measure essential indicators of performance. The results shows that knowledge creation influenced intellectual capital of pharmaceuticals companies.

Ode and Ayavoo (2020) carried out a study which aimed at evaluating the relationship between firm innovation and knowledge creation practices in organizations in developing countries. The study also evaluated the mediating role of applying knowledge on knowledge management practices in organizations in developing countries. The researchers developed a conceptual framework for the study. The research collected data using questionnaires from a sample size of 293 service organizations in Nigeria. The results revealed that knowledge creation, storing knowledge and applying knowledge have impact on innovative strategies of organizations. The study also shows that applying knowledge have a mediating effect on knowledge creation, storing of knowledge and innovations by organizations. The authors argue that managing knowledge practices contribute to SCs innovation. Future studies should employ longitudinal studies to examine long term impact of managing knowledge practices.

2.6 Conceptual Framework

Figure 2.1 below (Conceptual framework) shows the hypothesized relationship between the variables in the study. From the Conceptual framework, the study expects a direct effect of between data analytics capability and knowledge creation on supply chain innovation. While the study expects these direct relationships, it is also expected that knowledge creation will mediate the relationship between BDAC and Supply chain innovation as shown on Figure 2.1 below. The various relationships as shown on the framework are discussed in detail in the subsequent sections. The various relationships as shown on the framework are discussed in detail in the subsequent sections below. The study expects a direct effect of between data analytics capability and knowledge creation on supply chain innovation. While the study expects these direct relationships, it is also expected that knowledge creation will mediate the relationship between BDAC and Supply chain innovation.

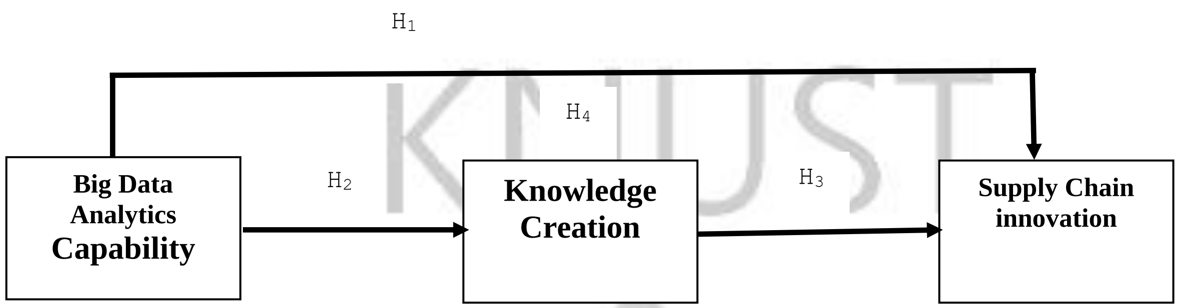

Figure 2. 1: Conceptual framework

2.6.1 Effect of Big Data Analytics Capability on Supply Chain Innovation

Organizations can consistently experience innovation thanks to BDA capabilities that can harvest environmental data to find and seize new business possibilities (Wang and Dass, 2017; Rialti et al.,2019; 2020; Ciampi et al., 2021). The capacity to alter technologies can be facilitated by functions made possible by powerful BDA capabilities (Mikalef et al., 2020; Bahrami et al., 2022). Contextual factors influence how important BDA resources are, and some combinations result in high capabilities for incremental and radical process innovation (Mikalef and Krogstie, 2018). Organizations can increase their dynamic capabilities through the use of BDA capabilities, which also have favorable implications on their capacity for incremental and radical innovation (Mikalef et al., 2019). BDAC is crucial for innovation, according to earlier studies (Lozada et al., 2019; Fernando et al., 2018; Bahrami et al., 2022). Little empirical study has examined the potentials of BDA in relation to innovation, despite the growing interest in comprehending the big data phenomena and its impact on diverse corporate contexts (Lozada et al., 2019; Bahrami et al., 2022). Drawing from the argument above, it is expected that firms with high BDAC are more likely to have the capacity to innovate their supply chain. This leads to the first hypothesis of the study;

H1: Big Data Analytics Capability has significant positive effect on supply chain innovation.

2.6.2 Effect of Big Data Analytics Capability on Knowledge Creation

A large number of people in an organization can be taught explicit knowledge by using information technology in the context of KC, which is the setting for group interactions in a virtual environment (Philip, 2018). In the Combination step, externally acquired structured or unstructured explicit knowledge is edited and transformed into new ordered forms of explicit knowledge. Then, employees inside an organization are given access to this new explicit information. When people interact with one another or their environments (physical or virtual space) throughout a shared period of time, energy, and location, knowledge is formed (Bag et al., 2021). BDAC will present a solid opportunity for combining and creating new types of explicit knowledge for big data (which is explicit knowledge made up of numbers, 3D data, audios/videos, customer log files, social media content, etc.). This will be done through databases, data analytical tools, and other computerized communication networks. Consumer relationship management (CRM) solutions allow managers and staff to learn more about customer requests, suppliers, and rivals (Chen and Popovich, 2003). In the data-driven environment, efficient knowledge generation requires frequent dialog exchanges between internal organizational members and external stakeholders like customers (more so than in the physical world). Prior study of Philip (2018) indicates that BDAC is important for achieving knowledge creation. However, empirical evidence on the relationship between BDAC and KC is scare. This study based on the OIPT expects that firms that have the capacity to process data generated their operations are likely to generate insight that can be shared with players within and outside the organization. Hence leads to the second hypothesis.

H2: Big Data Analytics Capability and Knowledge creation are positively correlated.

2.6.3 Effect of Knowledge Creation on Supply Chain Innovation

A firm is typically considered to be "a channel of knowledge flow" according to the knowledge-based idea of firm, which describes it as a singular collection of diverse knowledge whose main goal is to establish, incorporate, and apply knowledge as well as communicate it both inside and outside the firm (Abubakar et al., 2019; Alshanty and Emeagwali, 2019). The foundation for expecting innovation is knowledge (Lichtenthaler, 2016; Abbate et al., 2019). Knowledge is typically regarded as a crucial strategic tool for fostering innovation and enhancing a company's operations (Elrehail et al., 2018; Alshanty and Emeagwali, 2019). A firm that is capable of creating knowledge can continuously generate the knowledge reserves required to advance its goods and improve its processes, according to previous studies (Mahr et al., 2014; Alshanty and Emeagwali, 2019). Thus, a knowledge base enables a business to increase productivity, reduce expenses, or upgrade its products, and it improves the capacity to create novel procedures, goods, and services. Thus, prior studies have provided evidence that knowledge creation is key in innovation (Li et al., 2018; Abdi et al., 2018; Papa et al., 2018; Pérez-Luño et al., 2019). Thus, firms with high knowledge creation ability are likely to be innovative. Hence the third hypothesis

H3: Knowledge creation and Supply chain innovation are positively correlated.

2.6.4 Mediating Role of Knowledge creation

Through timely product and service improvements and organizational process improvement, innovation plays a crucial role in reacting to customers' shifting wants and needs (Kwak et al., 2018; Lee et al., 2011). Due to the complexity of creativity, the literature is dispersed, although prior studies have found a link between innovation and BDAC that is favorable (Lozada et al., 2019; Fernando et al., 2018; Bahrami et al., 2022). According to research, operational challenges and processes, which include networking, management techniques, procurement, and distribution, are the focus of SC innovation (Bahrami et al., 2022). As a result, services may gain a competitive edge and develop sustainably (Isaksson et al., 2010; Bahrami et al., 2022). Additionally, recent studies show that BDA skills, such as technical developments, enhance businesses' innovation and knowledge management (Bahrami et al., 2022). Decision-making is aided by business analytics skills, which also promote supply chain innovation. This improves corporate performance and lowers environmental variability (Singh, and Singh, 2019). BDA capabilities are essential for knowledge production and let organizations respond quickly and creatively. BDA gives businesses the chance to improve their KC capabilities for supply chain innovation. Although no study has provided evidence of the mediating role of KC in the BDAC-SCI relationship, the author drawn on the fact that BDAC may not jut drive innovation and KC, but rather the availability of KC will serve as avenue to reap maximum benefit of BDAC in enhancing innovation in the supply chain. Thus;

H4: Knowledge creation mediates the relationship between BDAC and SCI

Table 2.1 Summary of Literature Review

Author (Year)	Country	Purpose	Theory	Methods	Findings	Future Studies
Bag et al. (2020)	South Africa	To assessing the role BDAC plays in enhancing sustainability for SCP.	Dynamic Capability Theory	Statistical Survey	BDAC management has a significant impact on innovation of SCs and sustainability.	Conduct this study in other developing African countries.
Rodriguez and Da Cunha (2018)	Global	To identify characteristics of BDAC used to maintain SCI.	No theory	Literature Review	Absorptive capacity enables BDAC to influence SCI sustainability.	Future studies should focus on investigating and forming an action oriented research approach to validate the conceptual framework developed in their study within organizations.
Bahrami, Shokouhyar and Seifian (2022)	Iran	To examine how BDAC has an effect on supply chain performance (SCP) through supply chain	Dynamic Capability View.	Quantitative cross-sectional survey	BDAC enhance SCP through SCI and SCR.	Future studies should look at sociocultural factors and employ other models.

		resilience (SCR) and SCI.				
Dubey, Gunasekaran and Childe (2019)	India	To evaluate the time and approach firms use to develop BDAC to enhance supply chain agility SCA and innovation.	• Contingency Theory • Dynamic Capability View	Quantitative cross-sectional survey	BDAC has a positive influence on innovation and SCA.	Future studies should focus on conducting studies from various backgrounds in firms, industries and nations over a period of time.
Shokouhvar, Seddigh and Panahifar (2020)	India	To assess the effect of BDAC on SCs sustainability in companies and also to develop a theory.	• Contigency Theory • Grounded Theory	Quantitative	BDAC strongly affect SCs sustainability in the pharmaceutical industries and there was no significant effect on some dimensions such as technology innovations and management.	Future research should focus on factors that caused some part of the model to be eliminated.

Ferraris et al. (2018)	Italy	To assess BDAC and knowledge management on the performance of firms.	Resource-based View Theory	Quantitative	BDAC within firms increases the performance of the firms through knowledge creation management.	Future studies should focus on extending this study into other geographic location and should also gather data from other industries and companies since their data was gathered only in SMEs.
Pauleen and Wang (2017)	Global	To determine how knowledge creation and management must response to key changes that BDAC brings to organizational data and information operations.	Big Data/Analytics-Knowledge Management (BDA-KM)	Literature Review	Knowledge is a central principle when using BDAC in organizations.	Future studies should investigate how the integration of knowledge management and BDAC can be used in organizations for decision making and strategic planning.
Faroukhi, et al. (2020)	Global	The purpose of the study is a comprehensi	• Big Data Value Chain Theory	Systematic review	BDAC influence organizational decisions	Future studies should be geared towards forming a suitable Big Data

		ve review of big data value, value creation and data value.	• Data Value Theory		based knowledge creation.	Value Chain approach to global use.
Sumbal et al. (2019) The authors recommend future studies to carry out the study using quantitative research design.	USA, Russia, Netherlands, Australia, Middles East and Nigeria	To examine the role of big data in organizations and knowledge, and value creation.	Data Information Knowledge Wisdom model.	Qualitative	The findings of the study shows that value and knowledge creation through BDAC is an important aspect that influence performance.	The authors recommend future studies to carry out the study using quantitative research design.
Dahiya, et al. (2021)	Global	To investigate BDAC related with knowledge management in organizations	Resource-based View Dynamic Capability Life Cycle and Absorptive Capacity	Literature Review	BDAC solutions and public derived data will not create organization specific knowledge and will not provide competitive advantage.	Future studies should investigate in-depth into big data analytic solutions carried out by organizations and examine big data analytics knowledge along with knowledge management.
Jimenez-Jimenez,	Spain	To analyze the direct	Resource-based View	Quantitative	Supply chain influence	Future research should focus on

Martínez-Costa and Rodriguez (2018)		effect of innovations such as information technology and supply chain			technological innovations. The impact has to do with knowledge creation to ensure technology innovations.	using quantitative design for this study.
Ordieres-Meré, Prieto Remon and Rubio (2020)	France	To investigate the effects of knowledge creation influence innovation such as digitalization	Triple Bottom Line	Qualitative	The authors found that within the past fifteen years, air industry transportation through knowledge creation has developed strategic innovation in aircraft technologies and has enhanced their operations.	The authors suggests to other researchers to use quantification in future studies when investigating sustainable innovations in digital transformation.
Grimsdottir and Edvardsson (2018)	Iceland	To investigate and present results on knowledge	Open Innovation Model	Qualitative	The findings from the study says both companies use innovation but	Future studies should increase sample size and focus on cultural factors for the

		management, knowledge creation and innovations in SMEs			only one company uses knowledge from consumers and suppliers in their operations.	study.
Saide and Sheng (2020)	Indonesia	To identify big data and knowledge management can be used in recent issues.	Ambidexterity theory	Quantitative	There is a relation between knowledge exploration-exploitation capabilities and business process innovation.	Studies should be conducted in the future to investigate the survey in different geographic locations.
Mehralian, Nazari and Ghasemzadeh (2018)	Iran	To evaluate how knowledge creation and intellectual capital influence indicators of organizational performance	Socialization, Externalization, Combination and Internalization (SECI) model and Knowledge Creation Model	Quantitative	Knowledge creation influenced intellectual capital of pharmaceuticals companies.	Future studies should focus on longitudinal approach to investigate knowledge creation and intellectual capital on the performance of an organization.
Ode and Ayavoo (2020)	Nigeria	To evaluate the mediating	Knowledge-based View	Quantitative	The study also shows that	Future studies should employ

		role of applying knowledge on knowledge management practices in organizations in developing countries.			applying knowledge have a mediating effect on knowledge creation, storing of knowledge and innovations by organizations.	longitudinal studies to examine long term impact of managing knowledge practices.

CHAPTER THREE

RESEARCH METHODOLOGY AND ORGANIZATIONAL PROFILE

3.1 Introduction

Chapter three contains the study methodology which describes the study design employed, the population, sampling and sample size determination, methods of data collection and the methods of data analysis.

3.2 Research Design

The research design is the overarching plan for integrating the many components of the study in a cohesive and logical manner, ensuring that the research problem is properly addressed; it is the blueprint for data collecting, measurement, and analysis (Grey, 2014; Sovacool et al., 2018; Chege and Bowa, 2020). Research designs comes in different form, however, not all of them are suitable for a particular study. There are three types of research design, according to Robson (2002): exploratory, descriptive, and explanatory. Because each design serves a different end purpose, his classification system is based on the research area's objective. For example, the goal of a descriptive study is to paint a picture of a scenario, person, or event, or to demonstrate how objects are related to one another in the natural world (Blumberg, Cooper and Schindler, 2014). Descriptive studies, on the other hand, cannot explain why an event occurred and are best suited to a very new or uncharted research field (Punch, 2005). Alternative research designs, such as explanatory or exploratory approaches, are recommended in situations where descriptive data is abundant. When enough information regarding a phenomenon does not exist or a problem that have not been precisely characterized, exploratory research is conducted (Saunders et al., 2007). Its goal is not to provide definitive solutions to the research questions, but rather to examine the study issue in various depths. As a result, the focus of the conference is on new topics that have received little or no prior investigation (Brown, 2006). Even in the most extreme cases, exploratory research sets the initial research design, sample methodology, and data gathering method, laying the groundwork for more decisive research (Singh et al., 2007).

The goal of an explanatory study, on the other hand, is to explain and account for the descriptive data. Explanatory studies, on the other hand, seek to answer "why" and "how" questions, whereas descriptive studies may explore "what" questions (Grey, 2014). It builds on exploratory and descriptive research to determine the real reasons for a phenomenon's occurrence. Explanatory study seeks out causes and explanations, as well as data to support or contradict a theory or prediction. It is carried out in order to find and report some correlations between various components of the phenomenon under investigation. The study's major goal, as stated in the preceding section, is to examine how supply chain innovation could be achieved through BDAC and the mediating role of Knowledge Creation in the direct relationship. It accomplishes this by generating statistical, quantitative results and attempting to justify the established relationship with qualitative research. As a result, the most appropriate research design is an explanatory one that addresses both the how and why aspects of the central research issue.

3.3 Population of the Study

Population represents the entire group that the study seeks to draw conclusions about (Malhotra and Singh, 2007). For the purpose of this study, the population represents all multinational firms in Ghana. It is estimated that there are currently 50 multinational firms in Ghana. Hence the 50 multinational firms form the target population of this study. According to Creswell (2013), unit of analysis is the phase which include: individual, organization or group which will be used by the researcher to answer research questions and as well gather data. Since, the study variables are organizational level, the study targets senior managers especially, supply chain mangers, warehouse managers, production managers, quality assurance and other managers who have insight on BDAC, KC and Supply Chain Innovation in their firm.

3.4 Sample Size and Sampling Technique

The number of people or items to be included in the study is referred to as the sample size (Saunders et al., 2011). Several factors go into determining the sample size for a certain study, whether a researcher uses a qualitative or quantitative technique (Malhotra and Birks, 2007). Despite the fact that sample size is a critical decision for any research, there is no single method for selecting it (Bhat and Darzi, 2016). The A-priori sample size calculator for SEM is a popular method of finding sample size in structural equation modeling (SEM) (Soper, 2015). A total sample size of 264 respondents is considered appropriate for this study, based on an expected effect size of 0.2, desired statistical power level of 0.8, total of 3 latent variables (i.e. Supply chain Innovation, BDAC, and KC), total of 24 observed variables, and a probability level of 0.05.

The researcher must now determine the sampling technique for the study after determining sample size. Every researcher's dream would have been to collect data from every single person in a population. This scenario is only achievable when the researcher is working with small groups of people. When the population of interest is big, however, this census approach is not always viable. Accessing potential participants is also costly, time-consuming, and complicated. As a result of these issues, studies that use huge populations, such as this one, have depended on sampling procedures to pick a representative sample from the population of interest (Malhotra, 2010). Sampling is the process of selecting a sufficient number of components from a larger population or constituents in the hopes of using the data gathered from these sampled elements to make accurate judgments and inferences about the overall population (Hair et al., 2009).

There are two types of sampling procedures known in the literature: probability and non-probability sampling. In case study research, non-probability sampling is regularly used. While probability sampling is routinely employed in surveys and experiments, case study research frequently uses non-probability sampling. Despite this, when the sample population is exceedingly big, some researchers continue to utilize non-probability sampling in quantitative studies (Saunders et al, 2009).

Each element in the sample frame has an equal chance of being chosen in probability sampling, whereas in non-probability sampling, the opposite is true (Sekaran, 2003). As a result, valid inferences about the target population are difficult to make when nonprobability sampling is used. Despite the fact that non-probability sampling frequently relies on personal judgments and that samples obtained using this technique may not always be a true reflection of the population, generalizations about the population can still be made (Malhotra et al., 2010). Non-probability sampling procedures include quota, purposive, snowball, and convenience sampling. Purposive sampling is the process of selecting participants based on the researcher's judgment of who has the relevant information. The survey collected data from multiple respondents who were expected to have the best knowledge about the operation and management of SCM schemes on their firms or organization performance instruments as exist in their organization. This study purposively used senior executives, operational managers, Supply chain managers, Warehouse and Store managers and other middle or functional managers who have experience and knowledge in the area of the study to provide in-depth information for analytical purposes.

3.5 Data Collection

The study employed the five-point Likert scale, which is better since the point scale's position between positive, negative, and neutral options is properly balanced, reducing misunderstandings in participant's responses (Croasmun and Lee Ostrom, 2011; Sarstedt and Mooi, 2019). On a scale of 1 to 5, 1 means strongly disagree, 2 means disagree, 3 means neutral, 4 means agree, and 5 means strongly agree. The survey had two parts. Part one is for gathering background information from participants, while part two is divided into four sections for bringing together information focusing on the independent variables. Section A, B, C, and D of the second part was designed in gathering information on BDAC, Knowledge Creation and supply chain innovation correspondingly. Items used in the design of the questionnaire were sourced from previously validated instrument. BDAC was measured using five (5) items adapted and modified from previous studies of (Akter et al., 2016; Srinivasan and Swink, 2017). KC was measured as a multidimensional construct made up socialisation, externalisation, combination and internalisation. In all eighteen items were used for the KC construct and were adapted from (Lee and Choi, 2003; Lopez-Nicolas and Soto-Acosta, 2010). Supply Chain innovation was measured using seven (7) items adapted and modified from previous studies of (Panayides and Lun, 2009).

The current study used a sample of 30 respondents which is deemed appropriate as proposed by Hill (1998) (Treece and Treece, 1982) to undertake the pilot test. The result of the pilot data showed that the majority of the items except for two items of KC were reliable. Few issues including grammar errors and ambiguity were used to refine the questionnaire for the main data collection.

The revised questionnaire was self-administered by the researcher with assistance from three trained research assistants. All the respondents received a brief on the purpose and major concepts before the questionnaire was administered. The respondents were assured of their anonymity. Again, they were informed that participating in the study is not compulsory but purely voluntary. The survey instructions also sought the consent of the respondents. Before interacting with the respondents, permission was sought from the firm. The data collection lasted for three months. The respondents who were not ready or available for face-to-face interviews were asked to select between the hand delivery or online format. The questionnaire was administered in English.

3.6 Data Processing and Analysis

The Statistical Package for Social Sciences (SPSS) software version 23 was used to analyze the information acquired from the surveys and questionnaires. Data coding and data entry were the first steps in the data analysis process. The assignment of numerical values to variables within the "Variable View" of the SPSS software was the process of data coding. For example, the value 1 was assigned to males and the value 2 was assigned to females when it came to gender. The items measured on a five-point likert scale were given the values 1=strongly disagree, 2=disagree, 3=neither agree nor disagree, 4= agree and 5= strongly agree. The specific data preparation activities started with the retrieving or collection of the questionnaires from the respondents. The questionnaires items were assigned numerical codes for easy identification of items and the dimension of items. For example, questionnaires answered by respondents from the mining industry were coded “0” while those filled by the retail industry were coded “1”. After assigning codes to all the questionnaire items, the data processing tool, the Statistical Package for Social Sciences (SPSS version 25) was used to support the data entry exercises. Each of the questionnaire items was entered in the variables cells of the SPSS, and appropriate names, labels, and measures were assigned. Missing values were also treated to improve the data quality. Data was stored in the SPSS format.

Missing values were addressed using the listwise deletion method. This method requires that cases with missing values are omitted completely from the data. This is the most common and frequently used method for handling missing data. This method of treating missing values does not introduce bias in the dataset if only the remaining complete cases are more than the minimum sample size required (Donner, 1982). With respect to this study, the minimum sample size required for the study was 186 for the mining industry and 195 for the retail industry making total sample size of

381. However, 50% more of the questionnaire was administered so that after taking care of non-responses and treatment of missing values, the valid cases will be equal to or more than the minimum required sample size. After non-response rate and deletion were taken into consideration, the valid data cases for the mining industry was 210 and that of the retail industry was 258 and this brought the actual sample used for the study to 468 which is 23% more than the minimum required sample size. Thus, the listwise deletion method applied did not introduce any bias into the final data used for the analysis. Detailed information about the number of questionnaires retrieved and the number of valid cases that were analysed after the treatment of the missing values.

The study performed exploratory factor analysis using the principal component analysis for the various constructs of the study. Factor analysis was also performed for the various constructs. The robustness tests such as the Kaiser-Meyer-Olkin (KMO) test, Bartlett's test (BT), total variance explained (TVE) accompany the results. The KMO test is a test for sample adequacy and as a rule of thumb, KMO of 0.6 or more connotes adequate sample. The TVE also indicates the amount of variation in the constructs which is explained by the elements of the optimal factor chosen. The summary results of the optimal factor loading for the respective constructs are showed in subsequent chapter. KMO values for all the constructs are more than 0.6 hence there was sample adequacy achieved for the analysis. The Bartlett test also had probability values which were significant at 1% alpha level; thus there were no identity matrixes. Furthermore, the total variance explained for the optimal factor loadings were more than 50% indicating that the optimal factors explained more than half of the variation in the respective constructs. The indicators were therefore used to estimate an index for the respective constructs.

3.6.1 Partial Least Square-Structural Equation Modelling (PLS-SEM)

This research used Partial Least Square-Structured Equation Modelling (PLS- SEM) to examine gathered data. SEM is described as a statistical tool in testing and analyzing statistical data's causal relationships (Cepeda-Carrion et al., 2018; Tu, 2018). Partial Least Squares (PLS) is a variance-based approach that is likewise presented as a component-based approach used to evaluate structural equation models. Also, its referred to as soft modeling that does not require a standard assumption of distribution (Henseler and Schuberth, 2017). PLS can either be used for confirmation of theory (confirmatory factor analysis) or the development of the theory (exploratory factor analysis) (Crede and Harms, 2019). In comparison to multiple regression, SEM has been carefully thought-out as a better statistical strategy for predicting the association between variables. Characteristics of PLS are as follows: PLS makes no inference of distribution. PLS resist the premise that results obey a specific distribution pattern and must be distributed independently. Unlike covariance-based SEM, which calculates model parameters first and then case values, PLS starts by measuring case values and maximizing the variance of the dependent variable explained by the independent variable(Henseler, 2017). The non-observable variables that are latent Variables (LVs) are variables that are investigated in PLS as exact linear combinations of their evidence-based indicators.

PLS models, like SEM, typically have two parts: a structural component that depicts relationships amongst latent variables, and a measuring component that depicts interactions among latent variables and indicators. Another function of PLS is the weight relationships that are used to approximate case values for the latent variables (Aguirre-Urreta and Rönkkö, 2018). SEM may evaluate the relationship between model constructs at the same time, whereas, in the first generation approach, the variables are analyzed individually (Hair et al., 2019). It is important to consider the context and rationale for applying PLS to analyze the data before assessing the conceptual model. Considering the assumptions that underpin various statistical procedures might help the research in selecting the appropriate statistical instrument. The choice amongst CB-SEM and PLS-SEM, according to Hair et al., (2019), can be made depending on a few considerations, including the study goal, measurement model definition forms, structural process model modeling, data features, and model assessment. CB-SEM would be the best option to use if the goal of the study is to corroborate or test an established theory. Alternatively, PLS-SEM is the technique to use when the goal of the study is to build or predict a hypothesis.

Given that there is little evidence for an association between I4.0, CE moderated by GM and IP, the study employed PLS-SEM in establishing the justifications and predictions of the relationships. The justifications for introducing PLS are twofold in the present study: first, it is universally accepted and used in recent diversified literature, e.g. knowledge management (Cepeda-Carrion et al., 2019), innovation, and firm performance (Liao and Barnes, 2015; Osei et al., 2016) and so on (Henseler, 2018), in examining the relationship between knowledge acquisition and firm performance, most researchers use SEM for the verification (Liao et al., 2015; Zgrzywa-Ziemak 2015). The study investigated a somehow complex model where the constructs such as Knowledge Acquisition have a lot of dimensions, with product innovation, government support, and firm performance, As a result, PLS-SEM is a good fit for the study. PLS-SEM can also be used to analyze data with a medium or small sample size (Ali, et al., 2018; Henseler and Noonan, 2017). Finally, as regards the fundamental goal of the PLS is to analyze statistical models that have been proposed based on previous research, not to evaluate whichever alternative model best fits the data (Cepeda- Carrion et al., 2019). The statistical method adopted for this study will, therefore, be the use of PLS-SEM for evaluating the research model.

3.6.1.1 Measurement Model Assessment

The quality of the research findings is highly dependent on the research's credibility. The credibility of this study's research has been ensured through using two methods: validity and reliability. Credibility, as defined by De Vos, Strydom, Fouche, and Delport (2007), is the extent to which one can have faith in one's conclusions and, hence, one's methodology. Furthermore, credibility is "the key to providing readers with adequate evidence so that they trust the recounted events and accept the interpretations as believable," as stated by Neuman (2000) and cited by De Vos et al. (2007:353).

According to Singh (2015), validity is the extent to which a measurement tool provides reliable data on the constructs it was designed to assess. Robson (2011) also referred to validity as the extent to which a measuring device produces reliable data when used for its intended purpose. The questionnaire used to conduct the research must provide reliable and valid measures of the ideas at hand (Pallant, 2011). The research instruments used in this study were deemed reliable. Content validity, construct validity, and criterion-related validity are the three primary forms of validity assessment, as outlined by Pallant (2011). The type of validity that needs to be examined is construct validity because, as was previously indicated, the study will use validated instruments.

Construct validity

According to Dsanzi (2006), "construct validity" describes the extent to which a test measures an intended hypothetical construct. The study's author explains that it provides evidence for how well the test's findings accord with the hypotheses upon which it is based. Cooper and Schindler (2011) imply that in this form of validity, both the theory and the measuring instrument being used to test for any interesting effect of any construct must be taken into account, and they imply that this is the case. The literature review explains the ideas used to test the model (organisational climate, transformational leadership, emotional intelligence, and work satisfaction among youth-owned and managed small companies). There is a good match between the theory and the sections of the questionnaire that deal with the variables and components of the study. Below is a discussion of how convergent and discriminant validity are used to assess construct validity (Huck, 2007):

Convergent validity

It is the degree to which one measure's scores are highly, moderately, or poorly correlated with those obtained from another measure designed to assess the same construct (Singh, 2015). If the instrument is legitimate, the measurement should correlate with other variables; hence this concept of convergent validity checks for that. This is said to be the case when there is a strong relationship between the results of two tests assessing the same notion. To what extent do two independent variables correlate (Straub, 1989)? It is intended that items sharing a common construct will have factor loadings of 0.60 or higher on a single factor in order to establish sufficient convergent validity of the instrument (called same-factor loadings). Results of convergent validity is presented in the next chapter

Discriminant validity

It is established when, based on theory, two variables are predicted to be uncorrelated, and the scores obtained by measuring them are indeed empirically found to be so, that is, to differentiate one group from another. The lack of a relationship among measures should theoretically not be related (Singh, 2015). For adequate discriminant validity, it is expected that items belonging to a common construct should exhibit factor loadings of 0.30 or less on all other factors (cross-factor loadings). Results of discriminant validity is presented in the next chapter.

3.7 Ethical Considerations/Issues

Ethics are the moral principles that a person must follow, irrespective of the place or time (Akaranga and Makau, 2016). Research ethics focus on the moral principles that researchers must follow in their respective fields of research (Fouka and Mantzorou, 2011). A consent form was presented to the authorities of all selected SMEs to inform them of all benefits and risks involved in the participation and further sought their consent for their inclusion in the study. Selected SMEs had the right to decline their participation in the study. The researcher indicated in the consent form that all forms of anonymity and confidentiality would be observed. Privacy of SMEs in terms of freedom to define the time, extent and the conditions of sharing information was also observed. The researcher avoided any form of actions in their relation with participants that amounts to deception. All forms of plagiarism and falsification of data were also avoided by the researcher.

3.8 Profile of the Manufacturing Sector in Ghana

Ghana's manufacturing sector encompasses a range of industries, including food and beverages, textiles and garments, pharmaceuticals, chemicals, plastics, metal and metal products, wood and wood products, and electronics. The manufacturing sector contributes significantly to Ghana's Gross Domestic Product (GDP), providing employment opportunities and contributing to economic development. Ghana has established industrial zones, such as the Tema Industrial Area and the Sekondi-Takoradi Industrial Area, which host numerous manufacturing enterprises. Key Sub-Sectors:

- Food and Beverage: Processing of agricultural products, including cocoa, and production of beverages.
- Textiles and Garments: Production of textiles, apparel, and related products.

- Pharmaceuticals: Manufacturing of pharmaceutical products.
- Chemicals and Plastics: Production of chemicals, plastics, and related products.
- Metal and Metal Products: Manufacturing of metal goods and machinery.
- Wood and Wood Products: Processing of timber and production of wood-based products.

Manufacturing firms in Ghana face challenges such as inadequate infrastructure, energy fluctuations, and sometimes difficulty accessing finance. The Ghanaian government has implemented policies to promote the growth of the manufacturing sector, including incentives for local production and efforts to attract foreign investment. Some manufacturing firms in Ghana are oriented towards exports, contributing to international trade. The manufacturing landscape includes a mix of Small and Medium Enterprises (SMEs) and larger industrial entities.The adoption of technology and modern manufacturing practices is on the rise, contributing to increased efficiency in some manufacturing processes. Ghana's manufacturing firms often engage in regional and international trade, benefiting from regional economic integration agreements and partnerships. Manufacturing firms operate within a regulatory framework set by government agencies to ensure quality standards, safety, and compliance with environmental regulations.To obtain the most current and specific information about the profile of manufacturing firms in Ghana, it's recommended to refer to recent reports from governmental bodies, industry associations, and other reliable sources that provide up-to-date data and insights into the country's manufacturing sector. As of the second quarter of 2020, the manufacturing sector in Ghana contributed around 4.6 billion Ghanaian cedis (GHS), around 755.6 million U.S. dollars, to the country's GDP. Compared to the preceding quarter, this was a notable decrease. Within the period observed, the contribution of manufacturing to GDP fluctuated, peaking in the first quarter of 2021, at approximately 6.8 billion GHS (roughly 1.1 billion U.S. dollars). GDP from Manufacturing in Ghana decreased to 4538.66 GHS Million in the second quarter of 2023 from 6070.45 GHS Million in the first quarter of 2023. GDP from Manufacturing in Ghana averaged 3863.73 GHS Million from 2006 until 2023, reaching an all time high of 6357.80 GHS Million in the first quarter of 2022 and a record low of 2640.53 GHS Million in the first quarter of 2006.

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CHAPTER FOUR

DATA ANALYSIS, INTERPRETATION AND DISCUSSION

4.0 Introduction

The fourth chapter presents analysis of data gathered through the procedures in the previous chapter. This chapter has four (4) major sections. The first chapter presents the results of exploratory data analysis, the second part delt with descriptive analyses of demographic characteristics at the individual level. It also included descriptive and correlational analyses among the study variables. The third section presents the Confirmatory Factor Analysis, which assesses the validity and reliability of the model, and the model fit index is presented in the chapter too. The next section presents an evaluation of the structural model that tests the various hypotheses proposed in the study. Finally, there is a discussion of the main findings of the results. The analyses were done using SPSS version 25 and Smart-PLS version 4.

4.1 Exploratory Data Analysis

The first section of this study contains the exploratory data analysis. To ensure preliminary data quality check, the exploratory factor analysis was conducted in the study. The Statistical Package for Social Sciences (SPSS) was used in performing the exploratory factor analysis. The section has three subsections of which are the response rate, none response bias and common method bias. The subsequent sections below present the various tests and interpretation for this preliminary data quality check. The results from the are presented in the subsequent sections below.

4.1.1 Response Rate

Response rates are usually used to measure the quality of the data used in the study and thus a low response rate could result in nonresponse bias. Test for response rate was conducted to examine the rate of response to the survey. The test is essential especially in surveys that last for a longer duration. The data collection for this study was lasted between December 19th to 5th January, 2023. Thus, the period of data collection lasted approximately two weeks. Out of two hundred and sixty-four (264) questionnaires that were administered to respondents, 255 were retrieved and were found to be usable in this study. The yield a response rate of 96.6%, which is sufficient for further analysis (Giromini, Young and Sellbom, 2022; Jeon and Boeck, 2019).

Table 4.1 Data Response Rate

Distributed	**Collected**	**Percentage**
Response	255	96.6
Non-Response	14	3.4
Total	**264**	**100.0**

4.1.2 Test for Common Method Bias and Sampling Adequacy

EFA was used to evaluate common method bias using Harman's single factor test to validate the suitability of the constructs in the measurement model. According to Podsakoff et al. (2003), the one-factor test as the Harman considers all the observed variables in exploratory factor analysis (EFA) and assesses whether a single factor accounts for or explains more than 50% of the calculated variance. The result as presented in Table 4.2 below shows that the largest variance explained by a single factor is 40.8% which is below the 50% threshold of the EFA using the principal component analysis extraction method. This confirms the absence of CMB in the dataset. Additionally, the correlation matrix was used to further validate the absence of CMB following the limitations of Harman's one-factor approach. As per the recommendation of Tahseen et al. (2017), the correlations among the main constructs should not exceed a recommended threshold to confirm the absences of CMB. The result in our study revealed that the correlations among the principal constructs were small (r<0.9). This further confirms Harman's one-factor test result, hence there is no issue of CMB in this research model.

Table 4. 2: Test for Common Method Variance (CMV)

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	8.968	40.766	40.766	8.968	40.766	40.766
2	3.220	14.636	55.401	3.220	14.636	55.401
3	2.093	9.515	64.916	2.093	9.515	64.916
4	1.470	6.682	71.598	1.470	6.682	71.598
5	.879	3.998	75.596			
6	.591	2.684	78.280			
7	.528	2.401	80.681			
8	.506	2.298	82.979			
9	.464	2.110	85.089			
10	.410	1.865	86.954			
11	.371	1.687	88.641			
12	.357	1.624	90.265			
13	.335	1.522	91.787			
14	.295	1.343	93.130			
15	.260	1.183	94.312			
16	.238	1.081	95.393			
17	.231	1.052	96.445			
18	.215	.979	97.424			
19	.166	.754	98.178			
20	.160	.728	98.906			
21	.134	.610	99.516			
22	.106	.484	100.000			

Source: Field Survey, 2023

Additionally, the Bartlett sphericity test and the Kaiser–Meyer–Olkin (KMO) were employed to measure sampling adequacy. The result as presented Table 4.3 below showed the evidence of sampling adequacy as the Kaiser-Meyer-Olkin Measure of Sampling Adequacy was 90.9% while Bartlett's test also showed a significant value (χ^2 = 4213.312, df.: 909, $p < 0.000$).

Table 4.3: Bartlett's Test of Sphericity and KMO Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.909
Bartlett's Test of Sphericity	Approx. Chi-Square	4213.312
	df	231
	Sig.	.000

Source: Field Survey, 2023

4.1.3 Non-Response Bias

This study examined non-response bias. Thus, when fewer people than the population as a whole reply to a survey, this is known as non-response bias. Low survey response rates are a frequent cause of non-response bias, which can have an effect on the quality of the sample used to generate conclusions and the overall validity of the study. By contrasting the responses of early and late respondents, non-response bias in this study was examined in an effort to minimize it. Those that submitted their questionnaires early did so within the first one-week response window, whilst those who returned theirs later are referred to as "late respondents." As stated by Holmes and Oppenheim (2001), no statistically significant differences should be found between the two groups for any of the variables employed in the model. The results show that there is no non-response bias in this study and that the samples adequately reflect the target population. To be more precise, the first 127 responses were regarded as early responses, while the remaining 128 were regarded as late responses. A T-test was then performed to check for non-response bias. According to Table 4.4, the results of the t-test did not indicate a statistically significant difference. As a result, the study confirms that the data on the constructs acquired during the first week and the last week of the data collection are identical.

Table 4.4 Results of Independent-Samples t-Test for Non-Response Bias

			Levene's Test for Equality of Variances		
Variables	Group	Mean	F	Sig.	T
BDAC	1.00	20.67	1.804	0.016	0.512
	2.00	18.47			
KC	1.00	37.48	0.372	0.675	0.567
	2.00	35.05			
SCI	1.00	29.09	0.657	0.382	1.096
	2.00	26.19			
Gender	1.00	25.23	0.302	0.632	1.096
	2.00	24.18			
Age	1.00	26.43	1. 279	0.213	1.628
	2.00	25.87			

Source: Field Data, 2023

4.2 Socio Demographic Characteristics of Respondents

The study captures the demographic background information of the respondents involved in the study. The demographic background information captured in the study were gender, age, level of education, position in the firm, years of firm operation, number of employees in the firm, and type of firm ownership. The results from the study as indicated in Table 4.5 revealed that 78(30.6%) of respondents were females and 177 (69.4%) of respondents were males. Thus, majority of the respondents were males. The study revealed that 131(51.4%) of the respondents were 18-30 years, 109(42.7%) of the respondents were 31-40 years, and 15(5.9%) of the respondents were 41-50 years. Hence, majority of the respondents were within 18-30 years. The level of education was also captured in this study, the results indicate that 171(67.1%) of respondents were bachelor degree holders, 26(10.2%) of respondents were diploma holders, 9(3.5%) of respondents were postgraduate degree holders, 27(3.5%) of respondents were having other educational background and 22(8.6%) of respondents were having Senior High School. Thus, majority of respondents involved in the study were bachelor degree certificate holders which implied that respondents have enough education to understand the subject of the study. Respondents position in the firm was further captured in the study. The results from the study showed that 15(5.9%) of respondents were business owners, 1(0.4%) of respondents were business owners and managers, 66(25.9%) of respondents were production managers and 173(67.8%) of respondents were managers. Hence, majority of the respondents were managers in their firms. The study further indicates the years of the firm operation, the results from the study revealed that 18(7.1%) of respondents have 1-5 years of firm operation, 49(19.2%) of respondents also have 11-15 years of firm operation, 62(24.3%) of respondents have operated in the firm for 16 years and over and 126(49.4%) of respondents have operated in the firm for about 6 - 10 years. Thus, most of the firms have operated for over 5 years. Additionally, the results revealed that 56(22.0%) of respondents have 30-99 employees in the firm, 39(15.3%) of respondents have 5-29 employees in their firm, 33(12.9%) of respondents have less than 30 employees in their firm and 127(49.8%) of respondents have over 100 employees in their firm. The study finally revealed the type of ownership of the firm, the results showed that 161(63.1%) of the firms were fully locally owned firms and 94(36.9%) were jointly Ghanaian and foreign owned firms. Thus, majority of the firms involved in the study were fully locally owned firms.

Table 4.5: Socio Demographic Characteristics of Respondents

Variable	**Category**	**Frequency**	**Percent**
Gender	Female	78	30.6
	Male	177	69.4
Age	18-30 years	131	51.4
	31-40 years	109	42.7
	41-50 years	15	5.9
Level of Education	Bachelor Degree	171	67.1
	Diploma	26	10.2
	Graduate Studies	9	3.5

	(Master / PhD)		
	Others	27	10.6
	Senior High School	22	8.6
Your Position in the Firm	Business owner	15	5.9
	Business owner and Manager	1	.4
	Production Manager	66	25.9
	Managers	173	67.8
Years of firm operation	1 - 5 years	18	7.1
	11 – 15 years	49	19.2
	16 years and above	62	24.3
	6 - 10 years	126	49.4
Number of employees	30 – 99 employees	56	22.0
	31 – 40 employees	39	15.3
	Less than 30 employees	33	12.9
	More than 100	127	49.8
Type of ownership	Fully locally owned	161	63.1
	Jointly Ghanaian and foreign-owned	94	36.9
	Total	**255**	**100**

Source: Field Survey, 2023

4.3 Descriptive Statistics and Correlation Analysis

This section of the analysis employed a descriptive approach (mean and standard deviations) and correlational analysis in describing the views of respondents on the study variables. This model comprises three (3) variables namely; Big Data Analytics Capability, Knowledge Creation and Supply Chain Innovation. The results on the descriptive analysis are showed in Table 4.6 below.

Big Data Analytics Capability scored (Mean=3.91; Std=0.84) indicating that Big Data Analytics Capability (BDAC) was moderately high. Knowledge Creation (KC) scored (Mean=3.63; Std=1.06) indicating Data Analytics Capability (BDAC) was moderately high. Supply Chain Innovation (SCI) scored (Mean=3.95; Std=0.82) indicating Supply Chain Innovation (SCI) was moderately high. The correlation result showed statistically significant positive association between Big Data Analytics Capability (BDAC), Knowledge Creation (KC) and Supply Chain Innovation (SCI) (r=0.925; r=0.891). the study revealed a strong positive relationship between Knowledge Creation (KC) and Supply Chain Innovation (SCI) (r=0.935). Hence, the results implied that big data analytics capability and knowledge creation have a strong positive significant relationship with supply chain innovation.

Table 4.6 Descriptive and Correlation Analysis

Constructs	**Mean**	**StD**	**1**	**2**	**3**	**4**
Big Data Analytics Capability (BDAC)	3.91	0.84	1.000			
Knowledge Creation (KC)	3.63	1.06	0.925	1.000		
Supply Chain Innovation (SCI)	3.95	0.82	0.891	0.935	1.000	

Source: Field Survey, 2023

4.4 Confirmatory Factor Analysis

Confirmatory Factor Analysis was used to assess model validity and reliability using Smart PLS version 4. The validity and reliability of the constructs were tested using the maximum likelihood estimation approach. As a prerequisite for the structural model analysis, the model measurement evaluation was carried out. Cronbach Alpha (CA), Composite Reliability (CR), and Average Variance Extracted (AVE) were used to assess the model's reliability and validity.

The first phase in the model measurement evaluation is to examine the reflective model measurement. The outcome, as shown in Table 4.6 below, demonstrates that the indicator loading ranges between 0.804 to 0.950, indicating that the 0.70 criterion recommended by Hair et al. (2019) is achieved. The result demonstrates that the construct accounts for more than half of the indicator variance, indicating that item reliability is adequate. As indicated in Table 4.7 below, all the construct such as BDAC, KC and SCI had a respective p-value of 0.000, 0.006 and 0.000 which indicate they are statistically significant. In addition, the reliability of the constructs in this study was investigated using two internal consistency measures (Cronbach Alpha and Composite reliability). High Cronbach Alpha and Composite reliability values suggest high reliability (Hair et al., 2019). The Cronbach Alpha values in this study were all above the 0.70 threshold. CA values between 0.951 and 0.984 are considered satisfactory to good, according to Hair et al (2019). Composite reliability is another way to assess reliability of the constructs. Composite reliability in this study were 0.963, 0.985 and 0.965 for BDAC, KC and SCI respectively which were also greater than the 0.70 threshold. In conclusion, all of the constructs had strong scale reliability (i.e., Cronbach Alpha and Composite reliability were greater than 0.7) and hence had adequate internal consistency and reliability (Fornell and Larcker, 1981; Henseler et al., 2015; Hair et al., 2019).

The convergent validity of each construct measure is addressed in the third step of the reflective measurement model assessment. The extent to which a construct converges to explain the variance of its elements is known as convergent validity. The average variance extracted (AVE) for all items on each construct is the metric used to assess convergent validity. The AVE is computed by squaring the loading of each indicator on a construct and computing the mean value. A value of 0.60 or higher indicates that the construct explains at least 60% of the variance among its elements (Hair et al., 2019; Henseler et al., 2015). The result of this study as presented in Table 4.7 below indicates that AVE which was also used to assess convergent validity of the constructs were found above the 0.6 threshold (Hair et al., 2019).

Table 4.7: Reliability and Validity

Construct	Items	Loading	CA	CR	AVE	VIF	T statistic	P value
Big Data Analytic Capability (BDAC)	BDAC1	0.940	0.951	0.963	0.837	6.173	102.741	0.000
	BDAC2	0.937				6.150		
	BDAC3	0.950				7.609		
	BDAC4	0.841				2.982		
	BDAC5	0.903				4.625		
Knowledge creation (KC)	KC1	0.862	0.984	0.985	0.774	7.978	2.746	0.006
	KC10	0.922				9.659		
	KC11	0.900				11.950		
	KC12	0.907				18.006		
	KC13	0.840				5.647		
	KC14	0.901				9.942		
	KC15	0.807				5.709		
	KC16	0.811				7.173		
	KC17	0.804				6.678		
	KC18	0.904				14.586		
	KC19	0.882				7.362		
	KC2	0.884				8.605		
	KC3	0.895				7.403		
	KC4	0.916				10.265		
	KC5	0.885				7.591		
	KC6	0.872				6.670		
	KC7	0.913				10.746		
	KC8	0.890				8.132		
	KC9	0.911				16.045		
Supply chain innovation (SCI)	SCIN1	0.886	0.958	0.965	0.799	5.129	11.382	0.000
	SCIN2	0.926				6.143		
	SCIN3	0.930				5.699		
	SCIN4	0.908				4.340		
	SCIN5	0.880				4.656		
	SCIN6	0.873				3.905		
	SCIN7	0.851				3.234		

CA= Cronbach Alpha; CR=Composite reliability; Average Variance Extracted =AVE; VIF= Variance Inflation Factor

Source: Field Survey, 2023

4.4.1 Discriminant Validity

The fourth phase is to determine discriminant validity, or how different a construct is from other constructs in the structural model in terms of experimental validity. Fornell and Larcker (1981) introduced the standard metric, which recommended comparing each construct's AVE to the squared inter-construct correlation (as a measure of shared variance) of that construct and all other reflectively rated constructs in the structural model. The shared variance of all model constructs should not exceed their AVEs. Recent research, however, reveals that this metric is unhelpful in determining discriminant validity. The Heterotrait-Monotrait (HTMT) correlation ratio was proposed by Henseler et al. (2015) as a replacement (Voorhees et al., 2016). The HTMT is defined as the difference between the mean value of item correlations across constructs and the (geometric) mean of average correlations for items measuring the same construct. Discriminant validity difficulties develop when HTMT measurements are high. Henseler et al. (2015) offer a threshold value of 0.90 for structural models incorporating dimensions that are theoretically quite close, such as cognitive satisfaction, affective fulfillment, and loyalty. An HTMT score of more than 0.90 shows that discriminant validity is not present in this situation. A lower, more conservative threshold value, such as 0.85, is advised when constructs are more conceptually diverse (Henseler et al., 2015). Bootstrapping can be employed in addition to these criteria to examine if the HTMT value changes significantly from 1.00 (Henseler et al., 2015) or a lower threshold value of 0.85 or 0.90, which should be selected based on the study context (Franke and Sarstedt, 2019). As demonstrated in Table 4.7, all of the HTMT values are less than 0.90 or 0.85, indicating that discriminant validity has been proven. Table 4.9 shows the discriminant validity using HTMT. In conclusion, the result from using both Fornell and Larcker criterion and HTMT test revealed the presence of discriminant validity.

Table 4.8 Fornell and Larcker Criterion

Construct	**1**	**2**	**3**
Big Data Analytics Capability	0.915		
Knowledge Creation	0.925	0.880	
Supply Chain Innovation	0.891	0.935	0.894

Source: Field Survey, 2023

Table 4.9 HTMT Test

Construct	**1**	**2**	**3**
Big Data Analytics Capability			
Knowledge Creation	0.952		
Supply Chain Innovation	0.930	0.961	

Source: Field Survey, 2023

4.4.2 Model Fitness Indices

The results as shown in Table 4.10 showed the model fit indices of the model. The results showed that all the model fit indices (NFI: Fitness of Extracted-Index; SRMR: Standard Root Mean Square Residual; RMSE: Root Mean Square of Approximation and Chi-Square) are within acceptable range. The value of abnormal index and extracted index is less than 0.9, which is an acceptable limit. The root means the squared value of the residual and the common root means that the squared residual is not close to zero, an acceptable standard. Again, the the results on the model fit indices shows that the model is acceptable (Shi, Lee and Maydeu-Olivares, 2019).

Table 4.10 Model Fitness Indices

Indices	Saturated model	Estimated model
SRMR	0.049	0.049
d_ULS	1.187	1.187
d_G	4.352	4.352
Chi-square	4183.698	4183.698
NFI	0.709	0.709

Source: Field Survey, 2023

4.4.3 Coefficient of Determination (R^2)

The coefficient of determination is a number between 0 and 1 that measures how well the model used in the study help in predicting the outcome. Hence, according to Hair et al. (2020), R^2 values of 0.75, 0.50 and 0.25 are considered large, medium and weak respectively. Hair et al. (2020) however, argue that it is necessary to interpret R^2 with a focus on the context of appropriate discipline (Hair et al., 2020). The results as showed in Table 4.11 and Figure 4.1 below indicate that the model shows a strong predictive accuracy (R^2) value of 0.855 (85.5%) for knowledge creation and 0.879 (87.9%) for supply chain innovation. These results show that big data analytics capability and knowledge creation predicts 87.9% of the operation of the firms supply chain innovation.

Table 4.11 Coefficient of Determination

Construct	R-square	R-square adjusted
Knowledge Creation	0.855	0.855

Supply Chain Innovation	0.879	0.878

Source: Field survey, 2023

4.4.4 The Effect of Prediction Size (Q^2)

The effect of prediction size as a way for accuracy checks of a PLS model was done to calculate the value of Q^2 (Hair et al., 2020). This metric is based on the method of blindly removing a point from the data matrix, assigning missing points and estimating the phase of the model (Zhang, 2022). Thus, Q^2 is not a prediction method, but combines sample prediction data with the explanatory power of the model (Hair et al., 2020). Using this estimate as input, the blindfold method interprets the output data. A small difference between predicted values and baseline translates into higher Q^2 values and, therefore, indicates higher accuracy (Zhang, 2022). As a guideline, the value of Q^2 for a given endogenous should be greater than zero to demonstrate the accuracy of the design estimate for that construct. As a rule of thumb, Q^2 above 0, 0.25 and 0.50 indicates small, medium and small predictive values respectively for the PLS path model (Zhang, 2022). The results presented in Table 4.12 indicate that Q^2 value was 0.853 and 0.792 for knowledge creation and supply chain innovation respectively. Results indicated a moderate interaction in the model (Zhang, 2022). Thus, all Q-square values were above the threshold, indicating a good fit of the values and predictive value of the model.

Table 4.12 The Predictive Power of the PLs Model

Construct	**Q^2predict**	**RMSE**	**MAE**
Knowledge Creation	0.853	0.386	0.265
Supply Chain Innovation	0.792	0.459	0.322

Source: Field survey, 2023

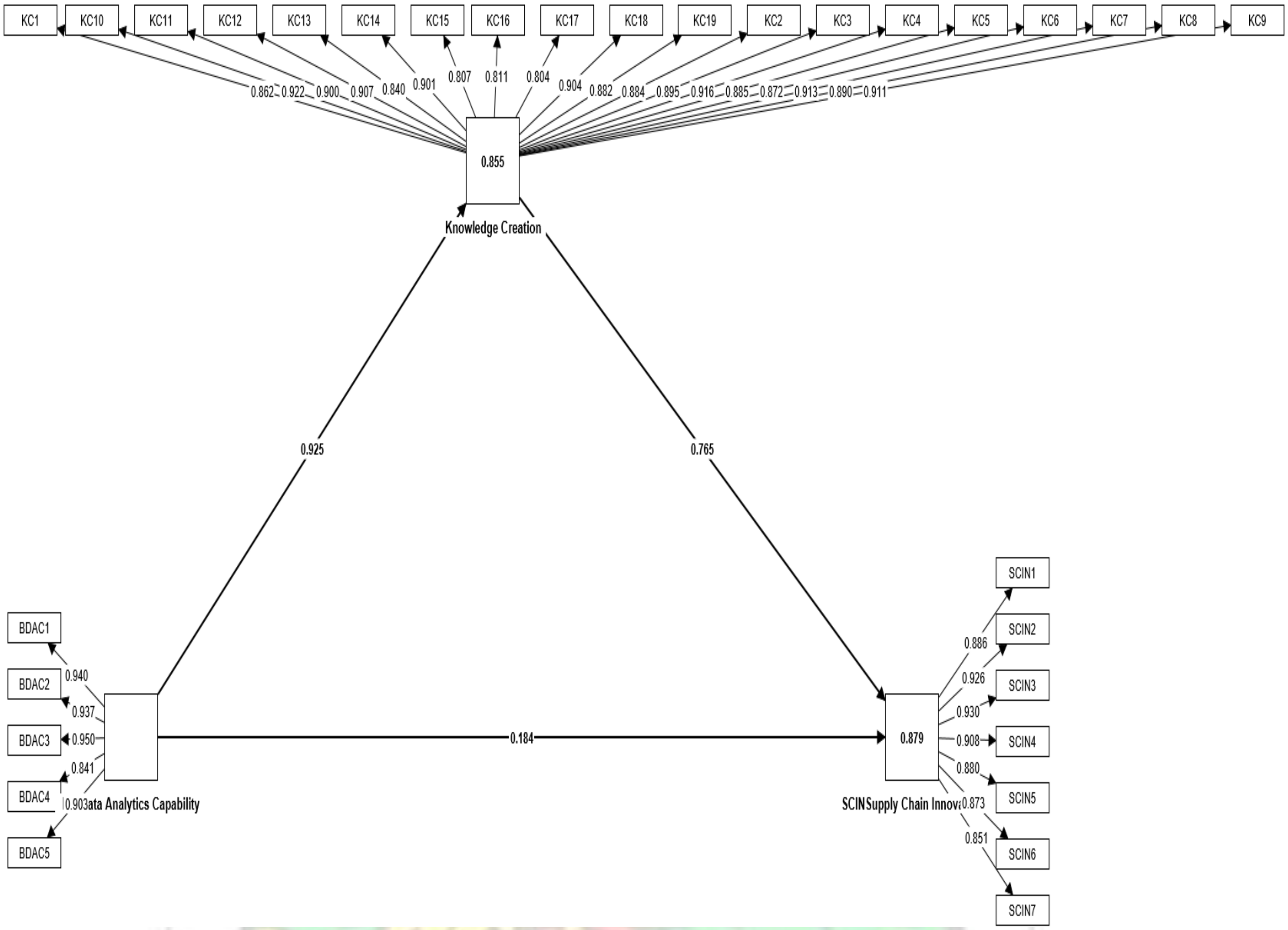

Figure 4.1: Measurement Model Evaluation for Supply Chain Innovation (SCI)

4.5 Hypotheses Testing for Hypothesis

Though Supply chin Innovation and Big Data Analytics Capability have received significant attention in supply chain literature, however knowledge contents as mediating role between Supply chin Innovation and Big Data Analytics Capability remain scanty in literature. This study envisages that in the face of knowledge creation, manufacturing firms that are able to implement new ideas tend to build a robust supply chain that could aid them in withstanding the implications of firm innovations as well as building stronger hedge against future challenges. This study examined the effect of big data analytics capability on supply chain innovation with the mediating role of knowledge creation. Based on the gaps identified in literature, a framework of four (4) hypotheses were developed. Data was gathered from managers at the manufacturing multinational firms in Ghana using questionnaire and the methods elaborated in the methodology chapter. The hypothesis and construct relationship were tested using the standardized path coefficients. The path's significance level was calculated using the bootstrap resampling procedure (Henseler et al., 2009), with 500 iterations of resampling (Chin, 1998). The result has been discussed in line with the hypotheses and objectives of the study in the subsequent section below.

4.5.1 Hypotheses Testing for Direct Effect

The result in Table 4.13 below shows that the first (H_1) hypothesis of the study which investigated the effect of Big Data Analytics Capability on knowledge creation among manufacturing firms was supported (B=0.925, t=10.775, P=0.000, Sig<0.005). The result shows that a unit improvement in big data analytics capability improves knowledge creation for approximately 92.5%. Hence, evidence from the results indicates that big data analytics capability significantly influences knowledge creation among manufacturing firms in Ghana.

Again, the second hypothesis (H_2) was also supported, thus Big Data Analytics Capability significantly effect Supply Chain Innovation among manufacturing firms in Ghana (B=0.184, t=12.306, P=0.000, Sig<0.005). The result revealed that a unit improvement in Big Data Analytics Capability increases Supply Chain Innovation for approximately 18.4%. Hence, evidence from the results indicates that Big Data Analytics Capability significantly enhances Supply Chain Innovation of manufacturing firms in Ghana.

The results again revealed that the third (H_3) hypothesis of the study which was to investigate the effect of Knowledge Creation on Supply Chain Innovation among manufacturing firms was supported (B=0.765, t=11.562, P=0.020, Sig<0.005). The result shows that a unit improvement in Knowledge Creation enhances Supply Chain Innovation for approximately 76.5%. Hence, evidence from the results indicates that Knowledge Creation significantly enhance Supply Chain Innovation among S manufacturing firms.

In summary all the three direct paths were significant, and thus knowledge creation and Big Data Analytics Capability significantly enhances Supply Chain Innovations among manufacturing firms in Ghana

4.5.2 Hypotheses Testing for Mediation Effect

Prior studies of (Preacher and Hayes, 2004; 2008; Hayes (2009), have attacked Baron and Kenny's "causal process of testing for mediation." Regardless, all that is required is a single inferential test of the indirect effect. When looking for mediation, several experts tend to propose that the direct influence does not have to be considerable (Shrout and Bolger, 2002; Zhao, Lynch and Chen, 2010). This is because a significant direct association may be missed due to a small sample size or other factors (e.g., moderating), or there may not be enough power to predict the impact that exists. As a result, the indirect effect remains important mediation analysis procedure (Hayes and Rockwood, 2016). This study examined the mediating effect using the bootstrapping indirect effect as recommended by Preacher and Hayes (2004; 2008).

The last hypothesis was to examine the mediating role of knowledge creating between Big Data Analytics Capability and Supply Chain Innovation. The study revealed that the fourth (H_4) hypothesis of the study was also supported. Thus, Knowledge Creation significantly mediate the relationship between Big Data Analytics Capability and Supply Chain Innovation among manufacturing firms in Ghana (B=0.708, t=3.091, P=0.002, Sig<0.005). This implied that a unit change in Knowledge Creation will positively improve the relationship between Big Data Analytics Capability and Supply Chain Innovation by 70.8%. Hence, the results indicates that Knowledge Creation significantly mediate the between Big Data Analytics Capability and Supply Chain Innovation among manufacturing firms in Ghana. The result further indicates that Knowledge Creation plays a partial mediation in the relationship between Big Data Analytics Capability and Supply Chain Innovation of among manufacturing firms, this conclusion was drawn by the fact that both direct and indirect effects are significant. Thus, firms that are able to implement new ideas which enhances supply chain innovation that could aid them in withstanding the implications of the firms innovations as well as building stronger hedge against future interruptions.

Table 4.13 Hypotheses Testing for Relationship

Hypothesis	Path Coefficient	T-Value	P-Value
BDAC -> KC	0.925	10.775	0.000
BDAC -> SCI	0.184	12.306	0.000
KC -> SCI	0.765	11.562	0.000
BDAC -> KC -> SCI	0.708	3.091	0.002

Source: Field survey, 2023

4.6 Results Discussion

Though Supply chin Innovation and Big Data Analytics Capability have received significant attention in supply chain literature, however knowledge contents as mediating role between Supply chin Innovation and Big Data Analytics Capability remain scanty in literature. This study envisages that in the face of knowledge creation, manufacturing firms that are able to implement new ideas tend to build a robust supply chain that could aid them in withstanding the implications of firm innovations as well as building stronger hedge against future challenges. This study examined the effect of big data analytics capability on supply chain innovation with the mediating role of knowledge creation. Based on the gaps identified in literature, a framework of four (4) hypotheses were developed. Data was gathered from 250 managers at the manufacturing multinational firms in Ghana using questionnaire and the methods elaborated in the methodology chapter. The hypothesis and construct relationship were tested using the standardized path coefficients. The path's significance level was calculated using the bootstrap resampling procedure (Henseler et al., 2009), with 500 iterations of resampling (Chin, 1998). The result has been discussed in line with the hypotheses and objectives of the study in the subsequent section below.

4.6.1 Big Data Analytics Capability on Knowledge Creation

The result shows that the first (H_1) hypothesis of the study which investigated the effect of Big Data Analytics Capability on knowledge creation among manufacturing firms was supported. Thus, a unit improvement in big data analytics capability improves knowledge creation for approximately 92.5%. Hence, big data analytics capability significantly influences knowledge creation among manufacturing firms in Ghana.

The findings that Big Data Analytics Capability significantly influences knowledge creation have important implications when viewed through the lens of Dynamic Capabilities (DC) theory. The acquisition and deployment of Big Data Analytics Capability can be seen as a dynamic capability within an organization. Dynamic Capabilities theory posits that organizations can build and deploy capabilities that enable them to adapt to changing environments. In this context, the ability to leverage big data analytics represents a dynamic capability as it involves configuring and reconfiguring resources to enhance knowledge creation in response to evolving challenges and opportunities. Dynamic Capabilities involve the capacity to learn and adapt in dynamic environments. Big Data Analytics, by providing tools to analyze large volumes of diverse data, enables organizations to adapt their knowledge creation processes based on insights gained from the analysis. It promotes a learning orientation by facilitating continuous improvement and innovation. Big Data Analytics facilitates the codification and diffusion of knowledge within the organization. Dynamic Capabilities involve the integration, reconfiguration, and renewal of organizational resources. In the context of knowledge creation, big data analytics enables the codification of valuable insights gained from data analysis. This codified knowledge can then be diffused throughout the organization, supporting a dynamic capability to spread and apply knowledge effectively. Big Data Analytics Capability contributes to innovation and strategic renewal. Dynamic Capabilities involve the ability to renew and adapt strategies. Big Data Analytics, by uncovering patterns, trends, and opportunities, provides organizations with the knowledge needed for strategic renewal and innovation. It supports a dynamic capability to continuously refresh the organization's strategies based on evolving market conditions and internal capabilities. Dynamic Capabilities theory suggests that organizations can achieve a competitive advantage by developing and deploying unique capabilities. In the context of knowledge creation, the ability to harness big data analytics represents a dynamic capability that can differentiate an organization from its competitors. Continuous learning and knowledge creation contribute to maintaining a competitive edge. In summary, the findings that Big Data Analytics Capability significantly influences knowledge creation align with the principles of Dynamic Capabilities theory. They highlight the strategic importance of leveraging dynamic capabilities, specifically in the form of big data analytics, to enhance an organization's capacity for continuous learning, adaptation, and knowledge creation in today's rapidly changing business environments. The outcome of this study is not different of Philip (2018) that opine that innovation in supply processes, methods, and arrangements are required for supply chain innovation; these changes provide significant latitude for planning, monitoring, forecasting, and replenishment, resulting in accurate, concrete, and quick decision-making in the event of a crisis, thereby strengthening firm innovation and resilience against surprising shocks (Fuchs, Hopken and Lexhagen, 2014; Ferraries et al., 2018; Pauleen and Wang, 2017). As a result, innovation can help supply chains become more accurate and error-proof (Smith, Collins and Clark, 2005; Saide and Sheng, 2020). Furthermore, extant literature (Goyal, Ahuja and Kankanhalli, 2020; Sumbal, Tsui and See-to, 2017; Afrazv et al., 2021) have indicated that implementing an innovative process can raise awareness of vulnerabilities and knowledge sharing with supply chain entities, allowing for continuous process innovation to effectively reduce risk occurrence and strategies to overcome and avoid adverse effects, thereby increasing the firm's robustness.

4.6.2 Effect of Big Data Analytics Capability on Supply Chain Innovation

Again, the second hypothesis (H_2) was also supported, thus Big Data Analytics Capability significantly affect Supply Chain Innovation among manufacturing firms in Ghana. The result revealed that a unit improvement in Big Data Analytics Capability increases Supply Chain Innovation for approximately 18.4%. Hence, evidence from the results indicates that Big Data Analytics Capability significantly enhances Supply Chain Innovation of manufacturing firms in Ghana. The result is in conformity with prior studies (Golgeci and Ponomarov, 2013; Kwak et al., 2018; Parast et al., 2019; Parast, 2020; Sabahi and Parast, 2020) which have argued that firms that invest in innovation have the potency of developing a resilient supply chain to mitigate the adverse implication of disruption. Thus, the outcome of this study demonstrated that Big Data Analytics Capability play essential role in firm’s innovations. When analyzing the implications of the findings that Big Data Analytics Capability significantly influences supply chain innovation from the perspective of Organizational Information Processing Theory (OIPT), several key insights emerge. Big Data Analytics Capability enhances the organization's capacity to acquire and process information relevant to supply chain processes and market dynamics. OIPT emphasizes the importance of information acquisition and processing for organizational effectiveness. Big Data Analytics, as a capability, allows organizations to collect, analyze, and interpret vast amounts of data. In the context of supply chain innovation, this capability facilitates a more comprehensive understanding of market trends, customer preferences, and operational inefficiencies. Big Data Analytics supports more informed decision-making and problem-solving in the supply chain domain. OIPT posits that effective information processing leads to improved decision-making. With Big Data Analytics, organizations can make data-driven decisions in real-time, identify areas for improvement within the supply chain, and proactively address challenges. This capability enhances problem-solving by providing insights based on comprehensive data analysis. Big Data Analytics contributes to better coordination and integration across supply chain functions. OIPT emphasizes the need for coordination and integration of information to achieve organizational goals. Big Data Analytics enables organizations to integrate information from various sources, both internal and external, leading to a more cohesive and well-coordinated supply chain. This, in turn, supports innovation by fostering collaboration and breaking down silos within the organization. In summary, the implications of the findings, viewed through the lens of Organizational Information Processing Theory, highlight how Big Data Analytics Capability serves as a critical enabler for effective information processing, decision-making, and innovation within the supply chain. The theory underscores the importance of aligning information processing capabilities with organizational goals to achieve enhanced supply chain innovation.

4.6.3 Effect of Knowledge Creation on Supply Chain Innovation

The results again revealed that the third (H_3) hypothesis of the study which was to investigate the effect of Knowledge Creation on Supply Chain Innovation among manufacturing firms was supported. The result shows that a unit improvement in Knowledge Creation enhances Supply Chain Innovation for approximately 76.5%. Hence, evidence from the results indicates that Knowledge Creation significantly enhance Supply Chain Innovation among S manufacturing firms. In summary all the three direct paths were significant, and thus knowledge creation and Big Data Analytics Capability significantly enhances Supply Chain Innovations among manufacturing firms in Ghana. Prior studies have established that knowledge creation relates to a supply chains ability to withstand disruptions and changes (Malhotra, Gosain and Sawy, 2005; Cappellin and Wink, 2009; Ivanov et al., 2014) as well as manage risks in order to maintain normal operations (Kazadi, Lievens and Mahr, 2016; Al-Omoush, Palacios-Marques and Ulrich, 2011; Monostori, 2018; Vujanovic et al., 2022). Extant literature also argues that knowledge creation creates an enabling environment to enhance firms supply chain innovation (Agyabeng-Mensah, Afum and Baah, 2022; Gloet and Samson, 2022; Mackay et al., 2020; Johnson et al., 2021).

4.6.4 Mediating Effect of Knowledge Creating on Big Data Analytics Capability and Supply Chain Innovation

The fourth hypothesis of this study was the mediating role of knowledge creating between Big Data Analytics Capability and Supply Chain Innovation. The study revealed that the fourth (H_4) hypothesis of the study was also supported. Thus, Knowledge Creation significantly mediate the relationship between Big Data Analytics Capability and Supply Chain Innovation among manufacturing firms in Ghana. This implied that a unit change in Knowledge Creation will positively improve the relationship between Big Data Analytics Capability and Supply Chain Innovation by 70.8%. Hence, the results indicates that Knowledge Creation significantly mediate the between Big Data Analytics Capability and Supply Chain Innovation among manufacturing firms in Ghana. The result further indicates that Knowledge Creation plays a partial mediation in the relationship between Big Data Analytics Capability and Supply Chain Innovation of among manufacturing firms, this conclusion was drawn by the fact that both direct and indirect effects are significant. Thus, firms that are able to implement new ideas which enhances supply chain innovation that could aid them in withstanding the implications of the firms innovations as well as building stronger hedge against future interruptions. The result also provides empirical support that firms can use a variety of measures to improve their resilience to supply chain innovations (Bahrami, Shokouhyar and Seifian, 2022; de Vries et al., 2021). Firms dealing with manufacturing might strive for robustness (Alkhatin and Valeri, 2022), which is proactive. Knowledge creation as indicated by previous studies helps firms to get a strong foundation which intend aid them in developing an enhanced supply chain innovations and again helps firms to avoid negative effects of Supply Chain disruptions (Iftikhar et al., 2022; Durach et al., 2015; Vlajic et al., 2012). To accomplish so, such businesses seek to eliminate the SC risk's root cause (Cepeda-Carrion et al., 2022; Durach et al., 2015) or reduce its impact probability (Hajmohammad and Vachon, 2016). Changing suppliers or raising safey stock are two examples (Munir et al., 2022; Manhart et al., 2020). The theoretical implications of the finding that Knowledge Creation significantly mediates the relationship between Big Data Analytics Capability (BDAC) and Supply Chain Innovation can be understood through the lens of Dynamic Capability (DC) theory. The finding aligns with the essence of DC theory, which emphasizes the importance of adaptive learning. In this context, organizations with a higher capacity for knowledge creation are better positioned to adapt to changes in the business environment, particularly when driven by insights from Big Data Analytics. DC theory suggests that firms need to orchestrate their resources dynamically. In this case, BDAC represents a technological resource, and Knowledge Creation acts as an integrative capability that helps in the dynamic reconfiguration of resources to foster innovation in the supply chain. The findings imply that organizations need to be strategically flexible in their resource deployment. While BDAC provides a technological foundation, the ability to create and apply knowledge dynamically enhances the flexibility to respond to new challenges and opportunities in the supply chain. DC theory suggests that innovation is not a one-time event but a continuous process. Knowledge Creation, as a mediating factor, indicates that the process of innovation is not solely dependent on the initial implementation of BDAC but requires ongoing learning and adaptation. The theoretical implication underscores the significance of human capital in the dynamic capability framework. Organizations should invest in developing the skills and knowledge of their workforce to effectively utilize BDAC and contribute to the process of knowledge creation. DC theory emphasizes the importance of mechanisms that facilitate the integration of new knowledge. In the context of the findings, organizations need to establish effective mechanisms for integrating insights derived from BDAC into the existing knowledge base, fostering a synergistic relationship between technology and human expertise. DC theory highlights the concept of ambidexterity, where organizations need to balance both exploitation of existing capabilities and exploration of new opportunities. In this context, BDAC represents an exploitative capability, while Knowledge Creation represents an explorative capability that contributes to supply chain innovation. DC theory recognizes the role of organizational culture in fostering dynamic capabilities. The finding implies that a culture of continuous learning and knowledge creation is essential for translating the potential of BDAC into innovative practices in the supply chain. In summary, the theoretical implications emphasize the dynamic and interdependent nature of capabilities within organizations, where the integration of Big Data Analytics Capability and Knowledge Creation becomes a key driver for achieving innovation in the supply chain, aligning with the principles of Dynamic Capability theory

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS AND RECOMMENDATIONS

5.1 Introduction

This section of the study contains the summary of findings from the study as well as conclusions drawn from the study which are done in line with the objectives of the study. The section further elaborates on the recommendations and suggestions for further studies.

5.2 Summary of Findings

Although Supply Chain Innovation and Big Data Analytics Capability have drawn a lot of attention in the literature on supply chains, there is still a scarcity of research regarding the knowledge contents that play a mediating role between Supply Chain Innovation and Big Data Analytics Capability. This study postulates that manufacturing companies that are able to apply new ideas in the face of knowledge creation tend to develop a strong supply chain that might help them to resist the effects of firm innovations as well as build a stronger hedge against future issues. The main focus of this study was to examine the effect of big data analytics capability on supply chain innovation with the mediating role of knowledge creation. Three specific objectives were developed to address the main objective of the study. Data were collected using a questionnaire from 250 managers at multinational manufacturing companies in Ghana using the techniques described in the methodology section.

The first objective of the study was to examine the effect of Big Data Analytics Capability on Supply Chain Innovation among manufacturing firms in Ghana. The result revealed that a unit improvement in Big Data Analytics Capability increases Supply Chain Innovation for approximately 18.4%. Hence, evidence from the results indicates that Big Data Analytics Capability significantly enhances Supply Chain Innovation of manufacturing firms in Ghana.

The second objective of the study was to examined the relationship between Big Data Analytics Capability and knowledge creation among manufacturing firms was supported. Thus, a unit improvement in big data analytics capability improves knowledge creation for approximately 92.5%. Hence, big data analytics capability significantly influences knowledge creation among manufacturing firms in Ghana.

Finally, the study was to examine the mediating role of knowledge creating between Big Data Analytics Capability and Supply Chain Innovation. The study revealed that Knowledge Creation significantly mediate the relationship between Big Data Analytics Capability and Supply Chain Innovation among manufacturing firms in Ghana. This implied that a unit change in Knowledge Creation will positively improve the relationship between Big Data Analytics Capability and Supply Chain Innovation by 70.8%. Hence, the results indicates that Knowledge Creation significantly mediate the between Big Data Analytics Capability and Supply Chain Innovation among manufacturing firms in Ghana. The result further indicates that Knowledge Creation plays a partial mediation in the relationship between Big Data Analytics Capability and Supply Chain Innovation of among manufacturing firms, this conclusion was drawn by the fact that both direct and indirect effects are significant. Thus, firms that are able to implement new ideas which enhances supply chain innovation that could aid them in withstanding the implications of the firms innovations as well as building stronger hedge against future interruptions.

5.3 Conclusions

The study was conducted to understand how big data analytics capability affect supply chain innovation with the mediating role of knowledge creation among multinational manufacturing companies in Ghana. To achieve this, 250 owners and managers of manufacturing companies in Ghana were sampled. A self-administered instrument was used to gather data from the 250 participants. The analyses were done using SPSS and Smart PL-SEM. The result showed that Big data analytics capability has a positive significant influence on supply chain innovation and knowledge creation. The result further showed that the relationship between supply chain innovation and big data analytics capability is mediated through knowledge creation. The practical implication is that the relationship among BDA, SCI and KC is not a single directional relationship.

5.4 Theoretical Contributions

The study's contributions are that Organizational Information Processing Theory (OIPT) and Dynamic Capability Theory (DCT) explain how businesses use Supply Chain Risk Management (SCRM) techniques to address the effects of extending the theory of prior theory research (Akter et al., 2016; Jha et al., 2020; Dubey et al., 2019). The outcomes also offer more details on the effects of SCRM adoption on firm supply chain ethics and improvement. These findings also aid in the identification of important strategies that organizations may employ to deal with supply chain innovations by evaluating the interaction between supply chain creativity and stability. The results support the fundamental ideas of DCT and OIPT, building on earlier studies (Gupta and George, 2016; Srinivasan and Swink, 2018; Fan et al., 2016; Wieland and Wallenburg, 2012). As a result, this study demonstrates how DCT and OIPT integration may be utilized to demonstrate how SCRM methodologies can be applied at different supply chain phases to enhance firm innovations.

5.5 Managerial Implications

The following recommendations are made based on the results obtained from the study. The result from the study showed that big data analytics capability has a positive significant influence on supply chain innovation and knowledge creation. Hence, it is recommended that the manufacturing industry should invest in building and developing their big data analytics capabilities to improve their supply chain innovation and knowledge creation. This includes acquiring the necessary tools, technologies and talent to effectively analyze and interpret large amounts of data. Additionally, the industry should create a culture that promotes and encourages innovation throughout the supply chain. This includes providing resources and support for innovative ideas, recognizing and rewarding individuals and teams for their contributions to supply chain innovation. Finally, the study revealed that knowledge creation significantly mediate the relationship between big data analytics capability and supply chain innovation among manufacturing firms in Ghana. Thus, it is recommended that manufacturing industries should encourage and facilitate the sharing of knowledge and best practices throughout the firms supply chain and its data analytics capabilities. This can be achieved through collaboration and partnerships with suppliers, customers and other stakeholders within the manufacturing industry.

5.6 Limitations and Suggestions for Further Studies

In order to accomplish the research objectives, this study relied on cross sectional data, which means that data was gathered only once and over a limited period of time. Time was of the essence because the research was for academic purpose. Therefore, it is advised that future research employ a longitudinal technique to data collection. This will make it possible to gather data over an extended period of time in order to confirm the association between the BDAC and SCI. The focus of this study was on manufacturing companies in Ghana, it would be beneficial to examine how BDAC can be developed in other industries like SMEs and how it can connect SCI-KC. Despite the fact that this study emphasizes on the important KC contributions and their implications for SCI-KC, the results must be understood in the context of the research.

Also, while this current sample size is comparable to the minimum required for this form of research, further study should attempt to reach a larger sample size to improve external validity. In addition, the study used the quantitative way of research paradigm, analyzing the research data using statistical tools like Smart PLS. Additionally, using a seven-point Likert scale in this study has its own drawbacks. This is because respondents' rate how much they agree or disagree with the study's findings, leaving no room to test the validity of respondents' questionnaire responses. As a result, it is advised that a qualitative research approach be used in a future study. This will give room for some interviews to be done in order to verify the accuracy of some of the questionnaire results.

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