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Effect of Supply Chain Intelligence on Business Model Innovation: mediating role of Data-Driven Decision Making

By

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DECLARATION

I hereby declare that this submission is my work towards the 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 acknowledgment has been made in the text.

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DEDICATION

This work is dedicated to my family for the unconditional love throughout the course.

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This research has been made possible by the Grace of God Almighty my creator. I would like to sincerely thank my supervisor Prof. Kwame Owusu Kwateng, for his good guidance, may the good Lord bless him.

ABSTRACT

The purpose of this study was to investigate role of data-driven decision making in the relationship between supply chain intelligence and business model innovation (BMI) among hotels in emerging markets. The study employed cross-sectional survey design and a quantitative approach that combined descriptive and explanatory research methods. Both the explanatory and descriptive designs were used to describe and then analyze the interplay between the variables. The participants in the survey were hotel and restaurant managers and owners in Ghana. The primary data was gathered via an in-depth questionnaire sent to 293 hotel and restaurant managers and owners in Ghana. The study used a convenient sampling strategy. The assumptions of the research were tested using Structural Equation Modeling in the form of SmartPLS 4. The data was summarized using descriptive statistics. The research results showed that supply chain intelligence significantly affects the business model innovation. The mediation research also found that the connection between supply chain intelligence and business model innovation is mediated by data-driven culture. The results suggest that if hotel managers actively engage in, and place a premium on, supply chain intelligence and a data-driven culture, then business model innovation will improve throughout the sector. It was recommended that hotel company managers optimize the supply chain in numerous ways via the use of cutting-edge technology and an increase in supply chain intelligence..

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Hotels are particularly affected by the decline in tourism and travel and the slowdown in economic activity (Jiang and Wen, 2020). The COVID-19 eruption has severely affected hotels around the world, with events around the world being canceled or delayed, or hotel accommodation rates plummeting. The global economy closed overnight as a result of the Covid-19 eruption (UNWTO, 2020). The hospitality industry is facing unprecedented challenges. Many hospitality businesses are temporarily shut down due to strategies and policies to compensate for the COVID-19 route, such as lockdowns, social distancing, homestay restrictions, travel, and morbidity (Hao, Xiao, and Chon, 2020). Virtually, many hotel facilities were asked to close down in both developed and developing economies. Restrictions on travel and accommodation orders issued by the authorities have led to significant reductions and layoffs of employees. However, the reopening process has begun slowly, and authorities have begun to ease restrictions, for example, to allow restaurants to reopen with less force through strict social distance guidelines. Gradually reduce restrictions on domestic and international travel (Filimonau, Derqui, and Matute, 2020).

During the COVID-19 pandemic, quarantine and other measures were used to prevent the spread of COVID-19 in African countries, but the number of infected people continued to rise sharply. This situation has put unprecedented pressure on the hospitality industry in many African countries. In West Africa, especially in Ghana, Deloitte Ghana (2020) reports that border closures have severely affected the hotel industry and gradually reduced tourism and the hospitality industry in general and the need for international travel. The government estimates that what will happen as a result of Covid-19 and other measures to reduce it will result in a 6.6 percent reduction in GDP, which is more than the 5% monetary policy set (Fiscal Responsibility law) (Deloitte Ghana, 2020; Dwomoh et al., 2020).

For this reason, the hospitality industry is now recovering slowly, the COVID-19 pandemic hit the hospitality industry hard. The hospitality business is expected to make significant changes to the COVID-19 business environment (Shin and Kang, 2020) to ensure the health and safety of workers and consumers and to strengthen customer commitment to support their businesses (Loi, Lei, and Lourenço, 2021). This boom could seriously affect the hospitality management professional. With the unexpected challenges of the hospitality industry in the COVID-19 era, hospitality professionals need to answer several important questions, such as how hospitality firms can return to business and remain competitive (Loi, Lei, and Lourenço, 2021).

Furthermore, the nature of their products and services precludes the potential of a long-term catch-up effect to make up for lost income. A meal that was not served during the crisis cannot be resold. Additionally, given the additional norms and regulations about hygiene and social isolation, as well as more hesitant and anxious consumers, the lockdown may have impacted how the hospitality business will be done in the future. Given the severity of the crisis, which is still ongoing, businesses in this industry require robust recovery strategies. Meanwhile, research on crisis management in the hospitality business argues that appropriate measures include stronger marketing for local consumers and infrastructure reduction (Breier et al., 2021). According to Ritter and Pedersen (2020), the outbreak of the covid 19 pandemic will have an impact on established business models (BM).

Thus, to maintain a competitive position or remain competitive in the eyes of consumers, managers must give prior attention to the indispensable role played by business model innovation (BMI). Interestingly, the impact of the pandemic has aroused the interest of managers to innovate their existing business models. Hence, BMI is increasingly receiving attention in management literature as an essential driver of competitive advantage and business continuity (Bocken and Geradts, 2020; Vaska et al., 2021; Breier et al., 2021; Haaker et al., 2021; Mostaghel et al., 2022; Clauss et al., 2022). BMI represents the capacity of firms to innovate the value creation, delivery, and capture mechanism to attract customers to pay for value and convert this into profits (Teece, 2010).

Prior studies have argued that the concept of BMI has been perceived as activities of large Organizations, which leads to new customer offerings and revenue streams (Wirtz et al., 2016; Massa et al., 2017). However, the hospitality sector in emerging economies is characterized by the high presence of SMEs which typically lack diversification and rely solely on one type of BM (Pal et al., 2012; Mostaghel et al., 2022). It must however be noted that innovating business models is not easy and may not always be as expected. Managers are therefore careful about how to undertake such innovations. Though there have been many strategies to enhance business model innovation, limited attention has been paid to how supply chain intelligence can be used to drive business model innovation among hospitality businesses, especially in the context of developing economies like Ghana.

Again, Peter et al. (2020) have argued that technology remains an important tool for achieving the business objective, and the persuasive effects of technology have radically reshaped many industries. Technology or digitization has to do with how emerging digital technologies including analytics, cloud, mobile, and social media play an essential role in modifying existing business processes (Arias-Perez et al., 2021). In the presence of these many technologies, Deloitte (2021) has identified supply chain intelligence as among the top three (3) most prioritized investments for enhancing customer value and revenue stream. Supply chain intelligence is defined as knowledge sourced and integrated from three main supply chain stakeholders-suppliers, customers, and competitors (Schoenherr and Swink, 2015). It is the integration of data collection, analysis, actionable information, dissemination, and response in a supply chain (Handfield, 2006). Supply chain intelligence enables a firm to get a holistic view of a supply chain from the perspective of customers (Yang et al., 2021). It is therefore expected that the greatest impact of supply chain intelligence in firms lies in the greater exploitation of new knowledge which can help to restructure existing business processes (Dahiya et al., 2021, Urbinati et al., 2019). While supply chain intelligence represents the ability of firms to capture and analyze data in the effort to generate novel knowledge or insight via efficient use of its data, technology, and talent, its usage in small businesses remains low (Henae-Garcia et al., 2021).

Firms in the post-covid era are increasingly becoming aware of the need to manage their internal and external data as a result of the recent growth of the data phenomenon, to seize new opportunities that will allow them to maintain their competitive advantage (Shan et al., 2019; Ciampi et al., 2021). "The future frontier for innovation, competition, and productivity," according to BD (Manyika et al., 2011). Firms can use customer-generated supply chain intelligence to achieve user-centered and user-driven innovation. For example, by using customer-generated BD (Trabucchi et al., 2018). The former employs customer analytics to investigate users' behaviors, assessments, and needs to improve the development of new goods that will meet their demands (Hooi et al., 2018). Though existing studies have shown that supply chain intelligence paves way for multiple organizational outcomes including supply chain performance, business performance, and product innovation (Jaharuddin et al., 2014; Schoenherr and Swink, 2015; Alzoubi et al., 2018; Yang et al., 2021), it is still unclear how firms can leverage supply chain intelligence to drive BMI. This creates a knowledge gap that needs to be explored. This study, therefore, examines the effect of supply chain intelligence on business model innovation among hospitality businesses in Ghana.

This study aims to fill this vacuum by drawing on literature that emphasizes the feasibility of following a transformational value creation pathway through the deployment of supply chain intelligence (Elia et al., 2019). Thus, it remains unclear how supply chain intelligence can drive BMI in the hospitality industry. This study, therefore, provides contemporary insight into how the supply chain intelligence -BMI link could be driven via data-driven decision-making.

1.2 Statement of the Problem

Business model innovation (BMI) received global attention as a way to recover from the COVID-19 pandemic, which included firms in the hospitality industry (Kraus et al., 2020). New opportunities can be addressed if a BM is innovated by significant modifications in the elements and/or their configuration (Foss and Saebi, 2018). This can assist hospitality enterprises to recover quickly. Although there is little research on BM and BMI in the hotel business, it appears that BM and BMI are empirically relevant in this industry (Yu et al., 2021). Also, extant literature has advanced that companies must identify or source BMI ideas from outside the company (e.g., Hock-Doepgen et al., 2020; Micheli et al., 2020). In such regard, customers, in particular, have been regarded as a valuable source of new BM ideas (Clauss et al., 2018; Ebel et al., 2016).

Supply chain intelligence is a kind of threat intelligence that focuses on identifying, detecting, and fighting virtual competitors that seek to hurt enterprises by launching cyber espionage, social manipulation assaults, and other criminal ruses against corporate supplier global production networks (Riahi et al., 2021). In addition, supply chain intelligence is also the process of gathering and showing processes to allow cooperative supplier relationship design, surveillance, assessment, analytics, and management (Olan et al., 2022). Moreover, supply chain intelligence also continually monitors each value embedded, alerting the decision-maker when the risk is increasing and providing information on pricing, service levels, and delivery schedules so they can fully assess all available choices (Dubey et al., 2021). In developing a strong capacity to be able to acquire and use knowledge from a customer, supply chain intelligence remains essential.

Hence, in the past decade, many businesses including hospitality businesses have invested large resources in developing appropriate infrastructures, technologies, skills, and business practices to collect, analyze, and use massive amounts of diverse and rapidly created data to aid decision-making in the quest to peruse BMI (Ciampi et al., 2020). Supply chain intelligence has the capacity of turning data into actionable information, despite its importance (Kwon et al., 2018). Though prior studies (Jaharuddin et al., 2014; Schoenherr and Swink, 2015; Alzoubi et al., 2018; Yang et al., 2021) have shown that supply chain intelligence drives multiple organizational outcomes including supply chain performance, business performance, and product innovation Till date, there is limited or no empirical studies on the relationship between supply chain intelligence and BMI (Ransbotham and Kiron, 2017).

In today's volatile economy, no BM can stay static and last indefinitely. To stay competitive over time, every company must constantly rethink, re-design, and develop its BM (Marolt et al., 2016; Pucihar et al., 2019; Nunes and Russo, 2019). Hence there is a need for more knowledge on what aids BMI. This study, therefore, examines the effect of supply chain intelligence on BMI in the hospitality setting.

The hospitality industry is among the major driver of the Ghanaian economy, and greater focus is needed to better understand their practices, innovativeness, and global competitiveness. Available statistics show that the hotel sector in 2018 contributed 10.4% of the global GDP and 20% of new jobs (World Travel and Tourism Council, 2018). Again, the sector remains one of the key growth drivers of Africa's economy generating 8.5% of GDP in 2018 with a growth rate of 5.6% in 2019. The sector is ranked the 2nd fastest-growing in the world and Ghana is no exception. As of 2016, the contribution of the hotel industry to Ghana's GDP was estimated at around 3% and increased to 3.5% in 2017. However, the covid pandemic distorted the performance of the sector, making existing BMs irrelevant to the new normal. Managers of the hospitality business are therefore looking for a new model that could bounce them back, hence they are making massive technology investments that could fast-track the process, hence the need to understand how supply chain intelligence can help them innovate existing or outdated business models.

Moreover, the contingency theory argues that it is usually not appropriate to consider a simple bivariate relationship between a dependent variable and an independent variable (Saiedi et al., 2017). The implication is that, in reality, other influential factors could shape the bivariate relationship, these variables could either be mediators or moderators. Hence, in the quest to develop a lasting remedy to BMI issues, it is imperative to develop a compressive model (at least a trivariate relationship model), hence, this study further explored the mediating role of data-driven decision making in the direct supply chain intelligence -BMI link which aligns with the DCT.

Szukits (2022) indicated that instead of searching for a direct link between supply chain intelligence and BMI, it should be understood in detail how data-driven decision-making can create value for an organization (Gillon et al., 2014; Seddon et al., 2017). As Sharma et al. (2014) indicated that data analytics was often argued to affect decision-making in some ways, as high-quality information allows better-informed decision-making (Cao et al., 2019; Kowalczyk & Gerlach, 2015) if the information is not only available but utilized by the managers in decision contexts (Popovičet al., 2012). In line with this, our study is driven by the question of whether and how the use of supply chain intelligence promotes data-driven decision-making to achieve enhanced BMI.

As a result, the study anticipates a relationship between supply chain intelligence and data-driven decision-making, which will affect BMI implementation in the hospitality industry. This study, therefore, is among the very few attempts to unearth how BMI could be driven through the interaction of supply chain intelligence and data-driven decision-making. The novelty of this lies in the fact that it is among the very few attempts to contribute to the role of supply chain intelligence and data-driven decision-making in driven BMI in the context of hospitality businesses. This study also affords a contemporary contribution in the context of developing economies, especially the Sub-Saharan African continent; by providing contemporary insight into the relationship between supply chain intelligence, data-driven decision-making, and BMI which is scarce in innovation management literature. The mediating role of data-driven decision-making in the relationship between supply chain intelligence and BMI which is missing in academic discourses is an essential discovery and contributes significantly to the DCT extension. Hence, this study contributes to existing management literature and expansion of knowledge on DCT in the area of business model innovation.

1.3 Objective of the Study

The study aimed to evaluate the relationship between supply chain intelligence and business model innovation (BMI) and the mediating role of data-driven decision-making in the context of hospitality businesses in emerging economies. Based on the gaps identified, three (3) specific objectives have been outlined below;

1. To examine how supply chain intelligence influences BMI among hospitality businesses in Ghana.
2. To explore the impact of data-driven decision-making on Business Model Innovation among hospitality businesses in Ghana.
1. To understand the moderating role of data-driven decision-making in the relationship between supply chain intelligence and BMI among hospitality businesses in Ghana.

1.4 Research Questions

In other to achieve the main objective of the study, the research seeks to answer the following:

1. How does supply chain intelligence influence BMI among hospitality businesses in Ghana?

2. What is the impact of data-driven decision-making on Business Model Innovation among hospitality businesses in Ghana?
3. What is the mediating role of data-driven decision-making in the relationship between supply chain intelligence and BMI among hospitality businesses in Ghana?

1.5 Significance of the Study

One of the unique contributions of the study is the researcher's novelty of the combination of supply chain intelligence impact and data-driven decision-making to investigate their impact on BMI among hospitality businesses in Ghana, the first of its kind in the hospitality businesses setting and a paradigm for scholars to direct their research focus. For contribution to knowledge, this study may provide a better understanding to researchers regarding the unique nature of hospitality businesses as the blood life of developing countries like Ghana and to help academicians to direct their future research effort into hospitality businesses to build a solid economy.

The novelty of this lies in the fact that it is among the very few attempts to contribute to the role of supply chain intelligence in driven BMI. This study, therefore, affords a two-fold contribution in the context of developing economies, especially the Sub-Saharan African continent; the first fold provides contemporary insight into the relationship between supply chain intelligence and BMI while it also examines the role of data-driven decision-making in the relationship between supply chain intelligence and BMI which is missing in academic discourses.

Theoretically, the study will also add to the literature in academia especially in Sub-Saharan Africa by providing direction on BM innovation in the context of hospitality businesses. BMI has gained popularity in developed and a few developing countries, especially in Sub-Saharan Africa (SSA).

1.6 Research Methodology

This study employed a survey research design approach as the main methodology for the study. This approach enabled an in-depth exploration of data about the subject matter of hospitality businesses regarding SCI, data-driven decision-making, and BMI. 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 hospitality businesses. A structured questionnaire adapted and modified from previous studies was used to collect the relevant data from 384 managers of hospitality businesses, analysis of the data will then be employed by the application of both descriptive and inferential statistical tools. Concerning 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 will include the partial least squares regression and correlation (PLS) analytical method. However, before the use of the data collection and analysis, both the instrument and data shall be validated for the test of reliability and validity.

1.7 Scope of the Study

The scope circles the context and limitations of the research. This study contextually focused on private business in developing economies, specifically in Ghana. Even though various issues affect hospitality businesses' survival in developing countries like Ghana, this study uniquely focused on examining the relationship between SCI and BMI and the role of data-driven decision-making in the context of private business in emerging economies. The researcher focused on star-rated hospitality businesses in Ghana. Theoretically, the study will employ the dynamic capabilities theory to understand the relationship between SCI and BMI and the role of data-driven decision-making IN hospitality businesses in the context of hospitality businesses in emerging economies.

1.8 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, and the relevance, among others.

The second chapter will examine relevant related literature reviews, 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 the study design employed, the study population, sampling and sample size determination, methods of data collection, the sources of data, and methods of data analysis.

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

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This thesis' second chapter is divided into four major sub-headings. The information in the chapter is arranged under conceptual review, theoretical review, empirical review, and finally the construction of the study model and hypotheses. Definitions, operationalizations, and examples of how the constructs were employed in this study are provided in the conceptual review section. The theoretical foundations of the work are also provided in the theoretical review section. A conceptual framework was used to illustrate the numerous prepositions provided in this study, and various relationships were well explained. The study's research shortcomings are noted in the chapter's conclusion.

2.2 Conceptual Review

Definitions, operationalizations, and an explanation of how the constructs were applied in this study are provided in this section. There are three main constructions in the model (Supply Chain Intelligence, Business Model Innovation, and Data-Driven Decision Making). The following sections made these constructions operational (see **2.2.1-2.2.3**).

2.2.1 Supply Chain Intelligence

In today's rapidly evolving and global economy, utilizing a company's supply chain capabilities has become essential for business success; this necessity may be summed up by the saying, "supply chains compete against suppliers" (Swain and Cao, 2019). In addition, it is considered to be particularly critical for innovative explorations to tap into and manage the business intelligence possessed by supply chain partners, rendering this a crucial topic of research (Gebremikael et al., 2019). Moreover, the degree to which a company gathers and implements technological knowledge relevant to product innovation from suppliers, consumers, and rivals is how the integration of supply chain intelligence is perceived. Concisely, the movements of rivals can be observed in order to gather competitive intelligence. According to studies, institutionalizing this acquired intelligence may be crucial for fostering a firm's capacity for innovation (Toorajipour et al., 2021), since it helps the company to look forward and imagine even larger developments depending on the examination of this data. This may help the company gain a transitory edge, particularly in contexts with high levels of competition (Haas, 2020). Nonetheless, caution should be used when analyzing competition intelligence because the data may be intended to persuade the business to adopt unfavorable countermeasures (Belhadi et al., 2021). Alternatively, supply chain intelligence is a kind of threat intelligence that focuses on identifying, detecting, and fighting virtual competitors that seek to hurt enterprises by launching cyber espionage, social manipulation assaults, and other criminal ruses against corporate supplier global production networks (Riahi et al., 2021). Moreover, the technique of aggregating and displaying workflows in order to enable cooperative supplier relationship design, surveillance, evaluation, analytics, and administration is known as supply chain intelligence (Olan et al., 2022). Furthermore, supply Chain Intelligence continuously tracks each value embedded, notifying the final choice when the risk is rising and giving data on costs, service levels, and delivery times so they can thoroughly evaluate all available options (Dubey et al., 2021).

2.2.1.1 Explorative Ambidextrous Leadership

Hou et al. (2019) stated that exploratory activities are variation, risk-taking, experimentation, and discovery. Exploration activities done by a leader are focused on the future, necessitating the enhancement of innovation to meet the needs and conditions of the organization. Explorative ambidextrous leadership is the ability of a leader to generate new ideas, products, procedures, and solutions for organizational growth (Oluwafemi et al., 2022). Explorative ambidextrous leadership is also described as the innovative behaviors of a leader to ensure new products and services are delivered by the organization (Alaghbari, 2022). This study will employ the definition of explorative ambidextrous leadership as innovative behaviors of leaders to foster new products and ideas (Oluwafemi et al., 2022).

2.2.2 Business Model Innovation

According to Shakeel et al. (2020), BMI is taken into account in the context of a new integrated logic of value creation and value capture, which may include a unique pattern of narration and classic financial products, as well as modifications to a company's position in the economy and support systems. Moreover, Geissdoerfer et al.2018) pursue BMI by modifying one or more parties who carry out any of the existing BMs, augmenting current BMs with revelatory activities, and utilizing unique links within the activity structure. According to Breier et al. (2021), BMI may be viewed as a multifaceted and planned collection of actions that result in the creation of at least two BM components to provide value in novel ways. Businesses must take leverage BMI's positive mediating role in the link between facilitative competence and organizational growth in order to boost firm value and recognize that BMI's function differs across various business strategies (Keiningham et al., 2020). In addition, the key steps in implementing a data-driven strategy are outlined by Parida et al. (2019): selecting the appropriate multiple sources with IT support; requirements of the product that forecast and improve results; and transforming the capacity of an organization. Finally, the art of business model innovation involves simultaneous and interrelated adjustments to an organization's value proposition to consumers and its fundamental operational model in order to increase benefit and value generation (Haaker et al., 2021).

2.2.2 Data-Driven Decision Making

Data-driven decision-making (DDD) is the technique of using hypothesis testing to make judgments rather than relying just on instinct (Wu et al., 2021). A designer might, for instance, choose advertising solely only on vast industry knowledge and a keen sense of what would succeed (Yu et al., 2021). Moreover, the decision was based on an examination of statistics pertaining to customer responses to various advertisements (Troisi et al., 2020). It might combine these strategies as well. In addition, business organizations use DDD to variable levels since it is not an all-or-nothing technique. Data-driven decision-making was shown to be advantageous (Ma et al., 2020). In a new finding as to how DDD impacts business results, researcher Erik Brynjolfsson and his associates from MIT and Penn's Wharton School examined the topic. Moreover, they created a DDD score that ranks businesses based on how much they rely on facts to create choices across the board. They demonstrate analytically that, even when accounting for a wide variety of potential extraneous variables, the more information a business is, the more productive it is (Tantalaki et al., 2019). The changes are also not slight: a 4-6% improvement in output is correlated with a DDD score increase in standard deviation. DDD is also associated with better-working capital, returns on equity, assets ratio, and market value, and the association appears causative (Roeder et al., 2022)

2.3 Theoretical Review

An abundance of knowledge and information in the scope of innovation makes the research process to become challenging, difficult, and lengthy (Soetanto, 2017). Thus, to focus the research direction, three underpinning theories were used as a research foundation in supporting and addressing the gap, and as a guide to align this research into an appropriate direction. The researcher examines underlying ideas in this part, as well as the effect of the supply chain on business model innovation, mediating the role of data-driven decision-making. The Knowledge-Based View and its extension to the Dynamic capabilities view (DCV) theory serve as the foundational theories for this investigation. Theoretical frameworks provide a clear prism or context through which a subject is studied; it explains the context and the connections between the various factors and dimensions

2.3.1 The Knowledge-Based View

The knowledge-based view (KBV) of the company (Grant, 1996) and the closely related dynamic capabilities viewpoint serve as the foundation for assumptions for connections involving supply chain intelligence (Teece, Pisano, and Shuen,1997). According to Wowak et al. (2013), on page 861, the KBV "helps drive research on knowledge resources and strategic capabilities," arguing that companies that successfully acquire, disseminate, and utilize intellectual capital produce long-term beneficial results (Grant, 1996). The potential of information to be communicated (transferability), absorbed (with a capacity for aggregation), and utilized for financial advantage are fundamental to this perspective (appropriability). This resolute perspective of information as a commodity has been expanded to include external players (Dyer and Hatch, 2006), and it has become a key theory for supply chain intelligence and the strategic planning of creativity (Shook et al., 2009). (De Luca and Atuahene-Gima,2007). A fundamental principle of the KBV is that before an organization can use acquired information, it must be interpreted and made appealing enough to be served domestically. Advantages in performance come from applying information through its transfer, not from the knowledge itself (Grant, 1996). Therefore, in order to utilize new information, an organization requires intervening skills. These skills are especially necessary for tacit information that is ingrained in an organizational setup (Szulanski, 2000). We describe how supply chain flexibility and product innovation capability enable enterprises to utilize supply chain knowledge for increased particular model launch success in the current study.

2.3.2 Dynamic capabilities view (DCV)

The Resource-Based View (RBV) was theoretically expanded into the Dynamic Competitive View (DCV) to illustrate how businesses might maintain their competitiveness over the long term in highly volatile situations (Ambrosini and Bowman, 2009). According to the RBV's founding principles, a company's potential to succeed depends on the availability and coordination of expensive, uncommon, unique, and non-replaceable resources that allow the adoption of real-worth methods that produce rents (Barney, 1991). A corporation can particularly achieve a sustained market advantage by obtaining and managing the assets deemed to be crucial and thereafter establishing organization competencies that are heavily reliant on the sorts of resources gathered (Makadok, 2001). More subsequently, research has demonstrated that the RBV's fixed method falls well short of understanding how businesses use their assets and abilities in fluid marketplaces, clearing the door for the DCV to become more widely used (Priem & Butler, 2001). The capacity of the company to combine, develop, and reconfigure internal and external competencies to handle constantly shifting surroundings is referred to as DCS (Teece et al.,1997, p. 516). Companies may use DCs to establish unique organizational and strategic practices and capabilities, which are essential to sustaining performance and opening up new markets (Fornell and Larcker, 1981). Prescott (2014) claims that failing to adjust the existing physical and immaterial assets to the most recent developments and needs of the external environment might put a company's competitive advantage in danger and hasten its transition into core restrictions. DCS grows with time and can significantly affect how well a company performs (Makkonen et al., 2014). The DCV is a good paradigm for examining how the supply chain affects business model innovation and how data-driven decision-making serves as a mediator. Indeed, researchers have employed the DCV as a philosophical approach in management literature to look at all of these dimensions (Jiang et al., 2018).

2.4 Conceptual Framework

The two major pillars of the theoretical model are the Dynamic capabilities view (DCV) and its extension to the Knowledge-Based View (see Figure 2.1). In today's rapidly changing and international economy, utilizing a company's supplier chain's capabilities is becoming essential for business success; this necessity may be summed up by the proverb, "suppliers compete versus distribution networks" (Wowak et al., 2013). It is considered to be particularly crucial for innovation efforts to access and manage the business intelligence held by supply chain partners, making this a crucial field of research (Craighead, Hult, & Ketchen, 2009). The extent that a company gathers and implements technical capabilities relevant to innovative products from suppliers, consumers, and rivals is how we perceive the integration of supply chain intelligence. These significant participants in a company's external environment are regarded as providers of priceless knowledge that support the success of new product launches. Independent (Supply Chain Intelligence), dependent (Business Model Innovation), and mediating variables are all included in the overall idea of (Data-Driven Decision Making). In this study, three types of variables were employed. It is anticipated that Supply Chain Intelligence and Business Model Innovation: The effect of the supply chain on business model innovation, mediating role of data-driven decision making.

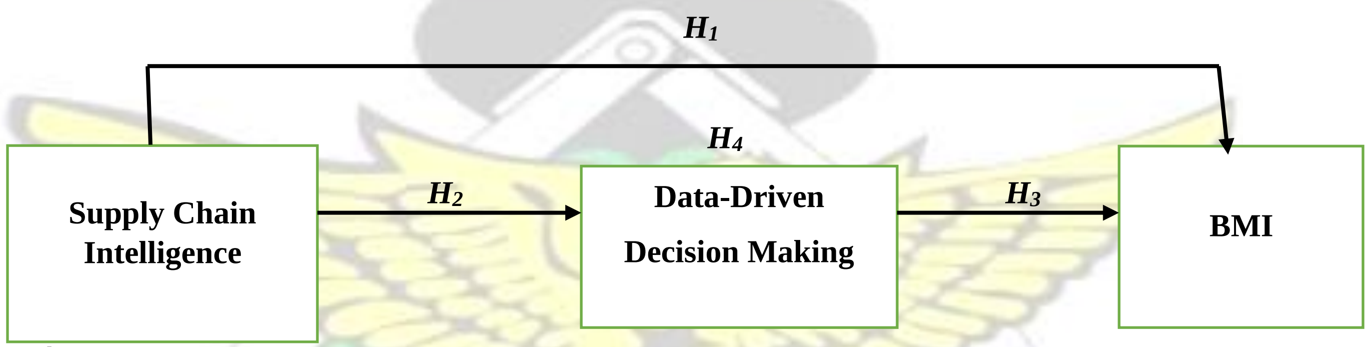

Figure 2.1: Conceptual framework of the study

This segment discusses the five key hypotheses as shown in Figure 2.1 above. Subsections have been created and discussed for each of the hypotheses as illustrated by the research model.

2.5 Empirical Review

This section assessed the research on prior studies that addressed the study's objective. These include the supply chain on business model innovation: The effect of the supply chain on business model innovation, mediating role of data-driven decision making. Literature related to the study's goal of the effect of the supply chain on business model innovation and the mediating role of data decision-making in previous and ongoing research projects was evaluated.

Marcinkowski and Gawin (2020) conducted a study to investigate ways small and medium-sized organizations (SMEs) develop their business models (BMs) around data to manage data-driven goods and how this impacts their effectiveness and ability to innovate. Moreover, the as-is BM of a global SME was drawn to analyze the issue, and a qualitative inquiry highlighted its limits. They employed the BM landscape. Then the hospitality industry business, where a large amount of operating and fingerprint data is being collected provides additional value in terms of new data-based products and, pioneered the data-driven approach. The findings indicate that a data-driven business model (DDBM) imperative for the FM industry has been provided, supporting the requirement to supplement provider processes with the data-driven methodology. A facilities director is given more management tools by improved BM, which enables them to reduce the cost of using an asset and creates new revenue-generating options. This article outlines the transition from a service-based to a data-driven business model and identifies the mindsets executives need to have to support and carry out DDBM. The author proposed that the DDBM provide guidance that aids FM companies in concentrating their operations on producing business value from data and monetizing data-driven goods depending on the study's results and constraints.

Awan et al. (2021) carried out a study to investigate decision-making using Big Data analytics, specifically the impact of information insight on the efficiency of the sustainable future. Moreover, the link between BDA capacity and CE effectiveness was experimentally researched, and the mediation function of data-driven insights in the relationship between BDA capability and decision-making was also addressed. Partial least squares structural equation modeling was used to examine the data, which were gathered from 109 Czech industrial companies. The findings show a significant correlation between BI&A and BDA capacity and decision-making quality. When the maker makes use of data-driven insights, this has a greater impact. The findings show that decision-making quality in businesses is driven by BDA capacity and is not mediated by data-driven insights. BI&A is a term used to describe the quality of decisions made using data-driven insights. These results give management crucial information since they serve as a guide for creating data-driven insights using the CE model within enterprises. Future research may evaluate the association between CE and environmental performance and may utilize a continuous study approach, the author advised in light of the results and the study's constraints. Future research may also look at the role that CE efficiency plays as a mediator in the link between BDA capabilities and environmental and entrepreneurial skills.

Belhadi et al. (2021) carried out a study to conduct an experimental inquiry on increasing digital creativity for improving efficiency and endurance under the influence of distribution network adaptation. A hierarchical linear modeling (SEM) strategy was employed to assess the created framework. 279 businesses of varying sizes, working in a range of industries and nations, provided the latest survey sample of data. The results show that although AI has a relatively brief direct influence on SCP, it is advised to take advantage of its knowledge acquisition skills to create SCRes for long-lasting SCP. This study is one of the first to offer empirical proof of utilizing the advantages of AI capabilities to produce long-term SCP. The researcher indicated that future research could be further expanded by utilizing a continuous examination to examine further aspects of the phenomena in light of the research outcome and constraints.

Alzoubi and Aziz (2021) conducted a study to investigate the link between senior shareholders' metacognition and the caliber of the operational decisions they make for their organizations. The top management of the UAE national banks was surveyed for this study's cross-sectional data using a survey methodology. Supervisor's responses to 213 surveys comprised the panel data, which was compiled and examined. The strength and positivity of the association between executives' emotional intelligence and the caliber of their strategic choices were as expected. The manner that senior bank executives make choices that are ultimately turned into policy has been changed by intellectual capital. Remaining aware of their environment is a necessary part of having the ability to make decisions. They, therefore, possess emotional intelligence, which is only strengthened by sophisticated data systems (IIS). IIS is an elevated kind of open innovation that improves the effectiveness of and method for making choices. Since no one has ever studied these aspects of emotional intelligence in the UAE, this study is unique. The researcher recommended that future research examine the same from many angles in light of the study's results and constraints. Additionally, pre-existing instruments from the literature were used to create the study measurement tool. The fact that the idea was accepted shows how closely empathy and decision-making are related. Therefore, as it will aid in future decision-making, experts advise recruiting managers to include an emotionally intelligent check element.

Ciampi et al. (2021) conducted a study to investigate how big data analytics capabilities influence the development of new business models and the mediating effect of export performance. In light of this, the study examines the relationship between BDAC and business model innovation using the Dynamic Capabilities View (DCV) (BMI). Moreover, it contends that Start-up costs (EO), a greater dynamic skill, mediates the effect of BDAC (a lower peak capability) on BMI. Utilizing survey data from 253 UK companies, the suggested model is evaluated using PLS-SEM (symmetric) and fuzzy-set Qualitative Comparative Assessment (oblique) approaches. The results show that BDAC has positive effects on BMI that are both immediate and indirect, with the latter being mediated by EO. These findings add to the body of knowledge in the field of strategy implementation on big data (BD) by demonstrating that BDAC has a substantial impact on a firm's strategic logic and goals instead of relying solely on these. Hence, merge studies should be used in future studies to see if our findings hold true in various foreign economic contexts. Finally, despite the fact that firm size and sector were accounted for in our analysis, we think that these factors do not account for all utilized for a variety of variations that can have an impact on the connections included in the conceptual model.

Liu et al. (2021) carried out a study to look at how supply chain strategy plays a role as a mediator between business model design and operational effectiveness. In addition, the study makes the claim that supply chain integration (SCI), encompassing organizational effectiveness and strategic implementation, mediates the link between BMD and operational performance. This idea is based on dynamic capacity theory. To validate our research approach, 131 Chinese manufacturing companies provided matched survey data and objective performance data over the span of three waves. The main findings are that the effectiveness of BMD significantly enhances service quality whereas the unique selling point of BMD fully mediates its impact on operations. It is explored how BMD and SCI may be used to assist operating efficiency from both a theoretical and tactical standpoint. The researcher hypothesized that future research that increases the representative sample and examines variations across businesses would give a richer conclusion on the results of this research and restrictions. Second, the conclusions are only applicable to China, whose organizational, historical, and financial structures diverge from those of the majority of other nations. It is necessary to do more studies in other nations to contrast the findings.

Yu et al. (2021) did a study that looked into the roles of decision-making and a data-driven culture when integrating big data analytics into corporate financing. The research introduces and experimentally analyzes a conceptual framework based on organizational information processing theory to examine how big data analytics capacity (BDAC) affects SCF Unification and how data-driven culture acts as a moderator. Utilizing structured questionnaire data gathered from a group of 307 Chinese industrial companies, the anticipated correlations were examined using structural equation modeling and mediated statistics. The findings show that corporate SCF Incorporation plays in facilitating the interactions between BDAC and SCF Integration with customers and suppliers and also that BDAC has a considerable beneficial impact on internal SCF Integration. Effectively reducing the impact of BDAC on internal SCF Integration is data-driven culture. The experimental results offer management current and practical advice on how to employ big data analytics and a data-driven culture to implement integrated SCF practices and thrive in the information and unpredictably changing world of today. Additional researchers can use our SCF Implementation concept to scientifically discover other processes that discuss management style design, cooperation, and regulation, as well as the need to match data processing needs with processing capabilities predicated on the research authors and its constraints.

Asamoah et al. (2021) conducted a study that looks at the effects of IOS adoption on a company's supply chain management (SCM) skills and efficiency. In addition, the study examines two frameworks that are crucial for effective supply chain achievement, pulling on the resource-based view theory: (a) effective IOS additional consumption concerning its interconnected partners; and (b) the enhancement of IOS strategic management capabilities in supply chain management. We validate all the study model's assumptions using data from 193 respondents who worked for different quick consumer products distributors and producers. The outcomes show how IOS adoption may both enhance operational supply chain performance and SCM competencies, as well as the mediation function that SCM skills play. We talk about the study's implications for policy and research. The complex first-order dynamics between the constructs may be further investigated in future studies. Such investigations may offer further knowledge regarding the impact of IOS use on particular SCM capabilities and supply chain performance characteristics for deliberate practice. Future research can examine in more depth how IOS utilization and SCM features work together to improve supply chain efficiency.

Nam and Thanh (2021) carried out a study that analyzes survey data of small and medium-sized companies (SMEs) in Vietnam from 2011 to 2015 to evaluate the impacts of bribery on business decisions regarding environmental innovation, in order to adjust for the roles of negotiating leverage and/or financial and organizational restrictions. The report divides bribery practices into tenancy and lubricating categories. Organizational restrictions are captured by self-assessments made by businesses regarding the unpredictability of government actions and the competitive landscape, whereas negotiating power is represented by company size and legal registration status. The list of credit-strapped businesses is further divided into those that need additional loans and those that aren't now looking to apply for one. Emulsifying bribery has a strong influence that is especially notable for large, legally registered businesses or businesses with no credit restrictions, though the magnitude of the impact is also influenced by specific organizational restrictions that businesses see as barriers to their expansion. Furthermore, there is evidence supporting the "sanding-the-wheels" notion of rent-seeking bribery when causality is regulated. This impact of grease fraud is also more significant. Based on the results and the study's constraints, the author proposed that the ministry include the private sector in the issuance and oversight of these certifications. This would increase the government's reliability and transparency and lower the trading costs for businesses.

Daradkeh (2021) carried out a study to investigate the mediating role of decision-making quality in the connection between information storytelling competence and project success. The association between data narrative proficiency, decision-making excellence, and firm profitability, meanwhile, is not well understood empirically. This study establishes and confirms the idea of data narrative competence as a complex construct made up of data quality, narrative quality, storytelling tool quality, storyteller skills, and storyteller domain knowledge by relying on the resource-based view (RBV). Additionally, it creates a mediator model to investigate the connection between data narrative proficiency. The findings of the study show that the data narrative skill is positively related to company success, which is partially mediated by decision-making efficiency, depending on an inductive examination of data gathered from business analytics experts. These findings offer a theoretical framework for further research on the potential causes and effects of data narrative proficiency. In order to enhance decision-making and corporate profitability, they also provide advice for practitioners on how to use data narrative skills in business analytics techniques. Future research could build on this study's research model by combining features like knowledge management, customer orientation, synergy, corporate strategy, and communication processing capacity that would help researchers recognize how data narrative abilities affect economic growth.

Table 2.1: Summary of Literature Review

Author/Year	Country	Purpose	Theory	Method	Findings	Future studies
Belhadi et al. (2021)	Morocco	The study's objective is to conduct an experimental inquiry on increasingly digital creativity for improving efficiency and endurance under the influence of distribution network adaptation.	Organizational Information Processing Theory	Quantitative	The results show that although AI has a relatively brief direct influence on SCP, it is advised to take advantage of its knowledge acquisition skills to create SCRes for long-lasting SCP. This study is one of the first to offer empirical proof of utilizing the advantages of AI capabilities to produce long-term SCP.	The researcher indicated that future research could be further expanded utilizing a continuous examination to examine further aspects of the phenomena in light of the research outcome and constraints.
Alzoubi and Aziz (2021)	United Arab Emirates	The study aims to investigate the link between senior shareholder's metacognition and the	Theory of generalized exchange	Quantitative	The strength and positivity of the association between executive's emotional intelligence and the caliber of their strategic choices was as expected. The manner that	The researcher recommended that future research examine the same from many angles in light of the study's results

		caliber of the operational decisions they make for their organizations .			senior bank executives make choices that are ultimately turned into policy has been changed by intellectual capital.Remaining aware of their environment is a necessary part of having the ability to make decisions. They therefore possess emotional intelligence, which is only strengthened by sophisticated data systems (IIS). IIS is an elevated kind of open innovation that improves the effectiveness of and method for making choices. Since no one has ever studied these aspects of emotional intelligence in the	and constraints. Additionally, pre-existing instruments from the literature were used to create the study measurement tool. The fact that the idea was accepted shows how closely empathy and decision-making are related. Therefore, as it will aid in future decision-making, experts advise recruiting managers to include an emotionally intelligent

					UAE, this study is unique.	check element.
Ciampi et al. (2021)	UK	The purpose of the project was to investigate decision-making using Big Data analytics, specifically the impact of information insight on the efficiency of the sustainable future.	Learning theory	Quantitative	The findings show a significant correlation between BI&A and BDA capacity and decision-making quality. When the maker makes use of data-driven insights, this has a greater impact. The findings show that decision-making quality in businesses is driven by BDA capacity and is not mediated by data-driven insights. BI&A is a term used to describe the quality of decisions made using data-driven insights. These results give management crucial information since they serve as a guide for creating	Future research may evaluate the association between CE and environmental performance and may utilize a continuous study approach, the author advised in light of the results and the study's constraints. Future research may also look at the role that CE efficiency plays as a mediator in the link between BDA capabilities and

					data-driven insights using the CE model within enterprises.	environmental and entrepreneurial skills.
Awan et al. (2021)	Italy	The goal of the study is to investigate how big data analytics capabilities influence the development of new business models and the mediating effect of export performance.	Dynamic Capabilities View (DCV	Quantitative	The results show that BDAC has positive effects on BMI that are both immediate and indirect, with the latter being mediated by EO. These findings add to the body of knowledge in the field of strategy implementation on big data (BD) by demonstrating that BDAC have a substantial impact on firm's strategic logics and goals instead of relying solely on these.	Hence, merge studies should be used in future studies to see if our findings hold true in various foreign economic contexts. Finally, despite the fact that firm size and sector were accounted for in our analysis, we think that these factors do not account for all utilized for a variety variations that can have an impact on the connections

						included in our conceptual model.
Liu et al. (2021)	China	The study looks at how supply chain strategy plays a role as a mediator between business model design and operational effectiveness .	Dynamic Capabilities View (DCV	Quantitative	The main findings are that effectiveness BMD significantly enhances service quality whereas unique selling point BMD fully mediates its impact on operations. It is explored how BMD and SCI may be used to assist operating efficiency from both a theoretical and tactical standpoint.	The researcher hypothesized that future research that increases the representative sample and examines variations across businesses would give a richer conclusion on the results of this research and restrictions. Second, the conclusions are only applicable to China, whose organizational , historical, and financial structures diverge from

						those of the majority of other nations. It is necessary to do more study in other nations to contrast the findings.
Yu et al. (2021)	UK	The study looked into the roles of decision making and a data-driven culture when integrating big data analytics into corporate financing.	Organizational Information Processing Theory	Quantitative	The findings show that corporate SCF Incorporation play in facilitating the interactions between BDAC and SCF Integration with customers and suppliers and also that BDAC has a considerable beneficial impact on internal SCF Integration. Effectively reducing the impact of BDAC on internal SCF Integration is data-driven culture. The experimental results offer management	Additional researches can use our SCF Implementation concept to scientifically discover other processes that discuss management style design, cooperation, and regulate, as well as the need to match data processing needs with processing capabilities predicated on the research

					current and practical advice on how to employ big data analytics and a data-driven culture to implement integrated SCF practices and thrive in the information and unpredictably changing world of today.	authors and its constraints.
Asamoah et al. (2021)	Ghana	The study looks at the effects of IOS adoption on a company's supply chain management (SCM) skills and efficiency.	Resource-based view theory	Quantitative	The outcomes show how IOS adoption may both enhance operational supply chain performance and SCM competences, as well as the mediation function that SCM skills play. We talk about the study's implications to policy and research.	The complex first-order dynamics between the constructs may be further investigated in future studies. Such investigations may offer further knowledge regarding the impact of IOS use on particular SCM capabilities

						and supply chain performance characteristics for deliberate practice. Future research can examine in more depth how IOS utilization and SCM features work together to improve supply chain efficiency.
Nam and Thanh (2021)	Vietnam	The study analyzes survey data of small and medium-sized companies (SMEs) in Vietnam from 2011 to 2015 to evaluate the impacts of bribery on	Institutional theory	Quantitative	Emulsifying bribery has a strong influence that is especially notable for large, legally registered businesses or businesses with no credit restrictions, though the magnitude of the impact is also influenced by specific	Based on the results and the study's constraints, the author proposed that the ministry include the private sector in the issuance and oversight of these certifications. This would

		business decisions regarding environmental innovation, in order to adjust for the roles of negotiating leverage and/or financial and organizational restrictions.			organizational restrictions that businesses see as barriers to their expansion. Furthermore, there is evidence supporting the "sanding-the-wheels" notion of rent-seeking bribery when causality is regulated. This impact of grease fraud is also more significant.	increase the government's reliability and transparency and lower the trading costs for the businesses.
Daradkeh (2021)	Jordan	The study investigated the mediating role of decision-making quality in the connection between information storytelling competence and project success.	Resource-based view theory	Quantitative	The findings of the study show that the data narrative skill is positively related to company success, which is partially mediated by decision-making efficiency, depending on an inductive examination of data gathered from business analytics experts. These	Future research could build on this study's research model by combining features like knowledge management, customer orientation, synergy, corporate strategy, and

					findings offer a theoretical framework for further research on potential causes and effects of data narrative proficiency.In order to enhance decision-making and corporate profitability, they also provide advice for practitioners on how to use data narrative skills in business analytics techniques.	communication processing capacity that would help researchers recognize how data narrative abilities affect economic growth.
Marcinkowski and Gawin (2020)	Poland	The purpose of the project is to investigate ways small and medium-sized organizations (SMEs) develop their business models (BMs)	Building theory	Qualitative	The findings indicate that a data-driven business model (DDBM) imperative for the FM industry has been provided, supporting the requirement to supplement provider processes with the data-driven methodology. A	The author proposed that the DDBM provides a guidance that aids FM companies in concentrating their operations on producing business value from data and

		around data to manage data-driven goods and how this impacts their effectiveness and ability to innovate.			facilities director is given more management tools by improved BM, which enables them to reduce the cost of using an asset and creates new revenue-generating options. This article outlines the transition from a service-based to a data-driven business model and identifies the mindsets executives need to have to support and carry out DDBM.	monetizing data-driven goods depending on the study's results and constraints.

CHAPTER THREE

RESEARCH METHODOLOGY AND ORGANIZATIONAL PROFILE

3.1 Introduction

This chapter provides the methodology that was followed to address the research questions. The sections give the choices of methodologies and the justification for the choices. The chapter is organized under six key headings. The chapter starts with an introduction, followed by the research design and approach, study population, sample size, sampling technique, research instrumentation, data collection procedure, validity and reliability, and data analysis.

3.2 Research Design

The positivist research philosophy is the underpinning philosophy for this study. This study will adopt the positivist paradigm which defines a worldview for research that is grounded in what is known as the scientific method of investigation in research methods (Kivunja and Kuyini, 2017). Adopting positivist assumptions enables the acquisition of knowledge through meticulous observation and analysis of the objective consensus of "out there" reality (Guetterman et al., 2015). In addition, this paradigm relies on deductive logic, the formulation of hypotheses, the testing of those hypotheses, the provision of operational definitions and mathematical equations, calculations, extrapolations, and expressions to conclude. It aims to provide explanations and make predictions based on measurable outcomes, as well as to identify the causes that produce outcomes or consequences (Patten, 2017).

Consequently, positivist research reflects the need to identify and assess the variables that influence observed outcomes, such as those identified in this study (Hennink et al., 2020). The objective of positivism is to generate some degree of abstraction regarding the outcomes of a population study (Iofrida et al., 2018). Not only is the premise of positivism that reality or the actual world exists independently of human consciousness, but also that objective knowledge of reality or the actual world can be acquired (Rassel et al., 2020).

This paradigm is appropriate for this study not because it is the favored worldview for scientific inquiry, but because it seeks to identify cause-and-effect relationships in nature. This makes the positivist paradigm more appropriate for achieving the goals of this study, which aims to examine the relationship between supply chain intelligence and business model innovation (BMI) and the mediating role of data-driven decision-making in the context of hospitality businesses. Subsequently, the study employed quantitative methods of data collection in a single study according to the nature of the study.

The quantitative research approach was chosen on the basis that it produces accurate and measurable data that can be generalized to a broader population (Goertzen, 2017). Aside from that, it is ideal for evaluating and verifying already known concepts about how and why events occur by testing hypotheses developed before data collection. In general, quantitative research is regarded as a deductive approach to the investigation (Ragab and Arisha, 2018). The study combines both descriptive and explanatory research types. While the descriptive describes the relationship between supply chain intelligence and business model innovation (BMI) and the mediating role of data-driven decision-making in the context of hospitality businesses. The explanatory research will also aid in examining the relationship between supply chain intelligence and business model innovation (BMI) and the mediating role of data-driven decision-making in the context of hospitality businesses.

Finally, the study will employ the cross-sectional survey design where deductive reasoning is applied to the quantitative data (Cohen, Manion, and Morrison, 2017). The survey design allows the collection of data from different units over a specific period. Since the study is conducted over a limited period, the cross-sectional survey is deemed more appropriate for examining the relationship between supply chain intelligence and business model innovation (BMI) and the mediating role of data-driven decision-making in the context of hospitality businesses.

3.3 Population of the Study

This section provides a description of the study population and the sample frame used in this study. Etikan, Musa, and Alkassim (2016) defined population as the range of the instances, persons, or objects that are the focus of a study. Thus, the target population reflects the group or individuals the study intends to conclude about. Differently put, the target population consists of a diverse variety of persons from whom a sample should be drawn (Shamsuddin et al., 2017). The study’s population of the study comprised owners, and managers of hospitality businesses in Ghana.

The sample frame refers to the list of individuals the researcher intends to collect the data from. Because owners and managers of hospitality businesses are many and the study cannot gather data from all, the study sets its sample frame to investigate the phenomena among owners and managers of hospitality businesses in the Greater Accra Region.

3.4 Sample Size and Sampling Technique

The issue of sample and sampling technique has a long debate in the academic space, this is because the choice of sample and the procedure has serious consequences on the outcome of any scholarly research. According to Kothari (2012), the sample reflects the researcher's effort or strategy to determine the number of study participants who should be included in the sample. In obtaining the sample size in a given population, three main methods for estimating a sample size can be identified. Firstly, the sample size can be calculated by using formulas (Israel, 1992). Secondly the use of a published statistical table to estimate the sample size, for instance, the published statistical table of Krejcie and Morgan (1970) and Cohen et al. (2013). Lastly, a researcher can decide to utilize census methods by collecting data from the entire population which is known as the census. For this study, sample size determination will be established from Singh and Masuku (2014) formula of sample size determination. The choice of the Singh and Masuku (2014) formula is justified by the fact that the actual population of hospitality businesses is not known by the researcher. Hence the formula is given as

$$n = \frac{Z^2(P)(1-P)}{C^2}$$

Where Z= the standard normal deviation set at a 95% confidence level

P=percentage picking a choice or response (50%)

C=Confidence interval

$n = \frac{(1.96)^2(0.50)(1-0.50)}{0.05^2}$

n=384.16

n~384

Based on the formula, 384 managers of hospitality businesses are drawn for the study. The processes used to choose a sample for a research endeavor are referred to as sampling techniques. Probability procedures and non-probability procedures are the two types of sampling procedures (Taherdoost, 2016). For this investigation, the convenience sampling technique will be used to select students who are available and ready to participate in the study.

3.5 Data Collection

A structured questionnaire is used to source information from the respondents. This study dwells on the use of primary data that will be collected using primary data. The model has three key constructs.

Supply chain intelligence was a first-order construct made up of 12 items adopted from (Renko, Autio, and Sapienza, 2001, Song, Almeida, and Wu, 2003, and Song and Di Benedetto,2008). Eight (8) items were used to measure Business Model Innovation, items were adapted and modified from the works of (Teece, 2018; Zott and Amit, 2008). Four items were used as measures for data-driven culture which were adapted from (Gupta and George, 2016; Duan et al.,2018, Ransbotham and Kiron, 2017, Vidgen et al., 2017). The constructs and their respective measures are shown in the appendix. All items used in the questionnaire were sourced from previously validated instruments.

3.6 Data Processing and Analysis

Data analysis is the process of using a systematic procedure to draw inferences from data gathered from the field as well as considering the various procedures that can be used to analyze the data (Churchill and Iacobucci, 2009). The researchers further suggest that the research design, the kind of data and assumptions made in the research, and concerns associated with the study will influence the suitability of a given technique. Data analysis may follow the quantitative or qualitative procedure in scrutinizing the large volume of information obtained from the field. In the quantitative context, the procedure includes the use of statistical techniques to describe and examine variation in the quantitative measures. The quantitative approach emphasizes the use of either inferential or descriptive statistics (statistical techniques), to understand and establish relationships between constructs.

In this study Statistical Package for Social Sciences (SPSS) version 23 and SmartPLS 3 software will be utilized to conduct descriptive statistics and inferential statistics respectively. The data collected will be coded, cleaned, and prepared for analysis. The data will first be coded in Microsoft excel. In excel the data will be thoroughly checked to avoid possible data entry errors. After cleaning the data will then be exported to SPSS. The data checks in SPSS include missing values, reliability, descriptive statistics, and test of assumptions for multivariate analysis. Subsequently, SmartPLS version 3 (Ringle et al., 2015) will be employed to conduct inferential statistics through multivariate data analysis

3.7 Reliability and Validity

To ensure external validity, participation in the study was purely voluntary. The selected participants were assured of the benefits of the study to the facility to ensure a minimum dropout rate. Both the content and the construct validity of this study were also ensured. The validity and reliability of a research study are two research criteria for consistency (Straus, 2017). An alpha coefficient of 0.70 is used as a cut-off point for assessing the internal consistency of the research item and scales to guarantee study reliability (Hair, Biasutti, and Frate, 2017). To eliminate logical flaws and biases in the study, the researcher emphasizes the validity and reliability of the results. This was done by adopting all of the questions and conducting a pilot study using 10 respondents.

3.8 Ethical Considerations/Issues

Ethical considerations are the principles that must be followed in conducting any type of research (Singh et al., 2015). According to Fleming and Zegward (2018), ethical issues of informed consent, risk of harm, confidentiality, anonymity, and conflict of interest must be considered and presented with a plan on how these ethical issues will be managed in a study.

Ethical considerations were followed during the data collection process the first of which was informed consent. All respondents of the study were duly informed of what the entire study was about and then allowed to decide whether they wanted to participate or not. Only participants who willingly agreed to participate in the study were included in the study for data collection purposes. However, individuals who were uncomfortable with releasing information about their workplaces were exempted from the study. In this regard, participation in this study was strictly voluntary and respondents could withdraw from the data collection process at any time.

Another ethical consideration that guided the data collection process was the confidentiality of the information gathered. The researcher ensured that every data gathered from the respondents through questionnaires were kept in safety such that no external party had access to them.

The anonymity of participants was also very essential during the data collection process. The researcher ensured to ensure that any kind of information that revealed the identity of the participants such as names, residential addresses; phone numbers among others were not part of the instruments used for data collection.

3.9 Profile of the Hospitality Industry

Tourism and hospitality's contribution to the global economy has expanded in recent decades, and it has developed into the fastest-growing and most dynamic economic sector in several countries (Agbola et al., 2020). Tourism alone generated 10.4% of the global Gross Domestic product and 10.6% of total employment in 2019, accounting for every four new jobs produced globally (WTTC, 2021). Despite its significant economic contribution, the sector is highly vulnerable to external shocks (Lee and Chen, 2020), such as the 1997 and 2009 financial crises, the SARS outbreak in 2003, social unrest, natural disasters (e.g. earthquakes, and floods) and the spread of coronavirus 2019 (COVID-19) (Zhang et al., 2021, Spanaki et al., 2021). External shocks, most notably the COVID-19 pandemic, significantly more extensive in scope than others, affect business performance across all industries (Wen et al., 2021). The hospitality sector bears the brunt of the impact (Gursoy and Chi, 2020). As a highly infectious disease that can transmit rapidly among humans (CDC, 2021), it instills widespread fear of contagion and prompts people to shun high-risk activities, including travel (Zheng et al., 2021). To halt the transmission of viruses, governments worldwide implemented travel restrictions (travel bans, visa controls, and quarantine), lockdowns, gathering restrictions, social distancing, and other policies that limit people's activities (Bharwani and Mathews, 2021). Because tourism activities need travel, any impediment to travel, such as fear or restriction, can significantly impact the sector, which results in decreased travel demand (Yeh, 2021). In 2020, foreign visitor arrivals fell by 74%, or around 1 billion persons, compared to the previous year. This downturn returned tourist numbers to levels seen 30 years ago (UNWTO, 2021). The year 2021 proved to be another difficult one, with arrivals remaining 72% lower than before the pandemic (UNWTO, 2022).

In many developing countries, a 20-30% drop could reduce international tourism receipts (exports) by $300-450 billion, or one-third of 2019's $1.5 trillion. Considering past market trends, COVID-19 will lose 5–7 years of growth. UNWTO states that international tourist arrivals fell 4% in 2009 due to the global economic crisis, but just 0.4% in 2003 due to the SARS pandemic. This situation affected the hotel industry deeply. Hotel occupancy plummeted drastically to 40% in 2020 and experienced an 11% upturn in 2021 compared to 2020, but still 33% below the pre-pandemic levels (BPS, 2022). Given the ongoing global pandemic with multiple waves' influence on the confidence of international visitors to travel and the freedom of travel between countries, it necessitates hotels to adopt measures to manage the situation and to survive and increase their performance.

CHAPTER FOUR

DATA ANALYSIS, PRESENTATION AND DISCUSSION OF RESULT

4.1 Introduction

The results of the data analysis are presented in this chapter. The study used descriptive statistics, exploratory factor analysis, and confirmatory factor analysis. Study hypotheses were evaluated using SmartPLS 4. In this section, the researcher looks more closely at the study's key results and compares them to those of similar research.

4.2 Exploratory Factor Analysis

First, the study used the gathered data to conduct an exploratory analysis. An exploratory factor analysis was undertaken to ensure that the data had undergone some kind of quality control. The majority of this work was accomplished via SPSS. Response rate, non-response bias, and common method bias or variance are each broken down into their respective part. For this early data quality evaluation, the study provides a breakdown of the various analysis run and their relative findings.

4.2.1 Response Rate

Following the procedure described in the previous chapter, a total of 384 questionnaires were sent to the heads of Ghanaian hotels and restaurants. Overall, 384 questionnaires were sent; 293 valid responses were received (76% response rate). According to Kamel and Lloyd (2015), a response rate of 50% or more is considered appropriate for analysis in the area of business management research. As a result, the researcher may confidently draw conclusions based on the study's anticipated 76% response rate.

Table 4.1: Responses Rate

Distributed	Collected	Percentage of Usable
Response	294	76%
Non-Response	91	24%
Total	**384**	**100%**

4.2.2 Test for Common Method Bias and Sampling Adequacy

This kind of bias may be particularly prevalent in quantitative research and self-reporting studies. The generalized likelihood ratio test for bias in research designs is required for any experiment or idea to be accepted as credible. Planning and experimentation may help reduce the impact of common method bias. Sincerity was used in developing the survey by including some of the recommendations from Podsakoff et al. (2003). Harman's one-factor analysis was employed by the researcher. The percentage of variables retrieved using a single technique was 48%, which is below the 50% criterion shown in Table 4.2, demonstrating that there is no possibility of common method bias.

Table 4.2: Common Method Bias

Component	Initial Eigenvalues			Extraction Sums of Squared Loadings		
	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	11.501	47.919	47.919	11.501	47.919	47.919
2	2.255	9.395	57.313	2.255	9.395	57.313
3	1.704	7.102	64.415	1.704	7.102	64.415
4	1.169	4.869	69.284	1.169	4.869	69.284
5	0.82	3.416	72.700			
6	0.731	3.045	75.745			
7	0.611	2.546	78.291			
8	0.508	2.118	80.409			
9	0.451	1.88	82.289			
10	0.446	1.857	84.146			
11	0.423	1.762	85.908			
12	0.397	1.655	87.562			
13	0.375	1.563	89.126			
14	0.329	1.37	90.496			

15	0.314	1.309	91.805			
16	0.296	1.234	93.039			
17	0.262	1.094	94.133			
18	0.254	1.06	95.193			
19	0.241	1.003	96.196			
20	0.212	0.882	97.078			
21	0.204	0.849	97.927			
22	0.192	0.801	98.728			
23	0.156	0.65	99.379			
24	0.149	0.621	100			
Extraction Method: Principal Component Analysis.						

Once again, the study's consistency is shown by the high KMO sample adequacy value of 0.937 displayed in Table 4.3. When compared to both zero and the identity matrix, this result reveals a strong connection between values along this dimension. If a sufficient number of samples are collected beforehand, exploratory factor analysis may provide credible estimates. Table 4.3 shows that if the p-value is less than 0.05, then the result is statistically significant. Conclusions are drawn from the data point to causes other than sample variance for the observed internal correlations among the variables. Most measurement approaches have undergone significant adjustments to assess the dormant concept.

Table 4.3: KMO and Bartlett's Test

KMO and Bartlett's Test		
Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		0.937
Bartlett's Test of Sphericity	Approx. Chi-Square	5174.907
	df	276.000
	Sig.	0.000

4.2.2 Non-response Bias

The purpose of this study was to examine the possibility of bias in the responses. Non-response bias occurs when a less percentage of the population responds to a survey than is present. When a survey invites a group of people but only a subset of them responds, this is called non-response bias. This lowers the validity of the findings and the trustworthiness of the data acquired. This study examined how to reduce non-response bias by comparing the responses of early and late respondents. Oppenheim (2000), states that there should be no differences in the dependent or independent variables between the two groups. This finding provides further evidence that the samples are representative of the target population and that non-response bias is not an issue. The first 147 answers were classified as early responses, while the subsequent 146 responses were classified as late responses. Non-response bias was then examined using T-tests. A summary of the results is provided in Table 4.4. A t-test failed to reveal any statistically significant differences. Thus, the study confirms the consistency between the first- and last-month construct data.

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**
Supply Chain Intelligence	1.00	49.3469	0.274	0.601	3.854
	2.00	46.0822			
Data-driven	1.00	16.2313	4.77	0.300	1.714
	2.00	15.6096			
Business Model Innovation	1.00	32.6054	0.102	0.749	2.949
	2.00	30.8356			

4.3 Demographic Information

In this section, the demographic information of the participants is displayed. The results are shown in table 4.5 below. From the result, the female participants represent 47.8% of the sample whiles the male participants represent 52.2%. The results also show that 25.9% of the participants were aged between 18 and 30 years, 39.2% were aged between 31 and 40 years, 27.0% were aged between 41 and 50 years, and 7.8% were also aged above 50 years. The findings also indicated that 22.9% of the participants were bachelor's degree holders, 28.0% were diploma holders, and 9.9% were master's/Ph.D. holders, 0.3% were HND holders, 10.9% were BECE holders, 0.3% hold other certificates and 27.3% were WASSCE holders. The findings also indicated that 22.5% of the participants were business owners, 48.8% were business owners and managers, 2.3% were proxy employees, 13.3% were managers, 10.6% were production managers, 0.3% were sales executives and 2.0% were proxy workers. The data also shows that 29.0% of the participants have worked in the firm for about 1-5 years, 27.3% have worked in the firm for about 11-15 years, 12.3% have worked for 16 years and above and 31.4% of the remaining have also worked in the firms for about 6-10 years. From the data also, 8.2% of the participants indicated 30-99 employees in their firm, 50.9% of them also indicated 6-29 employees in their firm, 38.2% also indicated less than 5 employees in their firm and 2.7% of the remaining indicated more than 100 employees in their firm. From the result also, 29.7% of the participants indicated that their firm produces 1-2 products, 30.0% also indicated their firm produce 3-5 products and 40.3% also indicated their firm produces more than 5 products. Also from the result, 29.4% of the participants indicated their firm has been in operation for about 1-5 years, 32.4% indicated for about 6-10 years and 38.2% also indicated more than 10 years. From the data also, 13.0% of the participants indicated that their firm is into animal farming, 0.3% also indicated arts, 2.0% indicated bakery, beads jewelry productions, detergents, education materials, electrical gadgets, mini banking service, and water packaging, 13.6% indicated cosmetics, 9.2% indicated fashion, 20.5% indicated food processing, 10.2% indicated metal fabrication, 6.1% indicated pharmaceuticals, 7.8% indicated textiles and 13.0% of the remaining indicated woodworks.

Table 4.5: Demographic Information

Variable	Dimension	Frequency	Percent
Gender	Female	140	47.8
	Male	153	52.2
Age	18 - 30 Years	76	25.9
	31 - 40 Years	115	39.2
	41 - 50 Years	79	27.0
	Above 50 Years	23	7.8
Level of Education	Bachelor Degree	67	22.9
	Diploma	82	28.8
	Graduate Studies (Master / Ph.D)	29	9.9
	HND	1	0.3
	Junior High School	32	10.9
	Others	1	0.3
	Senior High School	80	27.3
Your Position in the Firm	Business Owner	66	22.5
	Business Owner & Manager	143	48.8
	Employee (proxy)	7	2.3
	Manager	39	13.3
	Production Manager	31	10.6
	Sales executive	1	0.3
	Proxy Worker	6	2.0
How many years have you been working in your firm?	1-5 Years	85	29
	11-15 Years	80	27.3
	16 Years and Above	36	12.3
	6-10 Years	92	31.4
How many employees are in the firm?	30-99 employees	24	8.2
	6-29 employees	149	50.9
	Less than 5 employees	112	38.2
	More than 100	8	2.7
How many products does the firm produce?	1-2 Products	87	29.7
	3-5 Products	88	30
	More than 5 Products	118	40.3
How many years has the firm been in operation?	1-5 Years	86	29.4
	6-10 Years	95	32.4
	More than 10 Years	112	38.2
Type of business operated by the firm?	Animal Farming	38	13.0
	Art	1	0.3

	Bakery	6	2
	Beads Jewelry Production	1	0.3
	Communicator	1	0.3
	Cosmetics	39	13.3
	Detergents	1	0.3
	Education Materials	1	0.3
	Electrical Gadgets	1	0.3
	Fashion	27	9.2
	Food Processing	60	20.5
	Metal Fabrication	30	10.2
	Mini Banking Service	1	0.3
	Pharmaceuticals	18	6.1
	Sachet water production	6	2.0
	Textiles	23	7.8
	Water Packaging	1	0.3
	Wood Works	38	13
	Total	**293**	**100.0**

4.4 Measurement Model Assessment

The measurement model was evaluated in accordance with the standards set out by Hair et al (2019). Partial least squares structural equation modeling (PLS-SEM) was employed to evaluate the data, with SmartPLS version 4 serving as the primary analytical tool (Ringle et al., 2015). Before anything else, the researcher made sure that the indicator loadings were more than 0.70. It is good, since it means the construct is sufficiently robust to account for more than half the variation in the indicator, indicating the items may be depended upon. Table 4.6 reveals that the researcher eliminated all except the outer loading items that met the 0.700 cut-off.

After that, the Composite Reliability and Cronbach Alpha ratings were used in order to conduct an analysis into the reliability of the constructs' internal consistency. Cronbach's alpha scores ranged from 0.903 to 0.921, making this a reliable sample; composite reliability scores ranged from 0.929 to 0.935. All of the values were more than 0.7, making this a reliable sample (Hair et al., 2019).

After that, the convergent validity of the construct was investigated. An indicator of a construct's convergent validity is the degree to which it can explain variances in the components that make it up. The overall convergent validity of a collection of variables may be evaluated based on the average variance extracted (AVE) across all of the items on the collection, with values of 0.50 or above being considered acceptable. As a result of the AVE values falling within the range of 0.592 to 0.776, the requirements were successfully satisfied. The convergent validity tests are summarized in the following table, which may be found below (Table 4.6).

Multicollinearity is used to analyze the indicators' usefulness and their linkages to one another. Having too many indicators might be confusing, so choose one to concentrate on. The multicollinearity would turn the constructs from an independent to a dependent variable. One user's need to trigger such an alert is an indication of the importance they place on the constructs. Table 4.6 displays the multicollinearity analysis findings, which seem to meet expectations. (Nitzl, 2016; Fuchs, 2011).

Table 4.6: Reliability and Validity

Variable	Items	Loadings	CA	CR	AVE	VIF
Business Model Innovation	BMI1	0.815	0.921	0.935	0.643	2.889
	BMI2	0.806				2.898
	BMI3	0.773				2.145
	BMI4	0.811				2.684
	BMI5	0.817				2.863
	BMI6	0.804				2.776
	BMI7	0.767				2.107
	BMI8	0.819				2.499
Data-driven Culture	DDC1	0.834	0.903	0.933	0.776	2.158
	DDC2	0.900				3.289
	DDC3	0.894				2.769
	DDC4	0.893				3.132
SUPPLY chain Intelligence	SCI11	0.707	0.914	0.929	0.592	2.072
	SCI12	0.735				2.190
	SCI2	0.747				2.216
	SCI3	0.782				2.287

	SCI4	0.786	2.638
	SCI5	0.781	2.387
	SCI6	0.779	2.596
	SCI7	0.797	2.952
	SCI8	0.803	2.961

4.4.3 Descriptive Statistics

Statistical summaries of the research variables are provided in the following. Mean describe the data whereas standard deviations demonstrate how well the means represent the data (Field, 2009). Descriptive analysis findings are shown in Table 4.7. The data demonstrated that supply chain intelligence score (M=3.98; SD=0.834), data-driven culture score (M=3.98; SD=0.885), and business model innovation score (M=3.96; SD=0.811). The results reveal that the observed mean did not deviate from the calculated or statistical mean for any of the constructs.

Table 4.7: Descriptive Statistics

Constructs	Mean	Standard Deviation
Supply Chain Intelligence	3.98	0.834
Data-driven Culture	3.98	0.885
Business Model Innovation	3.96	0.811

The degree of an independent variable's departure from the other independent variables in the experiment's structural model was then evaluated using discriminant validity. The correlation of variables with one another needs to be lower than the square root of the average variance (AVE) across elements for the discriminant function to be valid (Fornell & Larcker, 1981). In Table 4.8, the square roots of AVEs are shown in bold diagonal figures, while the link between variables is highlighted by figures off the diagonal. There is high discriminant validity in this case since diagonal values are higher than non-diagonal ones.

Table 4.8: Fornell-Larcker test

Constructs	1	2	3
Exploitative ambidextrous leadership	0.85		
Explorative ambidextrous leadership	0.6	0.831	
Organizational Learning	0.699	0.625	0.739

A more rigorous measurement of discriminant validity, the heterotrait-monotrait (HTMT) ratio of correlations, has been developed as a reaction to criticisms leveled against the Fornell-Larcker criteria (Hair et al., 2019; Henseler et al., 2015; Voorhees et al., 2016). According to studies, it's best to use HTMT scores below 0.90, which would be characterized as the geometric mean of the average correlations for scales to measure the very same variable divided by the average value of the items' correlations across constructs (Henseler et al., 2015). According to Table 4.9, the model is valid up to an HTMT of 0.723

Table 4.9: HTMT Test results

Constructs	1	2	3
Exploitative ambidextrous leadership			
Explorative ambidextrous leadership	0.685		
Organizational Learning	0.778	0.695	

4.5 Model Fit Indices

Fitness of Extracted-Index, SRMR, Root Mean Square of Approximation, and Chi-Square all have acceptable values and ranges (Table 4.9). The extracted index and the abnormal index are both lower than 0.9, which is the minimum requirement for acceptance. If a residual has a square root or a common root, it means that the residual is not insignificantly tiny. Therefore, it will be crucial for future studies to consider all essential features and perspectives.

Table 4.10: Model Fit Indices

Indices	Saturated model	Estimated model
SRMR	0.065	0.065
d_ULS	0.968	0.968
d_G	0.496	0.496
Chi-square	840.193	840.193
NFI	0.817	0.817

4.6 Structural Analysis Results

Henseler (2018) defines R2 values of 0.75, 0.50, and 0.25 as very significant, moderate, and low, respectively. On the other hand, Chin et al. (2020) stress the importance of understanding R2 in the linked area. Business model innovation and data-driven culture both had modest R2 Adjusted values of 0.493 and 0.444, respectively, as shown in Table 4.11 and Figure 4.1. Supply chain intelligence was shown to be responsible for 49.6% of the variance in business model innovation and 44.4% of the variation in a data-driven culture. This allows the model to make reliable predictions and even glimpse into the future.

Table 4.11: Coefficient of Determination and Predictive Power of the PLs Model

Endogenous Variables	R-square	R-square adjusted
Business Model Innovation	0.496	0.493
Data-driven Culture	0.446	0.444

Q2 values may also be calculated to evaluate the prediction accuracy of the PLS path model (Geisser, 1974; Stone, 1974). Q2 values should be non-zero for a given endogenous construct to reflect the structural model's ability to forecast that construct (Hair et al., 2019). From the table 4.12 Q2 values varied between 0.382 and 0.433, demonstrating the model's usefulness for making predictions.

Table 4.12: Predictive Power of the PLs Model

Endogenous Variables	Q^2predict
Business Model Innovation	0.382
Data-driven Culture	0.433

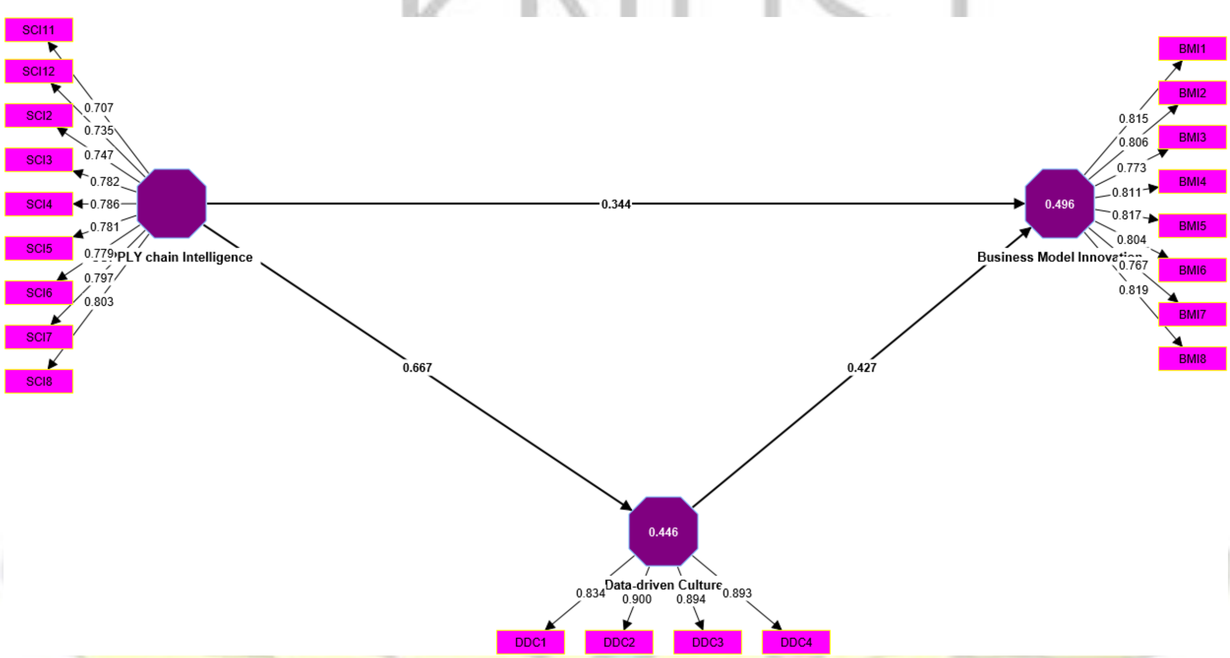

Figure 4.1: Measurement Model Assessment

4.7 Hypotheses for Direct Relationship

Here, the researcher utilizes smartPLS 4 to check whether the hypotheses about the research hold. The research set out to examine how data-driven decision-making may play a mediating role between supply chain intelligence and business model innovation (BMI) for hotels in developing countries. Table 4.13 outlined the results.

The study's first objective was to examine if and how supply chain intelligence's recent rise has influenced the business model innovation of hotels in underdeveloped nations. A strong and statistically significant impact of supply chain intelligence on business model innovation in hotels in emerging markets is shown in Table 4.13, (B=0.344; t=4.607; p-value=0.000 <0.05).

The study's results provide support for the predicted link between the two variables. This further reveals that, when all other parameters are held constant, 34.4% of the variance in business model innovation may be attributed to the degree to which the hotel industries prioritize supply chain intelligence. The findings imply that hotel industry business model innovation will be enhanced when managers actively participate in supply chain intelligence.

This study also recommended investigating the effective supply chain intelligence was having on the data-driven culture prevalent in the hospitality sector. Table 4.13 shows that an organization's embrace of a data-driven culture is positively and significantly affected by its capacity to use supply chain intelligence within the hotel sector (B=0.667; t=12.766; p-value=0.000 <0.05). The results of this study provide support for the proposed connection between the two factors. These findings demonstrate that when all other independent variables are kept constant, a one-unit change in supply chain intelligence accounts for 66.7% of the changes in a data-driven culture. The findings show that a company's data-driven culture will improve if its management put a priority on its capacity to deploy supply chain intelligence.

The study's second objective was to check whether and how the rise of data-driven culture has influenced the business model innovation of the hotel industries. Table 4.13 demonstrates that in the hospitality sector, business model innovation is positively and significantly impacted by the capacity to apply data-driven culture (B=0.427; t=5.902; p-value=0.000 <0.05). The results of this study support the proposed connection between the two variables. This further reveals that 42.7% of the difference in business model innovation can be attributed to the degree to which the hotel industry prioritizes data-driven culture. The findings imply that hotel industry managers will benefit from improved business model innovation if they actively participate in a data-driven culture.

The study's final objective was to determine whether or not the link between supply chain intelligence and business model innovation for hotels in developing nations was mediated by data-driven culture. According to Table 4.13, a data-driven culture significantly mediates the link between supply chain intelligence and business model innovation (B=0.285; t=5.177; p-value=0.000 <0.05). The results of this study support the expected connection between the variables. After accounting for other variables, the findings also reveal that a data-driven culture accounts for 28.5% of the variation in the impact of supply chain intelligence on business model innovation. Findings suggest that when management places a focus on a data-driven culture, supply chain intelligence may have a greater impact on business model innovation.

Table 4.13: Hypotheses for Direct Relationship

Hypotheses	Path Coefficient	Error	T Statistics	P Values	Decision
Supply chain Intelligence -> Business Model Innovation	0.344	0.075	4.607	0	Supported
Supply chain Intelligence -> Data-driven Culture	0.667	0.052	12.766	0	Supported
Data-driven Culture -> Business Model Innovation	0.427	0.072	5.902	0	Supported
Supply chain Intelligence -> Data-driven Culture -> Business Model Innovation	0.285	0.055	5.177	0	Supported

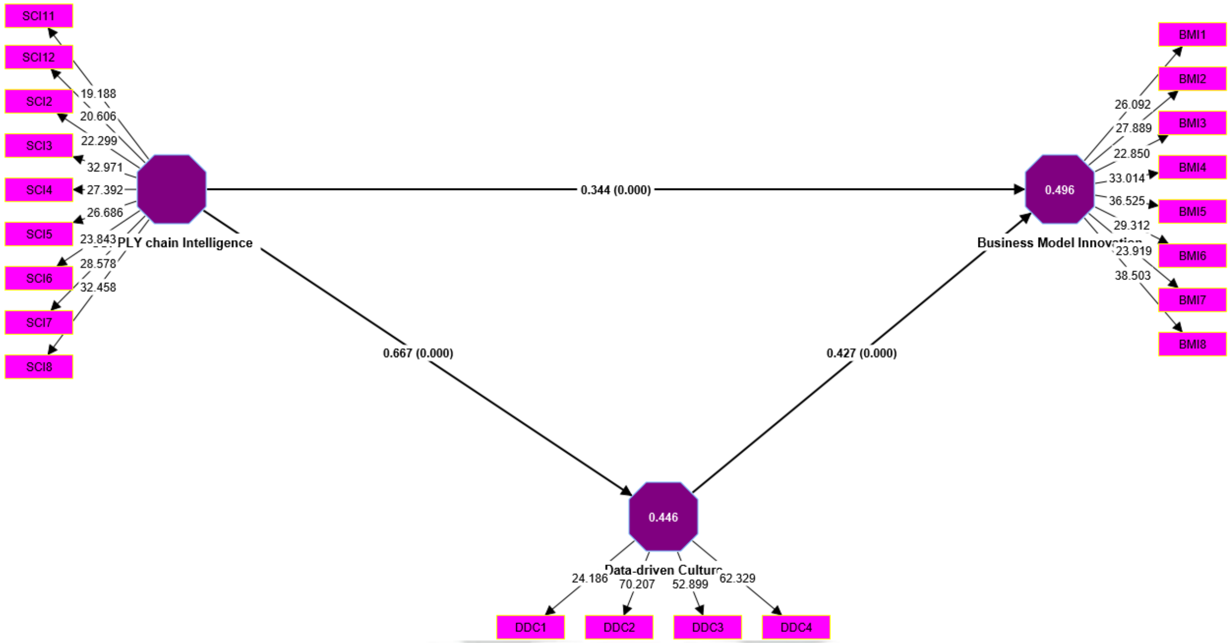

Figure 4.2 Structure Model Evaluation

4.8 Discussion of Findings

The main results are summarized, and relevant literature is reviewed in this section. The research set out to examine how data-driven decision-making may play a mediating role between supply chain intelligence and business model innovation (BMI) for hotels in developing countries. Three distinct goals were proposed in response to the identified needs. The findings are discussed in the subsections below.

The study's first objective was to examine if and how supply chain intelligence's recent rise has influenced the business model innovation of hotels in underdeveloped nations. A strong and statistically significant impact of supply chain intelligence on business model innovation in hotels in emerging markets was found (B=0.344; t=4.607; p-value=0.000 <0.05). The study's results provide support for the predicted link between the two variables. This further reveals that, when all other parameters are held constant, 34.4% of the variation in business model innovation may be attributed to the degree to which the hotel industries prioritize supply chain intelligence.

The findings imply that hotel industry business model innovation will be enhanced when managers actively participate in supply chain intelligence. The results are consistent with RBV research and theory, which seeks to examine the connection between businesses and innovation by concentrating on their resources and capabilities and asking whether differences in firm performance are caused by differences in the level of resources or the deployment of such resources (DeSarbo et al., 2007; Newbert, 2007). The findings are consistent with the research conducted by Jaharuddin et al. (2014), who found supply chain intelligence (SCI) to be an important driver of future business success through improving a company's competitiveness. Research indicates a favorable correlation between SCI and company success. The results corroborate the findings of Ghosh and Stieber (2021), who studied the impact of digital transformation on business models (BMs) and found that digitalization greatly boosts business model innovation.

The study's second objective was to check whether and how the rise of data-driven culture has influenced the business model innovation of the hotel industries. The result demonstrated that in the hospitality sector, business model innovation is positively and significantly impacted by the capacity to apply data-driven culture ($B=0.427$; $t=5.902$; p-value$=0.000 <0.05$). The results of this study support the proposed connection between the two variables. This further reveals that 42.7% of the difference in business model innovation can be attributed to the degree to which the hotel industry prioritizes data-driven culture. The findings imply that hotel industry managers will benefit from improved business model innovation if they actively participate in a data-driven culture. This outcome is consistent with DCV's stipulation that for a business to successfully adapt to its dynamic environment, it must integrate, expand, and rearrange both internal and external capabilities (Teece et al.,1997). This confirms the findings of Chatterjee et al. (2021), who studied the effects of a data-driven culture on a company's capacity for product and process innovation, which in turn boosts a company's performance and gives it an edge in the market and found that data-driven cultures have a significant impact on product and process innovation, which in turn increases a company's competitiveness in its industry.

The study's final objective was to determine whether or not the link between supply chain intelligence and business model innovation for hotels in developing nations was mediated by data-driven culture. According to the findings, data-driven culture significantly mediates the link between supply chain intelligence and business model innovation (B=0.285; t=5.177; p-value=0.000 <0.05). The results of this study support the expected connection between the variables. After accounting for other variables, the findings also reveal that data-driven culture accounts for 28.5% of the variation in the impact of supply chain intelligence on business model innovation. Findings suggest that when management places a focus on a data-driven culture, supply chain intelligence may have a greater impact on business model innovation. This confirms the findings of Al-Khatib (2021), who examines the role of a data-driven culture in bridging the gap between big data analytics expertise and Jordan's manufacturing sector's competitive edge. The findings support the idea that a data-driven culture mediated the link between radical eco-innovation, incremental eco-innovation, and a company's competitive advantage. Consistent with the results of Chaudhuri et al. (2021), who investigated the role of a data-driven culture in mediating the relationship between business analytics for product innovation and its impacts on organizational performance, this conclusion suggests that such a culture is indeed important. According to the study's findings, a company's bottom line may rise thanks to the improvement of the business's overall performance and the creation of new goods that are informed by data.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

This last chapter of the paper provides a concise summary of the study's results, conclusions, and suggestions for further research. Both the study's limits and some ideas for further exploration are provided.

5.2 Summary of findings

The research set out to examine how data-driven decision-making may play a mediating role between supply chain intelligence and business model innovation (BMI) for hotels in developing countries. Results from the experiment and conclusions gained from the prior literature are summed up in the next section. The results are organized into sections that correspond to the goals of the research.

5.2.1 Effect of Supply Chain Intelligence on Business Model Innovation

The study's first objective was to examine if and how supply chain intelligence's recent rise has influenced the business model innovation of hotels in underdeveloped nations. A strong and statistically significant impact of supply chain intelligence on business model innovation in hotels in emerging markets was found. The study's results provide support for the predicted link between the two variables. This further reveals that variation in business model innovation may be attributed to the degree to which the hotel industries prioritize supply chain intelligence. The findings imply that hotel industry business model innovation will be enhanced when managers actively participate in supply chain intelligence.

The computer revolution, machine learning, and other advances are fast changing the conventional supply chain into a more modern, more functional process that holds promise for optimizing fulfillment operations and accelerating logistics. Sourcing and supply chain management may aid in the development of novel value propositions for customers and guarantee a more resource-efficient business model overall. Those businesses that have adopted a long-term perspective on sustainability and incorporated it into their operations are reaping the rewards. To gain a competitive advantage and avoid falling behind, businesses must immediately begin investing in supply chain technology. But the difficulty in enhancing digital supply chain technologies is in avoiding being distracted by the newest and greatest. Instead, businesses should make informed decisions that cater to their actual need.

5.2.2 Impact of Data-driven Culture on Business Model Innovation

The study's second objective was to check whether and how the rise of data-driven culture has influenced the business model innovation of the hotel industries. The result demonstrated that in the hospitality sector, business model innovation is positively and significantly impacted by the capacity to apply data-driven culture. The results of this study support the proposed connection between the two variables. This further reveals that the changes in business model innovation can be attributed to the degree to which the hotel industry prioritizes data-driven culture. The findings imply that hotel industry managers will benefit from improved business model innovation if they actively participate in a data-driven culture.

The term data-driven refers to a method of strategic planning that emphasizes the use of data to discover and exploit new possibilities, enhance customer service, boost sales, enhance operations, and more. It enables businesses to make well-informed judgments and meticulous plans to achieve their goals. The business information gained from big data is useful for cutting down on company expenditures and improving profitability. The insights from big data may be utilized to revamp corporate procedures in order to save expenses and boost revenue. Data-driven businesses fared better financially, survived longer, and were more creative, according to the research. Companies that are data-driven may increase their profits by as much as 20%, according to a new McKinsey research. Internet stores like Amazon monitor their customers' actions and utilize data like click-through rates and bounce rates to figure out what products are getting the most attention. Because of this information, stores may suggest items you might be interested in buying before you ever know you need them.

5.2.3 The mediating role of Data-driven Culture on the link between SCI and BMI

The study's final objective was to determine whether or not the link between supply chain intelligence and business model innovation for hotels in developing nations was mediated by data-driven culture. According to the findings, data-driven culture significantly mediates the link between supply chain intelligence and business model innovation. These findings provide credence to the hypothesis that there is a correlation between the variables. The findings also imply that data-driven culture accounts for variation in the impact of supply chain intelligence on business model innovation. Findings suggest that when management places a focus on a data-driven culture, supply chain intelligence may have a greater impact on business model innovation.

Businesses may utilize data-driven decision-making to acquire insights and generate projections in real-time, helping them to enhance operations and efficiency. This helps them to measure the effectiveness of different ways and make smart business decisions that lead to long-term growth. The type of choices that will propel your organization ahead can only be made with the proper reporting tools in place and with the knowledge of how to effectively assess and monitor data.

However, in reality, it is still feasible to make judgments that neglect concrete understanding and instead rely on gut feelings, even if one has access to the world's finest data. This usually ends up being bad for business. The bulk of business choices should be backed by exact measurements, facts, statistics, or insights connected to company objectives, goals, or projects, which may serve as a firm basis for management reports and company operations. With data-driven decisions, the company can grow and react quickly to the dynamic nature of the market. It has to be the driving force behind all you do.

5.3 Conclusion

The purpose of this study was to investigate whether or not data-driven decision-making may serve as a mediator between supply chain intelligence and business model innovation (BMI) for hotels in emerging markets. The researcher attained the objectives via the use of a cross-sectional survey design and a quantitative approach that combined descriptive and explanatory research methods. Both the explanatory and descriptive designs were used to describe and then analyze the interplay between the variables. The participants in the survey were hotel and restaurant managers and owners in Ghana. The primary data was gathered via an in-depth questionnaire sent to 293 hotel and restaurant managers and owners in Ghana. The study used a convenient sampling strategy. The assumptions of the research were tested using Structural Equation Modeling in the form of SmartPLS 4. The data were summarized using descriptive statistics. The research results showed that supply chain intelligence significantly affects business model innovation. The mediation research also found that the connection between supply chain intelligence and business model innovation is mediated by data-driven culture. The results suggest that if hotel managers actively engage in, and place a premium on, supply chain intelligence and data-driven culture, then business model innovation will improve throughout the sector.

5.4 Recommendations

The purpose of this study was to investigate whether or not data-driven decision-making may serve as a mediator between supply chain intelligence and business model innovation (BMI) for hotels in emerging markets. The research results showed that supply chain intelligence significantly affects business model innovation. The mediation research also found that the connection between supply chain intelligence and business model innovation is mediated by data-driven culture. The results suggest that if hotel managers actively engage in, and place a premium on, supply chain intelligence and data-driven culture, then business model innovation will improve throughout the sector. The following suggestions have been made in light of the results.

1. Based on the findings of this study, it follows that raising the standard for supply chain intelligence would likewise raise the standard for business model innovation. Therefore, it is crucial for hotel company managers to optimize the supply chain in numerous ways via the use of cutting-edge technology and an increase in supply chain intelligence. To achieve an intelligent supply chain, businesses take use of available technology to gather data and draw conclusions that help them enhance the efficiency of their supply chain operations.
2. The research showed that data-driven culture is associated with more innovative business models, thus it stands to reason that expanding data-driven culture capabilities will likewise boost business model innovation. Therefore, hotel managers must invest massively in a data-driven culture, which will result in an improvement in the company's

ability to renovate its business model. As a consequence, the hotel's management must make significant investments in data-driven culture in order to enhance the company's capacity to revamp its business model.

3. It was shown that data-driven culture acted as a mediator between supply chain intelligence and business model innovation. This indicates that when hotel management sets a priority on data-driven culture, the impact of supply chain intelligence on business model innovation is enhanced. Therefore, it is imperative that hotel executives value data-driven culture by emphasizing the importance of data culture's human aspect and forming a team that is representative of the whole spectrum of employees.

5.5 Limitations and Suggestion for Future Research

There are certain limitations to this study that are common to survey designs in general, but the researcher has taken all the required efforts to minimize them. Scholars and practitioners are encouraged to consider these limitations while assessing the study's findings and recommendations. To begin, RBV and DCV inform the theoretical foundation and frameworks of this investigation. The theoretical concerns about SCI and data-driven culture may not be fully covered by the measure used to evaluate the hypotheses, as is the case with any theory-based study. Consequently, it is suggested that future studies combine qualitative and quantitative approaches to investigate further connections and occurrences. And second, this study is a cross-sectional survey. To verify the connections between SCI, Data-driven culture, and BMI, more in-depth longitudinal research is needed. Third, all the companies in this analysis are service-based even if they come from a wide variety of industries. For the results of this research to be applied to manufacturing as a whole, comparable studies need to be conducted. The sample size is still regarded to be low. To generalize these results to other sectors in Ghana, further research on this issue has to vastly expand its sample size.

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APPENDIX

SURVEY QUESTIONNAIRE

Dear Sir/ Madam,

My name is ………., a postgraduate student at the Kwame Nkrumah University of Science and Technology, Kumasi, Department of Supply Chain and Information Systems. This survey instrument has been designed to enable me carry out research on the topic: **“**Business Model Innovation”. Any information provided will be used for academic purposes ONLY. There are no risks associated with your participation, and your responses will remain confidential and anonymous.

SECTION A: RESPONDENT’S BIOGRAPHY AND COMPANY PROFILE

When completing this questionnaire, please tick **[√]** in the applicable box or provide an answer as applicable.

Please answer the following questions:

SECTION D: PERSONAL DETAILS Please indicate what applies to you the most							
1.	Your gender	1 male	2 female				
2.	Your age	1 Below 25	2 25-35	3 36-40	4 40 and above		
109	Level of education	1 Secondary	2 Diploma	3 Degree	3 Post grad/ Master’s Degree	4 Other	
110	How long have you worked in this organization?	1 Less than 1 year	2 1 - 3 years	3 4-6 years	4 More than 6 years		
	SECTION I: BUSINESS DETAILS						
111	Number of employees besides owner	1 Less than 10	2 [11- 50]	3 [51-100]	4 [101-500]	5 [501 and above]	
112	Age of business	1 Less than one year	2 2-5 years	3 6-10 years	4 11 years and above		

SECTION B: Supply Chain Intelligence

To what extent do the following statements use the scale1 to 5: Not at all – A very great extent

Statement	**1**	**2**	**3**	**4**	**5**
As soon as we acquire new knowledge from suppliers, we try to find applications for it					
The suppliers' technological knowledge has enriched the basic understanding of our innovation activities					
The suppliers' technological knowledge has reduced the uncertainty of our innovation activities					
The suppliers' technological knowledge helps us to identify new aspects of innovation activities that would otherwise go unnoticed					
As soon as we acquire new knowledge from customers, we try to find applications for it					
The customers' technological knowledge has enriched the basic understanding of our innovation activities					
The customers' technological knowledge has reduced the uncertainty of our innovation activities					
The customers' technological knowledge helps us to identify new aspects of innovation activities that would otherwise go unnoticed					
We regularly collect information about our competitors' product and strategies					
We systematically process and analyze competitor information					
We fully integrate information about competitors' products as a benchmark in our product design					
Our knowledge of competitors' strengths and weaknesses is thorough					

SECTION B: Data-driven culture

To what extent do the following statements describe your firm's data culture?

, using the scale1 to 5: Not at all – A very great extent

Statement	**1**	**2**	**3**	**4**	**5**
I believe decisions should be based on available information coming from a BA solution.					
Our firm has a practice of decision-making based on the available data					
Data plays an important role in new product development					
Data plays an important role in process improvement					

SECTION C: Business Model Innovation

In this section, we are trying to measure the Business Model Innovation . Please indicate the degree of your agreement with the following statements. Using the Likert scale, where 1=strongly disagree; 2=disagree; 3=neutral; 4=agree; 5=strongly agree

Procurement	**1**	**2**	**3**	**4**	**5**
We use an innovative business model to trade					
We introduce new operation processes, practices and norms in business model					
We introduce new ideas, methods and product in business model					
Our business model provides value-added products/services					
Our business model creates a new profit mode					
Our business model creates a new profit path					
Our business model creates a new profit point					
Our business model is novel					

Thank you for participating in the survey.