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TOPIC:

Supply Chain Collaboration and Logistics Performance: The Role of Supply Chain Integration and Big Data Analytics

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DECLARATION

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

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DEDICATION

I dedicate this research to my family - my mother and siblings, who have been my pillars of strength. Their unconditional love and support have inspired me throughout this journey. I also dedicate this work to God almighty, Jesus Christ and the Holy Spirit, for guiding me and blessing me with the determination to undertake this study.

ABSTRACT

This study examined the effects of supply chain integration and big data analytics on the relationship between supply chain collaboration and logistics performance. The motivation for the study is that although supply chain collaboration is recognized as critical for supply chain efficiency, research has shown inconsistent results regarding its impact on performance outcomes. Furthermore, the mechanisms through which supply chain collaboration drives performance have not been thoroughly examined. Using the resource-based view as the theoretical lens, the study develops a model that posits supply chain integration and big data analytics as moderators in the supply chain collaboration-logistics performance relationship. The objectives are to examine the direct effect of supply chain collaboration on logistics performance and the moderating roles of supply chain integration and big data analytics. The study adopts a quantitative approach with a sample of 385 firms. Data is collected via questionnaires and analyzed using regression analysis. The key findings indicate a significant positive relationship between supply chain collaboration and logistics performance. However, supply chain integration and big data analytics individually do not significantly moderate this relationship. Rather, the interaction between supply chain integration and big data analytics positively and significantly moderates the effect of supply chain collaboration on logistics performance. The study recommends supply chain managers to improve collaborative practices with partners through increased information sharing, coordinating decision-making, and aligning incentives. The research recommends that supply chain integration and big data analytics tools should be used together to enhance collaboration, which can lead to improved logistics performance. The study contributes by elucidating the mechanisms through which supply chain collaboration drives logistics performance.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

RBV	Resource based view
OLR	Ordinary Least Regression
EFA	Exploratory Factor Analysis

SCC	Supply chain collaboration
SCI	Supply chain integration
BDA	Big data analytics
LP	Logistics performance
VIF	Variance Inflation Factor
CFA	Confirmatory factor analysis
AVE	Average variance extracted

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

The concept of a supply chain (SC) connects various business flows among partners with the shared aim of reaching a common goal. The importance of SC collaboration is highlighted by Pakdeechoho and Sukhotu (2018), emphasizing that it involves sharing information, materials, finance, and risk across the chain. According to Al-Doori (2019), the willingness to share network resources among members is vital in defining collaboration within the supply chain. Logistics, which is a crucial aspect of trade affecting the volume of bilateral transactions, enhances competitiveness for both companies and nations. Göçer et al. (2022) noted the global significance of logistics, leading to the development of specific measurement systems for logistics performance and strategies to improve country-level performance. Effective supply chain collaboration could drive improvements in logistics performance, as Khan et al. (2017) have pointed out. However, the relationship between supply chain collaboration and logistics performance is significantly influenced by big data analytics (BDA). As Tsai et al. (2015) identified, BDA facilitates seamless and two-way information sharing, enabling partners to gather and share necessary supply chain information in real-time, which promotes sustainability. Additionally, the integration of supply chain collaboration could be enhanced through a standardized and centralized system, allowing buyers and suppliers to work together to streamline logistics and distribution. Khanuja and Jain (2020) found this integration essential for optimizing the efficiency of the supply chain. With this background, the study explores how supply chain integration and big data analytics mediate the relationship between supply chain collaboration and logistics performance, utilizing the Relational and Resource-based view theories. The focus of this research is on private firms operating in the Greater Accra Region of Ghana, examining how these elements interact and influence one another.

1.2 Statement of the Problem

Supply chain collaboration (SCC) is recognized as a vital aspect in sustaining a supply chain's competitive edge, and it has emerged as a significant area of research within the field of supply chain management. Its importance has been highlighted in numerous publications, with the understanding that supply chains, given their inter-organizational and inter-functional nature, perform more effectively when there is coordinated collaboration among partners (Soosay and Hyland, 2015).

Interestingly, the existing research on SCC has shown inconsistent findings. Some studies, including those by Pradabwong et al. (2015, 2017), Pakdeechoho and Sukhotu (2018), Chilkapure and Pillai (2019), and Peng et al. (2022), have discovered positive effects of SCC on various outcomes such as firm performance, operational performance, supply chain sustainability, competitive advantage, and organizational performance. On the other hand, works by Gunasekaran, Subramanian and Rahman (2015), Scholten and Schilder (2015), Cui et al. (2022) have reported only indirect effects of SCC. Still, other research, such as the findings by Chen et al. (2017) and Hofman et al. (2020), have pointed to negative impacts of SCC on different outcome variables.

Several researchers, such as Jimenez-Jimenez et al. (2019), Wang et al. (2021), and Wu and Chiu (2018), have argued that SCC alone is insufficient to bring about improvements in different performance outcomes. They have emphasized the role of mediating and moderating variables like trust, transparency, knowledge sharing, and balance of power in influencing the extent of SCC.

Despite the clarity in existing literature regarding the connection between SCC and various outcome variables, there is a noticeable deficiency of understanding concerning the role of supply chain integration (SCI) and big data analytics in mediating the effects of SCC on logistics performance. This study seeks to fill this void by proposing a unique research model that explores how SCI and big data analytics serve as mediators in the relationship between supply chain collaboration and logistics performance. By focusing on these specific areas, the study aims to contribute fresh insights and address the gaps in the current body of knowledge.

1.3 Research Objectives

The main objective of this study is to examine the role of supply chain integration and big data analytics in the relationship between supply chain collaboration and logistics performance. The study's specific objectives include to:

1. To examine the relationship between supply chain collaboration and logistics performance
2. To examine the role of big data analytics on the relationship between supply chain collaboration and logistics performance
3. To examine the role of supply chain integration in the relationship between supply chain collaboration and logistics performance

1.4 Significance of the Study

The findings of this study carry significant implications for both the academic community and supply chain practitioners.

The research delves into how supply chain collaboration influences social, environmental, and economic sustainability. It particularly explores the moderating and mediating roles of big data analytics and supply chain integration in defining the relationship between supply chain collaboration and logistics performance. In alignment with prior studies, such as those by Chen et al. (2017) and Um and Kim (2019), the outcomes of this investigation are anticipated to enrich our comprehension of the connections between supply chain collaboration and sustainability performance. The study intends to apply rigorous testing to measurement items to ensure reliability and validity. This clear definition and methodology could assist both scholars and industry professionals in crafting an environment that is conducive to efficient and effective supply chain collaboration and logistics performance.

From a practical perspective, the development of the model and the empirical results derived from this study provide valuable insights for managers overseeing supply chain relationships. Initially, the study serves as a guide for managers in structuring supply chain collaboration activities, by taking into account various dimensions of supply chain collaboration. It emphasizes that if collaboration is not executed effectively, it may not lead to enhanced sustainability performance. Hence, managers are encouraged to establish an optimal level of collaboration by considering different degrees of supply chain integrations.

1.5 Research Methodology

To achieve the study's objectives, the researcher adopts explanatory research. The research strategy chosen for this study is the survey of private firms. The research approach for the study is quantitative research. The study's sample size is three hundred and eighty-five (385), drawn from the target population using convenient sampling. The data collection instrument for the study is an online questionnaire. IBM SPSS version 26 would be used to perform descriptive, inferential analysis and structural equation modelling for the mediation, respectively.

1.6 The Organisation of the Study

The study is organised into five chapters. The first chapter is the introduction, covering the background to the study, motivation, statement of the problem, the study's objective, the significance of the study, methodology, and organisation of the study. The second chapter presents the review of pertinent literature relevant to the study. Chapter two comprises four main sections: conceptual review, theoretical review, empirical review, and conceptual framework. The third chapter presents the study's methodology. It presents the research design, the population and sampling techniques, data collection method, data analysis, reliability and validity tests and ethical consideration. The fourth chapter presents the analyses of data and a discussion of the results. It contains the Response rate, Descriptive statistics, a test of validity and reliability, Inferential statistics, and a discussion of results. Chapter five summarises the study's findings, makes recommendations and conclusions, and makes suggestions for future studies.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews the literature on Supply chain collaboration, Supply chain integration, Big data analytics and logistics performance. The chapter contains the conceptual review, theoretical review, conceptual framework and empirical review.

2.2 Definition of Variables

Supply chain collaboration is the process of two or more supply chain partners working closely together to strategically align their objectives, share information, jointly make decisions, and integrate operations toward common goals and mutual benefits. It goes beyond traditional buyer-supplier relationships to involve deep coordination and planning between manufacturers, suppliers, distributors, retailers and other stakeholders across the end-to-end supply chain (Cao and Zhang, 2011; Soosay et al., 2008).

Logistics performance refers to how effectively and efficiently organizations manage the flow and storage of goods, services, and related information across the supply chain to maximize customer value. It involves the ability to deliver the right products to the right locations in the right quantities and at the right time, while meeting requirements and minimizing total costs. Logistics performance is measured through key indicators like order fulfillment rate, on-time delivery, operational flexibility and responsiveness, resource utilization, and logistics costs as a percentage of sales (Li et al., 2005; Neely et al., 2005).

Supply chain integration refers to the strategic collaboration and seamless alignment between a focal company, its suppliers, distributors, logistics providers, and customers to enable information sharing, collaborative planning, and joint workflow execution. It emphasizes breaking down functional barriers both internally between departments, and externally between organizations to manage processes holistically across the end-to-end supply chain. Integration success depends on the extent of information connectivity, operational transparency, and shared incentives between supply chain partners (Flynn et al., 2010; Vickery et al., 2003).

Big data analytics involves the use of advanced statistical analysis, data mining, predictive modeling, and machine learning techniques to derive value from massive, fast-moving, unstructured data sets. By discovering patterns and extracting meaningful insights, big data analytics enables organizations to guide decision-making, optimize processes, preempt risks, personalize services, and shape strategies. Effective big data analytics requires significant technology infrastructure, analytical capabilities, and organizational readiness to leverage datadriven insights (Gandomi & Haider, 2015; Oracle, 2015).

2.3 Conceptual Review

This section reviews the concepts of Supply chain collaboration, Supply chain integration, Big data analytics and logistics performance in terms of the different definitions provided in the literature.

2.3.1 Supply Chain Collaboration (SCC)

Supply chain collaboration (SCC) has emerged as a strategic focus for firms aiming to achieve a comparative advantage over their competitors (Pakdeechoho and Sukhotu, 2018; Peng et al., 2022). Defined as the cooperative efforts of at least two independent firms working across their boundaries to achieve a common goal (Mofokeng and Chinomona, 2019b), SCC has become a vital aspect of modern business strategies. Cui et al. (2022) further articulated SCC as the creation of close, enduring partnerships where supply chain members work together, sharing information, resources, and risks to realize mutual objectives.

SCC's value is underlined by several benefits, including the ability to share gains and losses, leverage external partner resources, reduce transaction costs, boost productivity, and enhance profitability, as emphasized by Um and Kim (2019). These advantages find support in various existing organizational theories that have contributed to the growth and understanding of collaboration within supply chains.

In the existing literature, the concept of SCC has been explored and conceptualized through several facets. These include collaborative planning, collaborative execution, information sharing, joint activities, dedicated investment, goal congruence, communication, incentive alignment, risk sharing, knowledge creation, decision synchronization, and resource sharing (Brun et al., 2020; Mofokeng and Chinomona, 2019b, 2019a; Pradabwong et al., 2017). By investigating these diverse aspects, researchers have constructed a multifaceted view of SCC, reflecting its complexity and its essential role in shaping successful and sustainable supply chain relationships.

However, supply chain collaboration is conceptualised in this study using information sharing, Decision synchronisation and incentive alignment. These are discussed in detail below.

2.3.1.1 Information Sharing (IS)

Information sharing (IS) is a core component of supply chain collaboration, often described with significant terms such as the "heart," "lifeblood," "nerve centre," "essential ingredient," "key requirement," and "foundation" (Al-Doori, 2019; Alzoubi et al., 2020; Jimenez-Jimenez et al., 2019; Wu and Chiu, 2018). Various definitions and perspectives on IS exist in the literature, reflecting its multifaceted nature.

Hofman et al. (2020) defined IS as the extent to which transaction-related information is shared among supply chain members, with the quality of information gauged by its appropriateness, accuracy, completeness, confidentiality, and timeliness. Al-Doori (2019) offered another perspective, defining IS as the readiness to share strategic and tactical data, such as inventory levels, forecasts, sales promotions, and marketing strategies, with firms that form part of the supply chain network. Similarly, Salam (2017) characterized IS as the degree to which a firm shares various relevant, accurate, complete, and confidential information in a timely manner with its supply chain partners.

The importance of IS within the supply chain is further emphasized by Al-Doori (2019), who likened information to blood within the supply chain collaboration framework, vital for its functioning. The objective of IS is to boost efficiency and effectiveness across the entire network of organizations, ultimately enhancing firm performance and operational performance (Gunasekaran et al., 2015). By sharing key information such as sales data, inventory levels, forecasts, and promotions, supply chain members can collaboratively plan goals and accurately predict future occurrences (Soosay and Hyland, 2015).

2.3.1.2 Decision synchronisation

Decision synchronisation in supply chain operations focuses on aligning the interests of all parties involved. Peng et al. (2022) describe it as the alignment of interests using relevant information in each process to maximize supply chain benefits. Similarly, Pakdeechoho and Sukhotu (2018) define it as orchestrating decisions in supply chain planning and operations to optimize the overall advantages. Pradabwong et al. (2015) further break down the concept into seven key decision categories in managing the supply chain: operations strategy planning, demand management, production planning and scheduling, procurement, promise delivery, balancing change, and distribution management.

2.3.1.3 Incentive alignment

Incentive alignment within the context of supply chain collaboration involves the balanced sharing of costs, risks, and benefits among supply chain members. As outlined by Mofokeng and Chinomona (2019b), incentive alignment enables the fair distribution of gains and benefits and the corresponding sharing of costs and risks. It ensures that participants in the supply chain receive outcomes that are proportionate to their responsibilities for risks.

Similarly, Cui et al. (2022) define incentive alignment as the process of apportioning costs, risks, and benefits among supply chain partners, which includes identifying these factors and developing incentive schemes. They emphasize that for supply chain partnerships to be successful, all participants must share gains and losses equitably, with collaboration outcomes being measurably advantageous to everyone involved.

Gunasekaran et al. (2015) further stress the need for a meticulous definition of mechanisms that distribute gains fairly in incentive alignment. They articulate that the gains should be in line with the level of investment and risk, ensuring a just and balanced collaboration within the supply chain.

2.3.2 Supply Chain Integration (SCI)

Supply Chain Integration (SCI) is characterized by the extent to which a company can collaborate with its supply chain partners to manage processes within and between organizations for efficient product, service, information, money, and decision flows (Chaudhuri et al., 2018). Khanuja and Jain (2020) view SCI as the firms' ability to form strategic alliances, integrate resources, create seamless processes, and share information, covering internal integration, supplier integration, and customer integration. Ataseven and Nair (2017) define SCI as the coordination of product flows between supply chain partners, including transactions, materials movements, procedures, and optimization processes, considering the related information flows.

2.3.2.1 Supplier Integration

Supplier integration refers to the collaboration and partnership between a central firm and its suppliers to manage upstream inter-organizational activities. This integration encompasses information sharing, joint decision-making, system coupling, and collaborative planning (Wong et al., 2017). The main objectives of supplier integration include the establishment of collaborative planning, forecasting, and replenishment capability with suppliers to minimize supply risk, inventory, and associated costs (Vanpoucke et al., 2017). Additionally, supplier integration allows a central firm to access resources and competencies beyond its organizational boundaries and lowers transaction costs by adhering to established standards and norms of exchange. By facilitating collaboration through information sharing and supplier involvement, supplier integration contributes to a mutual understanding across partner firms (Munir et al., 2020).

2.3.2.2 Customer Integration

Customer integration refers to the collaboration and partnership between a central firm and its customers, focusing on the management of downstream inter-organizational activities. This includes information sharing, joint decision-making, system coupling, and collaborative planning (Saragih et al., 2020). Such integration permits the assimilation of information and resources from customers into the processes and decisions of the central firm (Mofokeng and Chinomona, 2019a). The benefits of customer integration are seen in the improved understanding of market needs, allowing firms to create and develop products with higher acceptance levels (Kaliani Sundram et al., 2016). By fostering an enhanced grasp of market demands through information-sharing between manufacturers and customers, firms can make more suitable adjustments to production plans. This alignment with customer needs and expectations can lead to better operational outcomes, including reduced costs and improved delivery performance (Flynn et al., 2016).

2.3.2.3 Internal Integration

Internal integration pertains to the extent to which a firm unifies its functional strategies, practices, and processes into collaborative and synchronized workflows (Khanuja and Jain, 2020). It includes activities such as information sharing between internal functions, strategic cross-functional partnerships, and cooperative work across various functions within the organization (Khanuja and Jain, 2020). Instead of operating as isolated compartments or silos, different functions within a firm are encouraged to function as an integrated process. Flynn et al. (2016) further describe internal integration as the level to which organizational structures promote information sharing and collective decision-making across internal functions to enhance workflows and encourage collaborative decisions. This form of integration assists firms in dismantling functional barriers, thereby increasing communication and information sharing across internal divisions for unified planning and decision-making (Mofokeng and Chinomona, 2019b). Although internal integration focuses on specialized activities within functions, it also facilitates the internal processes to work collaboratively towards the common goal of customer satisfaction (Munir et al., 2020).

2.3.3 Big Data Analytics

Big Data refers to a data analysis methodology that leverages recent technological advancements to support the rapid capture, storage, and analysis of data (Chong and Shi, 2015). Unlike traditional data sources that rely on structured database records, Big Data encompasses a broader range, including emails, mobile device outputs, sensor-generated data, and unstructured data with standard formatting (Wang, 2017). Big Data's definition has evolved and varies among stakeholders, with no uniform agreement. One early definition came from a Gartner report in 2001, which characterized Big Data by three V's: volume, velocity, and variety. Later, in 2012, Gartner added a fourth V, veracity, to represent trust and uncertainty in data and its analysis outcomes (Singh and Reddy, 2015).

Big Data Analytics involves processing unstructured information from various sources like call logs, mobile banking transactions, online content, searches, and images, transforming them into valuable business insights using computational techniques to reveal trends and patterns (Chiang et al., 2017). As Hariri et al. (2019) note, Big Data is not only large and complex, but it requires innovative technology for analysis and processing. It often exceeds conventional methods' capabilities, necessitating novel approaches to questions that were previously inaccessible.

Furthermore, Big Data also signifies large datasets that cannot be handled by typical software tools (Ristevski and Chen, 2018). This includes huge, heterogeneous, and complex data sets, encompassing operational, transactional, sales, marketing data, and more in various formats like text, sound, video, and images (Najafabadi et al., 2015). With unstructured data growing faster than structured, comprising 90% of all data (Singh and El-Kassar, 2019), new processing capabilities are needed to gain insights leading to enhanced decision-making (Wang et al., 2018).

2.3.4 Logistics Performance

Logistics performance is conceptualized as a subset of broader organizational performance, with studies indicating that it positively influences organizational outcomes (Göçer et al., 2022; Yusufkhonov et al., 2021). Larson (2020) defines logistics performance as the "ability to deliver goods and services in the precise quantity and at the precise times as required by the customers." This means fulfilling the '7Rs' of logistics management objectives, which include delivering the right product, in the right quantity, condition, place, time, to the right customers, and at the right costs (Bakar and Jaafar, 2016).

Various ways to categorize logistics performance exist, with quality, time, cost, and flexibility often considered foundational dimensions (Mariano et al., 2017). Cost efficiency refers to a firm's capacity to enhance performance while using resources economically (Fugate et al., 2010; Göçer et al., 2022). Service quality embodies the firm's ability to meet customer demands with reliable, flexible, accurate services within a reasonable cycle time (Saggi and Jain, 2018).

The time dimension highlights a firm's ability to meet customer demands, orders, or delivery promptly, with shorter or more precise timing equating to better logistics performance (Saragih et al., 2020). Flexibility, as defined by Elgendy and Elragal (2016), denotes a firm's ability to adapt to a constantly changing and uncertain environment. The swifter and more flexible a firm can respond to changes, the better it can fulfill customer needs, positively impacting overall performance (Flynn et al., 2016).

2.4 Theoretical Review

This study draws on the Resource-based view theory to examine the roles of supply chain integration and big data analytics in the relationship between supply chain collaboration and logistics performance.

2.3.1 Resource-based view theory

The resource-based view (RBV) theory posits that a firm's growth and development are contingent on its available resources (Barney, 2020). It argues that adequate resources are essential for a firm to gain a competitive edge in the market (Amis et al., 2020), with resources being the primary determinant of firm performance and capacities (Molloy and Barney, 2015). RBV has been applied in numerous studies to analyze industry conditions, asserting that companies with a dominant position in the business environment possess sufficient resources within their industry (Cichosz, 2018).

The uniqueness of company resources is emphasized in RBV, allowing firms to utilize them efficiently to foster growth and development (Barney, 2020). The theory suggests that a company's resources define its superiority and competitiveness in the market and dictate the firm's ability to leverage resources to attain desired outcomes. Resources are considered heterogeneous, and a company's strength lies in its resource competitiveness (Barney, 2020). To dominate the market, managers must ensure appropriate utilization of resources to meet goals and objectives. RBV underscores the importance of internal resources in enhancing operational performance (Barney, 2020).

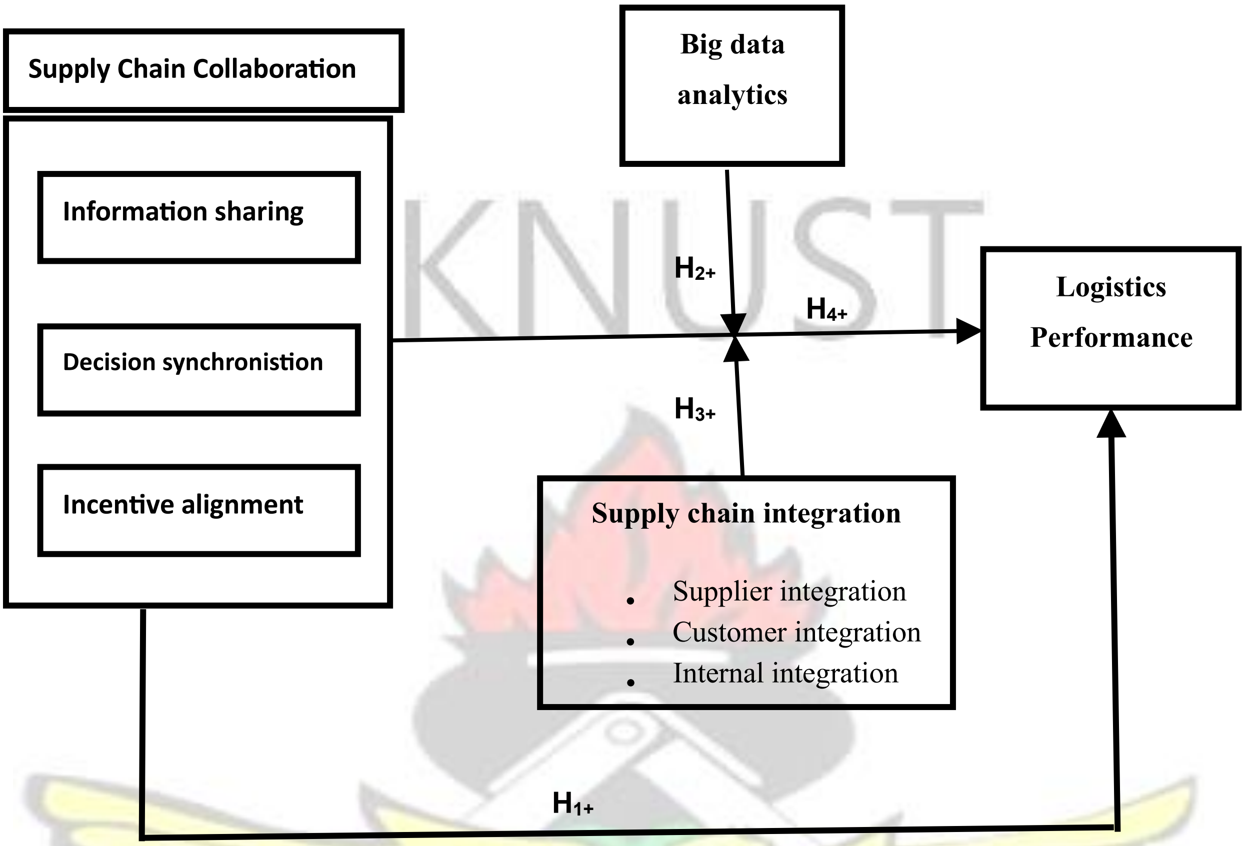
RBV also argues that sustainable advantages can be achieved by uniquely combining resources like core competence, dynamic capability, and absorptive capacity (Barney, 2020). It suggests that a buying firm can strengthen core values by investing in relation-specific assets and leveraging the resources, knowledge, and expertise of key suppliers, making imitation by competitors difficult (Beaulieu and Bentahar, 2021).

Furthermore, the theory also regards supply chain collaboration (SCC), supply chain integration (SCI), and big data analytics as resources leading to improved sustainability performance (Barney, 2012). The complex capabilities and processes needed for collaboration and integration with partners are seen as hard to replicate and replace (Chen et al., 2009). From an extended RBV perspective, even resources obtained from outside a firm can generate competitiveness (Das and Teng, 2000). Interfirm integration offers valuable resources such as joint knowledge and relational governance (Lavie and Rosenkopf, 2006), and these interconnected resources, embedded in long-term relationships, become even more challenging to duplicate.

2.5 The Conceptual Framework

Based on the resource-based view (RBV), this study argues for a positive and significant influence of supply chain collaboration (SCC) on logistics performance. The research also suggests a positive and significant moderating effect of big data analytics on the relationship between SCC and logistics performance. Additionally, the study's model posits an indirect impact of SCC on logistics performance through supply chain integration (SCI). In a specified figure (2.1), the research model visually represents these direct, indirect, and moderating effects among the study's variables

Figure 2.1 Research Model



Source: Researcher's Construct (2022)

2.5.1 Supply Chain Collaboration and Logistics Performance

Drawing from the resource-based view (RBV), which emphasizes the unique resources and capabilities owned by a firm as essential to its performance outcomes, this study explores the relationship between supply chain collaboration (SCC) and logistics performance. The RBV suggests that firms combine valuable, heterogeneous, imperfect, and mobile resources to achieve success (Barney, 2020). In this context, SCC, defined as forming close, long-term partnerships where supply chain members collaborate and share information, resources, and risks to reach common goals (Cui et al., 2022), is considered a critical resource. The study posits a positive connection between SCC and logistics performance, with the understanding that effective and efficient SCC can enhance a firm's social, economic, and environmental performance. For instance, the importance of SCC in improving information sharing has been emphasized, with information sharing seen as vital for enhancing environmental and social logistics performance (Gunasekaran et al., 2015). Further, Chen et al. (2017) have noted that SCC has become a strategic concern for companies aiming to meet their logistics objectives.

Thus, within this framework and guided by the insights of the RBV, the research explores and argues for the positive impact of SCC on logistics performance, with the expectation that collaboration in the supply chain could be leveraged as a valuable resource to attain the desired outcomes in logistics.

H_1: Supply chain collaboration has a positive and significant effect on logistics performance

2.5.2 The Moderating role of Big Data Analytics

The study advances the notion that the impact of supply chain collaboration (SCC) on logistics performance may be influenced by different levels of big data analytics. Although numerous researchers have shown that SCC drives performance outcomes (Pakdeechoho and Sukhotu, 2018; Peng et al., 2022; Pradabwong et al., 2015, 2017), the precise nature of the relationship between SCC and performance remains ambiguous. Existing empirical studies present inconclusive findings, which may be attributed to overlooked and unaccounted-for environmental factors. There is, therefore, a need to re-examine this relationship under various environmental contingencies, and several studies have proposed different mediation and moderation variables to study the link between SCC and performance (Alzoubi et al., 2020; Jimenez-Jimenez et al., 2019; Um and Kim, 2019). Calls have been made for more research to identify potential unknown moderators affecting the SCC-performance relationship (Mofokeng and Chinomona, 2019b). This study posits that the connection between SCC and logistics performance cannot be fully understood through direct association alone. It argues that when big data analytics is high, the relationship between SCC and logistics performance should be positive. This rationale stems from the understanding that big data analytics could enhance transparency and information sharing, leading to increased trust, cooperation, and commitment to promoting logistics initiatives. Conversely, when big data analytics is low, an increase in SCC might not lead to better logistics performance. The logic behind this reasoning is that under such conditions, real-time information sharing required to foster trust, communication, and transparency might be lacking, hindering the collaborative relationship's improvement. Therefore, the study suggests that big data analytics' moderating effect is crucial to understand and leverage the potential benefits of SCC on logistics performance.

H_2: The effect of supply chain collaboration on logistics performance is positively moderated by big data analytics

2.5.3 Moderating role of supply chain integration

This study continues to suggest that supply chain integration (SCI) acts as a catalyst for enhancing the positive impact of supply chain collaboration (SCC) on logistics performance. Therefore, SCI is utilized as a mediating variable in the link between SCC and logistics performance. SCI represents firms' abilities to forge strategic alliances, integrate resources, create seamless processes, and share information (Khanuja and Jain, 2020). SCC is seen as a vital factor in achieving a win-win solution for various stakeholders in a supply chain (Pakdeechoho and Sukhotu, 2018), and it goes beyond integration to include long-term commitments to technology sharing and closely integrated planning and control systems (Pradabwong et al., 2017). Trust, joint decisions, and information sharing, all integral to SCC, can be achieved through SCI (Flynn et al., 2016). A high level of integration and collaboration within the supply chain tends to result in superior supply chain performance (Kaliani Sundram et al., 2016). Although past research has highlighted positive effects of SCC on various performance aspects, such as firm performance, operational performance, supply chain logistics, competitive advantage, and organizational performance (Pradabwong et al., 2015, 2017; Pakdeechoho and Sukhotu, 2018; Chilkapure and Pillai, 2019; Peng et al., 2022), others have noted an indirect or even negative effect of SCC (Gunasekaran, Subramanian and Rahman, 2015; Scholten and Schilder, 2015; Cui et al., 2022; Chen et al., 2017; Hofman et al., 2020). Based on these considerations, the study proposes that SCI may mediate the relationship between SCC and logistics performance, acknowledging the complex and multifaceted nature of this relationship. It hypothesizes that a higher level of integration in the supply chain could potentiate the benefits of collaboration, ultimately leading to improved logistics performance.

H_3: The effect of supply chain collaboration on logisitcs performance is positively moderated by supply chain integration

2.5.4 Interaction effect of big data analytics and supply chain integration

The study further posits that the effect of supply chain collaboration (SCC) on logistics performance is contingent on the varying levels of interaction between big data analytics (BDA) and supply chain integration (SCI). During SCC, integration facilitates the sharing of real-time data transparently and coherently. However, the success of this integration is also reliant on the availability and utilization of big data. Supply chains are known for generating vast amounts of data, and analytics can be employed to interpret and optimize this data (Kang et al., 2018). According to Papadopoulos et al. (2017), big data analytics plays an essential role in supply chain integration. It ensures that the information and communication systems of all stakeholders are capable of seamlessly exchanging information throughout all stages of transport and logistics operations for a product's entire life cycle (Kaliani Sundram et al., 2016). In essence, the study proposes that both SCI and BDA play significant roles in understanding and leveraging the benefits of SCC. While SCI enables the sharing and alignment of resources and information, BDA offers the necessary tools to process, interpret, and act upon the data effectively. Therefore, the interaction between SCI and BDA is perceived as a vital determinant in translating SCC efforts into tangible improvements in logistics performance. This integrated approach emphasizes the importance of data-driven insights in facilitating collaboration and integration within supply chains, ultimately enhancing overall performance.

H_4: The effect of supply chain collaboration on logistics performance is positively moderated by the interaction between big data analytics and supply chain integration

2.6 Empirical Review

This section reviews studies previously conducted on supply chain collaboration, supply chain integration, big data analytics and logistics performance.

2.6.1 Supply Chain Collaboration and logistics Performance

Chen et al. (2017) explored the impact of supply chain collaboration (SCC) on sustainability through a systematic literature review, focusing on how collaboration speeds up change towards sustainability. Using quantitative bibliometric analysis, they found that research on sustainability collaboration is growing, especially in environmental and economic areas. However, social aspects, such as child labor and personal development, were underrepresented. They also noticed a lack of attention to collaboration with competitors and other horizontal partners, primarily focusing on collaboration between a company, its suppliers, and customers.

Hofman et al. (2020), in a different vein, studied the relationship between SCC and ecoinnovations using an institutional perspective within the Chinese context. They examined how collaboration with suppliers and customers could enhance product and process ecoinnovations, and how regulatory, market, and community pressures might influence these relationships. Utilizing structural equation modeling, they analyzed data from medium and large enterprises in the automotive, electronics, and textiles sectors. Their findings revealed that community pressure positively influences supplier collaboration, leading to enhanced process eco-innovation. However, while market pressure boosts customer collaboration, it doesn't strengthen product eco-innovation. Surprisingly, they found that regulatory pressures did not affect collaboration for innovation. This study thus uncovered complex and divergent effects of different institutional factors on supply chain collaboration and eco-innovation.

Wiengarten et al. (2010) conducted an empirical study to investigate the impact of supply chain collaboration on key performance outcomes including quality, delivery, flexibility, and cost. Drawing on contingency theory and the relational view, they hypothesized that collaborating with suppliers and customers can directly and indirectly improve operational performance. Using survey data from 196 manufacturing firms across multiple industries, they tested their hypotheses with PLS-SEM analysis. The findings revealed supplier and customer collaboration has a significant direct positive effect on both delivery performance and flexibility. Interestingly, cost performance is enhanced indirectly through the mediating role of quality improvement enabled by collaboration. The authors conclude that collaborative initiatives should focus on quality management to achieve cost efficiency gains. They call for future research to examine the moderating role of environmental uncertainty on the collaborationperformance relationship. Replicating the study across different cultural settings is also recommended.

Ralston et al. (2015) analyzed how supply chain collaboration and IT integration initiatives affect overall supply chain performance. Drawing from resource-based theory, they proposed that IT integration strengthens the relationship between collaboration and performance. Survey responses were gathered from 200 US manufacturing firms representing over 20 industries. Regression analysis indicated IT integration does positively moderate the linkage between collaboration and performance. Supply chain performance was measured through fulfillment, responsiveness, and efficiency metrics. The findings imply that manufacturers need to pursue IT-enabled information sharing and connectivity in tandem with partnering efforts to maximize performance gains. The authors recommend further investigation into other contingencies that may alter how collaboration translates to performance, such as supply uncertainty, network complexity, and environmental dynamism.

Cao et al. (2010) examined the intricate collaborative relationships between suppliers, manufacturers, and customers within the supply chain context. They collected empirical evidence from 497 Chinese manufacturing firms across various industries. Structural equation modeling was utilized to test the hypotheses. The results demonstrated cooperative relationships with suppliers and customers enhances customer satisfaction and firm performance. However, the hypothesized three-way interaction between suppliers, manufacturers and customers was found to be insignificant. The findings imply dyadic collaborative efforts are more impactful than complex multi-party engagement. The authors suggest re-testing the three-way interaction model using samples from other cultural and geographic settings to verify its validity. Additionally, they recommend incorporating objective performance data to supplement survey-based perceptions.

Blome et al. (2013) tested how supply chain management collaboration fosters innovation performance through both incremental and radical innovations. Drawing from knowledgebased theory, they hypothesized that supplier and customer collaboration are more critical for incremental innovations, while R&D partnering has a stronger impact on radical innovation outcomes. Survey data was gathered from 167 manufacturing firms across multiple industries in Germany. Regression analysis supported the notion that collaborating with suppliers and customers enhances incremental innovation performance, while R&D collaboration is more pivotal for radical innovation success. The study provides empirical evidence on how firms should strategically leverage different forms of collaboration to achieve innovation objectives. However, the findings are limited by the focus on German manufacturers. Future research could extend the investigation to service firms and across different cultural settings.

Sanders (2007) assessed the impact of strategic alliance learning mechanisms on the ability to collaborate and overall firm performance. The study collected survey responses from 284 US firms engaged in supply chain alliances. Factor analysis was first conducted to validate the measurement scales. Regression analysis showed knowledge acquisition, dissemination, and collective memory capabilities positively impact both collaboration and performance outcomes. By developing alliance-based learning capacities, firms can enhance partnering skills and achieve greater success. While valuable, the study relies solely on survey-based perceptual measures. The author recommends applying network analysis tools to map and visualize interactive learning between alliance partners in future studies.

Vereecke and Muylle (2006) investigated the pivotal role of collaborative planning approaches in improving supply chain management performance. They conducted in-depth case study analysis of four planning concepts - efficient consumer response, continuous replenishment, vendor managed inventory, and collaborative planning, forecasting and replenishment. The findings indicated that collaborative planning leads to enhanced operational efficiency, higher customer service levels, and lower costs across the supply chain. However, the study is qualitative with a limited sample. The authors suggest quantitative modeling and real-time tracking of performance metrics across a wider sample of firms to robustly validate the business value derived from collaborative planning in future research.

Cao and Zhang (2011) developed and empirically tested a model examining the antecedents and consequences of supply chain collaboration, grounded in commitment-trust theory. Hypotheses were developed to link relationship commitment and mutual trust to collaboration, which further enhances operational and firm performance. Survey data was collected from 220 Chinese manufacturing firms to validate the hypotheses using structural equation modeling. The results confirmed the pivotal role of commitment and trust as relational foundations that drive collaborative activities and enhance performance outcomes. The findings imply that inter-firm partnerships require cultivating affective commitment and mutual trust to truly succeed. As a limitation, the model should be tested in other cultural settings for generalization. Replications could also incorporate objective performance data.

Zacharia et al. (2011) examined the effect of collaboration between shippers and logistics service providers on key outsourcing performance outcomes including cost reduction and service enhancement. Drawing from relational exchange theory, they proposed relational mechanisms moderate this relationship. Analysis of survey data from 166 US firms showed collaboration positively influences both cost and customer service performance. Further, social relational norms and behaviors facilitate the translation of collaboration to performance. By fostering relational governance, partners can enhance the success of collaborative initiatives. As a limitation, the study only focused on relational factors as moderators. The authors recommend incorporating other variables like asset specificity and environmental uncertainty in future research.

Liao et al. (2010) explored collaboration activities between producers, packers/shippers, distributors, and retailers within food supply chains. They also analyzed how supply chain collaboration affects quality management initiatives. Survey data was collected from produce suppliers in Taiwan and analyzed using structural equation modeling. The findings revealed information sharing with supply chain partners positively influences quality management practices and performance. Regulatory support from government agencies further encourages collaborative efforts. However, the study is limited to a single product category and geographic context. Examining other food supply chains and cultural settings would enrich understanding of collaboration in agri-food networks.

Autry et al. (2010) analyzed how commercial and government entities can effectively partner to enhance disaster relief operations and humanitarian supply chain performance. They collected survey responses from managers involved in emergency response and used modeling to test their hypotheses. The results highlighted that collaborative execution between entities and rapid, transparent information sharing are critical success factors in complex disaster environments. While valuable, the study relies solely on survey-based assessments. The authors recommend incorporating objective performance data and social network analysis to gain a richer understanding of partnerships in future humanitarian supply chain research.

2.6.2 Moderating effect of Big Data Analytics

Dubey et al. (2019) conducted two separate but related research studies focusing on the role of big data analytics (BDA) in various contexts.

The first study explored the relationship between big data analytics and social and environmental sustainability in Indian manufacturing organizations. Drawing on the dynamic capability views and organizational culture, they used variance-based structural equation modeling (PLS) to analyze data from 205 organizations. The findings showed that BDA has a significant impact on social and environmental sustainability. Interestingly, they did not find evidence to support the moderating roles of flexible orientation and control orientation in the connections between BDA and sustainability.

In the second study, Dubey et al. (2019) sought to understand how big data analytics capability (BDAC) as an organizational culture could foster trust and collaborative performance in disaster relief operations involving civil and military organizations. The research was grounded in organizational information processing theory (OIPT), and they used WarpPLS 6.0 to test hypotheses using data from managers across 373 organizations, including military forces, government agencies, UN agencies, NGOs, and contractors. The results demonstrated that BDAC positively affects swift trust (ST) and collaborative performance (CP). They also found that flexible orientation (FO) had a positive moderating effect on the relationship between

BDAC and CP, while control orientation (CO) had a negative effect. Interestingly, neither FO nor CO significantly influenced the building of ST.

2.6.3 Moderating Effect of Supply Chain Integration

Mofokeng and Chinomona (2019b) investigated the impact of collaboration, partnership, and integration on supply chain performance, with a focus on the small and medium enterprise (SME) sector. The study was guided by the relational view theory and was based on data collected from 271 SMEs in Gauteng. Using SmartPLS for data analysis, the findings underscored the positive influence of the research constructs on supply chain performance, reinforcing the importance of these elements in enhancing performance within the sector.

In a study by Nahm et al. (2008), the authors explored the relationship between supply chain partnerships, information quality, and information sharing, and their effect on supply chain integration. Analyzing a sample of 60 Korean firms engaged in supply chain activities, the research demonstrated that supply chain partnerships have a direct impact on the quality of information shared. However, the influence on the scope and frequency of information sharing was found to be indirect and mediated through information quality. The results provide insights into the nuanced relationships among these factors within supply chain integration.

Kang et al. (2018) examined the role of supply chain integration (SCI) in fostering sustainability management practices (SMPs) and enhancing performance. Based on data from 931 manufacturing firms across various countries and regions, the study employed structural equation modeling to validate the hypotheses. The findings revealed that integration with suppliers and customers is crucial for implementing both intra- and inter-organizational SMPs.

Table 2.1 Empirical Review Table

Author and Year	Objectives	Methodology	Findings	Future Suggestions

Chen et al. (2017)	Explore the impact of supply chain collaboration (SCC) on sustainability through a literature review.	Quantitative bibliometric analysis of existing literature.	Research on sustainability collaboration is growing, but social aspects and collaboration with competitors is lacking.	More research needed on collaboration with horizontal partners and social sustainability.
Hofman et al. (2020)	Examine how SCC with suppliers and customers enhances ecoinnovations and the influence of institutional pressures.	Structural equation modeling analysis of survey data from Chinese automotive, electronics and textiles firms.	Community pressure positively affects supplier collaboration and process ecoinnovation. Market pressure increases customer collaboration but not product ecoinnovation. Regulatory pressure had no effect.	Further study into why regulatory pressure did not influence SCC and ecoinnovation.
Dubey et al. (2019)	Investigate the relationship between big data analytics (BDA) and sustainability in manufacturing firms.	PLS-SEM analysis of survey data from 205 Indian manufacturers.	BDA significantly impacts social and environmental sustainability. Flexible and control orientations did not moderate the relationship.	Examine why the moderators were not significant as hypothesized.
Dubey et al. (2019)	Examine how BDA culture	WarpPLS analysis of	BDA positively affects trust and	Verify findings in other contexts

	fosters trust and collaboration in disaster relief operations.	survey data from 373 military, government, NGO and contractor organizations.	collaboration. Flexible orientation strengthens and control orientation weakens the collaboration impact.	beyond disaster relief.
Mofokeng and Chinomona (2019b)	Assess the impact of collaboration, partnership and integration on SME supply chain performance.	SmartPLS analysis of survey data from 271 South African SMEs.	Collaboration, partnership and integration positively influence SME supply chain performance.	Expand research to SMEs in other countries and industries.
Nahm et al. (2008)	Investigate how partnerships affect information quality/sharing and supply chain integration.	Analysis of survey data from 60 Korean supply chain firms.	Partnerships directly influence information quality, which indirectly affects information sharing via quality.	More research on nuanced relationships between these factors.
Kang et al. (2018)	Examine the role of SCI in enabling sustainability practices and performance.	SEM analysis of survey data from 931 international manufacturers.	SCI with suppliers/customers crucial for intra- and interorganizational sustainability management practices.	Extend study to service industries and nonmanufacturing contexts.
Wiengarten et al. (2010)	Explore the impact of SCC on quality, delivery, flexibility and	Survey data from 196 manufacturing firms.	SCC with suppliers/customers directly improves delivery and flexibility.	Examine moderators like environmental uncertainty.

	cost performance.			
Ralston et al. (2015)	Analyze how SCC and IT integration affect supply chain performance.	Survey responses from 200 US manufacturers.	IT integration strengthens collaborationperformance relationship.	Investigate other contingencies like supply uncertainty.
Cao et al. (2010)	Examine collaborative relationships between suppliers, manufacturers and customers.	SEM analysis of 497 Chinese firms.	Cooperation with suppliers/customers enhances satisfaction and firm performance.	Re-test threeway relationship model.
Blome et al. (2013)	Test how SCC drives innovation performance.	Survey data from 167 German manufacturers.	SCC boosts incremental innovation. R&D collaboration critical for radical innovation.	Extend study beyond manufacturing industry.
Sanders (2007)	Assess impact of alliance learning mechanisms on collaboration and performance.	Survey responses from 284 US firms.	Knowledge acquisition, dissemination and memory enhance collaboration and performance.	Incorporate network analysis tools.
Vereecke and Muylle (2006)	Investigate the role of collaborative planning in supply chains.	Case studies of four planning approaches.	Collaborative planning improves efficiency and customer service.	Real-time tracking of performance metrics.
Cao and Zhang (2011)	Develop and test a model of SCC antecedents and consequences.	Survey data from 220 Chinese manufacturers.	Relationship commitment and trust drive collaboration and performance.	Replicate study in other cultural contexts.

Zacharia et al. (2011)	Examine the effect of SCC on logistics outsourcing performance.	Survey data from 166 US firms.	SCC enhances cost and service performance, facilitated by relational mechanisms.	Consider other moderators beyond relational factors.
Liao et al. (2010)	Explore SCC in food supply chains and impact on quality management.	Survey of produce suppliers in Taiwan.	Information sharing with partners drives quality management.	Examine other food supply chains.
Autry et al. (2010)	Analyze commercial and government partnerships in disaster relief.	Survey data modeling.	Collaborative execution and information sharing critical in humanitarian supply chains.	Incorporate additional data sources beyond surveys.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter discusses the techniques used by the researcher to accomplish the study's objectives. It includes information on the research design, the study's population, the sampling method and sample size, data collection, data analysis, validity and reliability, and ethical considerations

3.2 Research Design

A research design lays the groundwork for data collection and analysis. Consider the relative importance of various research process components while selecting a research design. Experiments, cross-sectional or sociological surveys, longitudinal studies, case studies, and comparative studies are all examples of research designs (Bryman, 2009). The study is based on a survey of the firms operating with the Greater Accra Region of Ghana.

The term "research approach" refers to the technique used to conduct business research. It is possible to do quantitative or qualitative research. Quantitative research is a kind of research that focuses on hypothesis testing and quantification in data collection and analysis. It also approaches the relationship between theory and research logically. On the other hand, qualitative research may be described as a research method that stresses an inductive approach to the relationship between theory and study, prioritising theory formation over statistics when collecting and evaluating data (Bell and Roberts, 1984). This study was conducted using a quantitative method by the researcher.

3.3 Population of the Study

According to Saunders et al. (2009), a population is the whole collection of people, things, or numerical values that an investigator wants to investigate. The study targets the employees and management of Ghanaian firms

3.4 Sampling technique and Sample Size

Sampling is the process of selecting people at random from a statistical population to assess the group's characteristics (Babbie, 1975). Babbie (1975) divided sampling techniques into probability sampling and non-probability sampling procedures, depending on their likelihood of occurrence. Probability sampling techniques are employed when each sampled instance's likelihood (probability) from a population is known and is usually equal in all instances. Nonprobability sampling techniques, on the other hand, have an unknown chance of picking each instance from the whole population. The study draws a sample of four hundred (400) respondents from the target pop using convenient sampling. Convenience sampling is a type of non-probability sampling that involves the sample being drawn from that part of the population that is close to hand. Convenient sampling was chosen because it enabled the researcher make use of respondents that are readily available, thus reducing cost and time associated with data collection.

3.5 Data Collection

This research makes use of primary data. A primary data source is one that the researcher collected to conduct research or complete a project (Cohen et al., 2000). The main data collection tool is an online questionnaire.

The researcher resorts to a primary data source to achieve the study's goals: a structured/selfcompletion questionnaire. Five parts of the questionnaire corresponded to the four research constructs: Respondents' demographic data may be found in Section A, while Supply Chain Collaboration is the independent variable in Section B. Section C discusses Supply Chain Integration, the mediating variable. Section D discusses big data analytics, the moderator variable. Section E presents Logistics performance, the dependent variable. The survey was created online using Google Forms and distributed to survey respondents through email and social media. A summary of the measurements and items examined may be found in Table 3.1.

Table 3.1 Summary of Measurement Items

Variables	No. of Items	Sources
SUPPLY CHAIN COLLABORATION		
• **Information sharing**	**3**	Cao and Zhang (2011)
• **Decision Synchronisation**	**3**	Cao and Zhang (2011)

• **Incentive Alignment**	**3**	Cao and Zhang (2011)
SUPPLY CHAIN INTEGRATION		
• **Supplier integration**	**5**	Huo et al. (2016)
• **Customer integration**	**5**	Huo et al. (2016)
• **Internal Integration**	**5**	Huo et al. (2016)
BIG DATA ANALYTICS	**7**	Dubey et al. (2021)
LOGISTICS PERFORMANCE	**8**	Green et al. (2008)

Source: Author's Construct (2022)

3.6 Data Analysis

Data analysis is a process that involves collecting data, cleaning it, modifying it, and modelling it to aid in the discovery of important information, the drawing of conclusions, and the making of choices (Berry, 2004). The researcher uses both descriptive and inferential analysis to extract critical information from the gathered data and to test the study's hypotheses. Descriptive analytics include Mean, standard deviation, skewness and kurtosis. The inferential analysis includes correlational analysis, ordinary least squares regression, and moderated regression. All analyses are conducted using IBM SPSS version 26.

3.7 Validity And Reliability

Reliability is concerned with the reproducibility of research findings and the consistency of the measurements used to evaluate each component. On the other hand, the degree to which an indicator used to assess a notion accurately measures that concept is referred to as validity (Barnes, 1995). The research verifies that the data collected adheres to established standards of validity and reliability. This was accomplished by conducting Cronbach's Alpha for reliability and exploratory factor analysis for validity using IBM SPSS.

3.8 Ethical Considerations

The term research ethics' refers to a set of rules that regulate the behaviour of scientists' behaviour in research. Researchers must follow ethical standards to safeguard participants' dignity, rights, and well-being (Burns, 2000). To guarantee conformity to all ethical norms, the study considers the following factors. To begin, the research safeguards all participants' privacy. As a result, the survey asks for no names or other personally identifying information. Second, before disseminating surveys, the researcher obtains the permission of all participants.
No one is forced to participate in the research.

CHAPTER FOUR

DATA PRESENTATION, ANALYSIS AND RESULTS

4.1 Introduction

This chapter presents the data analysis results, including the discussion of the results and the study's implications. First, the responses are analysed regarding the response rate and respondents' demographic information. Descriptive statistics then follows, which includes mean, standard deviation, skewness and kurtosis. The nest section is the measurement model analysis, which seeks to ensure data consistency and accuracy. Measurement model analysis include Cronbach Alpha, Composite reliability, Average variance extracted (AVE), cross loadings and multicollinearity. The next section focuses on the model testing, including correlation analysis, linear regression and moderated hierarchical regression, hypotheses table. The last section is discussion of results, which discusses the study’s results in the light of reviewed literature. All analysed are conducted using SmartPLS4 and IBM SPSS version 23.

4.2 Response Rate

A total of four hundred (400) online questionnaires were distributed to employees and management of firms operating within the Greater Accra Region. The region was divided into two main zones: Tema and Accra central zones. Two hundred (200) questionnaires were distributed to firms in the Tema zone, while two hundred were distributed to firms within the Accra zone. However, out of the four hundred (400) questionnaires issued out, three hundred and eighty-eight (388) were responded to, giving a response rate of 97%. This figure is above the minimum threshold of 200 sample size required for using statistical tools (e.g., SEM, PROCESS) considered in the study (Sivo et al., 2006).

Table 4.1 Results of Response Rate Analysis

Study area	Questionnaires administered (A)		Questionnaires received (B)		Questionnaires used (C)		Questionnaires rejected (D)		Effective response rate = (C/A) *100%
	No.	%	No.	%	No.	%	No.	%	%
Tema zone	200	50	192	49	192	40	0	0	96
Accra zone	200	50	196	51	196	60	0	0	98
Total	**400**	**100**	**388**	**100**	**388**	**100**	**0**	**0**	**97**

Source: Field study (2022)

4.3 Demographic Profile of the Respondents

The demographic information of the respondents and their firms are analysed in this section using firm age, gender of respondents, age of respondents, highest qualification, and work experience. The results of the respondent's profile are analysed in Table 4.2.

Table 4.2 Firm and respondent profile information

Variable/category		Frequency	Percent (%)
Firm age	1 - 5 years	95	24.5
	6 - 10 years	108	27.8
	11 - 15 years	76	19.6
	Above 15 years	109	28.1
Gender	Male	206	53.1 49.9
	Female	182	
Age	Below 20 years	12	3.1
	20 to 29 years	149	38.4
	30 to 39 years	174	44.8
	40 to 50 years	43	11.1
	Above 50 years	10	2.6
Highest qualification	HND	70	18
	1st Degree	148	38.1
	Masters	132	34
	PhD	18	4.6
	Professional/vocational	13	3.4
	Others	7	1.8
Work experience	1 - 5 years	186	47.9
	6 - 10 years	149	38.4
	11 - 15 years	38	9.8
	Above 15 years	15	3.9

Source: Field study (2022)

According to Table 4.2, 24.5% of the responding firms have been in existence for not more than five years, 27.8% between 6 to 10 years, 19.6% between 11 to 15 years and 28.1% above.

This indicates that majority of the firms that constituted the study's samples have been in existence for a long time, and therefore have adequate data to respond to the study's questionnaire. The table also reveals that majority of the respondents, 51.1% are males whiles the remaining 49.9% females. This indicates that the respondent for the study is well represented. The age distribution also revealed that majority of the respondents, 96.9% age more than 20 years, with the remaining 3.1 below 20 years. This indicates that the study relied on respondents who are matured to respond to the questionnaire. 18% of the respondents also have HND as the highest qualification, 38.1% 1st degree, 34% masters, 4.6% PhD, 3.4% professional and 1.8% other qualifications. This distribution indicates that the study's respondents have the requisite qualification required to respond to the study's questionnaire. The profile information also revealed that majority of the respondents, 52.1% have more than five working experiences.

4.4 Descriptives Analysis

The descriptive analysis results on Supply Chain Collaboration, big data analytics, supply chain integration and Logistics performance are analysed in this section in sustainable logistics practices, environmental awareness, environmental commitment, and supply chain sustainability.

4.4.1 Supply Chain Collaboration

Supply Chain Collaboration was operationalised using nine items adopted from Cao and Zhang (2011) on a seven-point Likert scale, where 1-1.99 = strongly disagree, 2.0-2.99 = disagree, 3.0-3.99 = somewhat disagree, 4.0-4.99 = neural and 5.0-5.99 = somewhat agree, 6.0-6.99 =agree and 7 = strongly agree. The descriptive results for Supply Chain Collaboration is detailed in Table 4.3.

Table 4.3 Descriptive Results on Supply Chain Collaboration

Code	*Supply Chain Collaboration*	Mean	SD	Kurtosis	Skewness
SCC_1	Our organisation and its supply chain partners exchange relevant information.	5.31	1.66	0.08	-0.93
SCC_2	Our business and its supply chain partners communicate often.	5.24	1.56	-0.2	-0.7
SCC_3	Our business and its supply chain partners share accurate information.	5.38	1.51	0.02	-0.82
SCC_4	Jointly plan on promotional events	4.96	1.61	-0.17	-0.67
SCC_5	Jointly develop demand forecasts	5.2	1.49	0.24	-0.81

SCC_6	Jointly manage inventory	5.09	1.57	0.25	-0.83
SCC_7	Our firm and this supply chain partner codevelop systems to evaluate and publicize each other's performance	4.88	1.64	-0.24	-0.68
SCC_8	Share costs (e.g. loss on order changes)	4.85	1.7	-0.25	-0.72
SCC_9	Share benefits (e.g. saving on reduced inventory costs	4.99	1.65	-0.13	-0.8
	COMPOSITR SCALE	**5.1**	**1.21**	**-0.01**	**-0.69**

Source: Field sturdy (2022) SCALE: 1= "strongly disagree" via 4= "neutral" to 7= "strongly agree"

The descriptive results of Supply Chain Collaboration are provided in Table 4.3. According to the results, the extent of Supply Chain Collaboration amongst firms operating within the Greater Accra region is high, given a composite mean of 5.1 and standard deviation of 1.21.

The item 'Share costs (e.g. loss on order changes)' scored the lowest mean (4.85), whiles the item 'Our business and its supply chain partners share accurate information' scored the highest mean (5.38). These two extremes indicate that although supply chain collaboration was revealed to be high, much of this is accounted for through the accurate sharing of information between the supply chain partners.

4.4.2 Supply Chain Integration

Supply chain integration was operationalised using fifteen items adapted from Huo et al. (2016) on a seven-point Likert scale, where 1-1.99 = strongly disagree, 2.0-2.99 = disagree, 3.0-3.99 = somewhat disagree, 4.0-4.99 = neural and 5.0-5.99 = somewhat agree, 6.0-6.99 =agree and 7 = strongly agree. The descriptive results for Supply chain integration are detailed in Table 4.4

Table 4.4 Descriptive Results on Supply chain integration

Code	*Supply chain integration*	**Mean**	**SD**	**Kurtosis**	**Skewness**
SCI_1	We maintain cooperative relationships with our suppliers	5.54	1.57	1.1	-1.29
SCI_2	We help our suppliers to improve their quality.	5.31	1.58	-0.05	-0.85
SCI_3	We maintain close communications with suppliers about quality considerations and design changes.	5.41	1.54	0.23	-0.92
SCI_4	Our key suppliers provide input into our product development projects.	5.26	1.52	0.07	-0.81

SCI_5	We strive to establish long-term relationships with suppliers	5.47	1.48	0.26	-0.9
SCI_6	We frequently are in close contact with our customers.	5.49	1.51	0.4	-1
SCI_7	Our customers give us feedback on our quality and delivery performance.	5.48	1.49	0.22	-0.9
SCI_8	Our customers are actively involved in our product design process.	5.23	1.62	0.23	-0.94
SCI_9	We strive to be highly responsive to our customers' needs.	5.53	1.5	0.75	-1.09
SCI_10	We regularly survey our customers' needs.	5.43	1.49	0.39	-0.93
SCI_11	Departments in the plant communicate frequently with each other	5.39	1.55	0.37	-0.96
SCI_12	The functions in our plant work well together	5.37	1.55	0.34	-0.97
SCI_13	The functions in our plant cooperate to solve conflicts between them, when they arise.	5.41	1.54	0.56	-1.03
SCI_14	Our plant's functions coordinate their activities.	5.34	1.56	0.37	-0.98
SCI_15	Our plant's functions work interactively with each other.	5.3	1.5	0.24	-0.85
	COMPOSITE SCALE	**5.4**	**1.22**	**1.1**	**-1.07**

Source: Field study (2022) SCALE: 1= "strongly disagree" via 4= "neutral" to 7= "strongly agree"

The descriptive results of Supply chain integration are provided in Table 4.4. According to the results, Supply chain integration is high amongst firms operating in the Greater Accra Region, giving a composite mean score of 5.4 and standard deviation of 1.22. The item 'Our key suppliers provide input into our product development projects' scored the lowest mean (5.26), whiles the item 'We maintain cooperative relationships with our suppliers' scored the highest mean (5.54). These two extremes imply that although supply chain integration was revealed to be very high, cooperative relationship with suppliers' accounts for a larger percentage.

4.4.3 Big data analytics

Big data analytics was operationalised using seven items adopted from Dubey et al. (2021) on a seven-point Likert scale, where 1-1.99 = strongly disagree, 2.0-2.99 = disagree, 3.0-3.99 = somewhat disagree, 4.0-4.99 = neural and 5.0-5.99 = somewhat agree, 6.0-6.99 =agree and 7 = strongly agree. The descriptive results for Big data analytics are detailed in Table 4.5

Table 4.5 Descriptive Results on Big data analytics

Code	*Big data analytics*	Mean	SD	Kurtosis	Skewness

BDA_1	Our company collects data using smart, adaptable technology.	5.37	1.7	0.48	-1.16
BDA_2	Our business uses a variety of data sources to aid decision-making.	5.18	1.55	-0.09	-0.76
BDA_3	Using sophisticated analytical methods, our company can make more informed decisions (e.g., simulation, optimisation, and regression).	5.21	1.57	0.11	-0.88
BDA_4	Our company visualises data using dashboards for root cause analysis and continuous improvement.	5.14	1.51	0.33	-0.82
BDA_5	Our organisation is dependent on accurate, up-todate data.	5.39	1.49	0.45	-0.95
BDA_6	Our company leverages data visualisation tools (such as dashboards) to help users and decisionmakers comprehend complicated data.	5.25	1.54	0.38	-0.91
BDA_7	Our company extensively uses data visualisations and application models on a big scale.	5.22	1.54	0.15	-0.81
	COMPOSITE SCALE	**5.25**	**1.28**	**0.38**	**-0.87**

Source: Field study (2022) SCALE: 1= "strongly disagree" via 4= "neutral" to 7= "strongly agree"

The descriptive results of Big data analytics are provided in Table 4.5. According to the results, the extent of big data analytics adoption and application are high amongst firms operating within the Greater Accra region, given a composite mean of 5.25 and standard deviation of 1.28. The item 'Our company visualises data using dashboards for root cause analysis and continuous improvement' scored the lowest mean (5.14), whiles the item 'Our organisation is dependent on accurate, up-to-date data' scored the highest mean (5.39). This shows that although the study indicates higher adoption and application of big data analytics, up-to-date and accurate data accounts for a larger percentage of the big data analytics.

4.4.4 Logistics performance

Logistics performance was operationalised using eighteen items adopted from Green et al. (2008) on a seven-point Likert scale, where 1-1.99 = strongly disagree, 2.0-2.99 = disagree, 3.0-3.99 = somewhat disagree, 4.0-4.99 = neural and 5.0-5.99 = somewhat agree, 6.0-6.99 =agree and 7 = strongly agree. The descriptive results for Logistics performance are detailed in Table 4.6

Table 4.6 Descriptive Results on Logistics performance

Code	*Logistics performance*	Mean	SD	Kurtosis	Skewness

LP_1	Increased delivery speed	5.81	1.028	-1.396	3.743
LP_2	Increased delivery dependability	5.63	1.082	-0.76	0.945
LP_3	Increased responsiveness	5.57	1.05	-0.806	1.629
LP_4	Increased delivery flexibility	5.42	1.074	-0.834	1.61
LP_5	Increased order fill capacity	5.4	1.113	-1.184	3.228
LP_6	Reduced transportation cost	5.53	1.083	-1.032	2.41
LP_7	Increased inventory turnover	5.42	1.08	-1.017	2.36
LP_8	Increased on-time-in-full deliveries	5.42	1.105	-0.972	1.892
	COMPOSITE SCALE	**5.42**	**1.22**	**1.1**	**-1.03**

Source: Field study (2022) SCALE: 1= "strongly disagree" via 4= "neutral" to 7= "strongly agree"

The descriptive results of Logistics performance are provided in Table 4.6. According to the results, there is a strong logistics performance of firms operating within the Greater Accra region given a composite mean of 5.42 and standard deviation of 1.22. The item 'Increased order fill capacity' scored the lowest mean (5.4), whiles the item 'Increased delivery speed" scored the highest mean (5.81). This shows that though the study revealed a strong logistics performance, increased delivery speed accounts for a major percentage of such performance.

4.5 Measurement Model Analysis

This section seeks to statistically validate the scales/items used in measuring the study's variables: supply chain collaboration, supply chain integration, big data analytics, logistics performance. These model test include Variance Inflation Factor (VIF) for Multicollinearity Test, Cronbach Alpha and Composite reliability for reliability test, factor loadings, and cross loadings and Average variance extracted for validity.

4.5.1 Multicollinearity Test (Variance Inflation Factor)

A variance inflation factor (VIF) is a measure of the amount of multicollinearity in regression analysis. Multicollinearity exists when there is a correlation between multiple independent variables in a multiple regression model. A VIF of below 5 indicates no issues of multicollinearity. Table 4.7 provides the results of the Multicollinearity Test

Table 4.7 Variance Inflation Factor (VIF)

Coefficients[a]								
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	.630	.142		4.426	.000		
	Collaboration	.059	.044	.059	1.349	.178	.326	3.067
	Integration	.475	.053	.472	8.886	.000	.219	4.567
	Big Data	.367	.047	.385	7.776	.000	.252	3.976

a. Dependent Variable: Logistics Performance

Source: Field study (2022)

Table 4.7 provides the results of the multicollinearity test. Supply chain collaboration, the predictor variable, scored a VIF of 3.067, supply chain integration, scored a VIF of 4.567 and big data analytics scored a VIF of 3.976. All three variable's VIF loaded less than 5 and therefore the data for the study does not have multicollinearity issues.

4.5.2 Test of Reliability

Reliability is a measure of consistency and is assessed in this study using Cronbach Alpha and composite reliability. Table 4.8 below provides the reliability results

Table 4.8 Results of Cronbach's Alpha and Composite Reliability

Construct	Number of items	Cronbach's Alpha	Composite reliability
Supply chain collaboration	9	0.91	0.92
Supply chain integration	15	0.96	0.96
Big data analytics	7	0.92	0.94
Logistics performance	8	0.94	0.95
Total	**39**	**-**	**-**

Source: Field study (2022)

Table 4.8 provides the results of the Cronbach's Alpha and Composite reliability test. Supply chain collaboration had an Alpha value of 0.91 and composite reliability of 0.92, supply chain integration Alpha value of 0.96 and composite reliability of 0.96, Big data analytics Alpha value of 0.92 and composite reliability of 0.94 and Logistics performance an Alpha value of 0.94 and composite reliability of 0.95. All four-variables scored above the 0.70 threshold for Cronbach Alpha and composite reliability: the data exhibited high internal consistency and therefore reliable.

4.5.3 Test of Validity

To test the validity of the data obtained, the study used Average variance extracted (AVE), Fornell-Larcker and confirmatory factor analysis.

4.5.3.1 Convergent Validity

Convergent validity refers to how closely a test is related to other tests that measure the same (or similar) constructs. Average variance extracted (AVE) is used to test the study's data for convergent validity. An AVE of above 0.50 is ideal. Table 4.9 presents the results

Table 4.9 Results of Average variance explained

Construct	Number of items	Average variance extracted (AVE)
Supply chain collaboration	9	0.68
Supply chain integration	15	0.58
Big data analytics	7	0.63
Logistics performance	8	0.70
Total	**39**	**-**

Source: Field study (2022)

According to Table 4.9, all the items designed to measure Supply chain collaboration, Supply chain integration, Big data analytics and Logistics performance, averagely loaded above the 0.50 threshold. This implies that all items converge accurately measure their respective constructs. The data therefore meets all requirements of convergent validity.

4.5.3.2 Discriminant Validity

Discriminant validity specifically measures whether constructs that theoretically should not be related to each other are, in fact, unrelated. Fornell-Larcker criterion is used to test the data for discriminant validity. With the Fornell Larcker criteria, the correlation of the squared variance of the variables amongst itself must be greater than the correlation of the squared variances with other variables.

Table 4.10 Results of Fornell-Larcker Criteria

Construct	SCC	SCI	BDA	LP
Supply chain collaboration (SCC)	**0.76**			
Supply chain integration (SCI)	0.65	**0.79**		
Big data analytics (BDA)	0.61	0.69	**0.82**	
Logistics performance (LP)	0.55	0.70	0.73	**0.84**

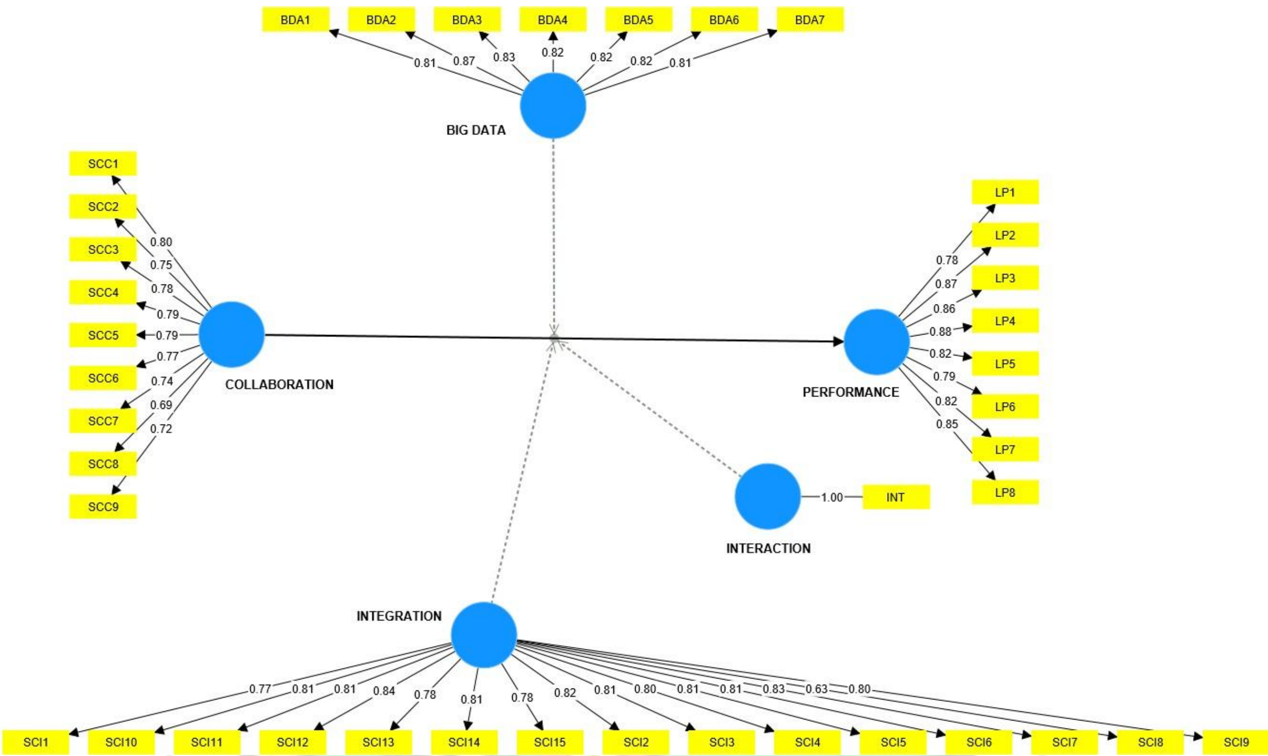
Source: Field study (2022)

As shown in Table 4.10 above, SCC had a correlation coefficient of 0.76 with itself, but had a correlation of 0.65, 0.61 and 0.55 with SCI, BDA and LP respectively. SCI also had a correlation coefficient of 0.79 with itself and correlation coefficients of 0.65, 0.69 and 0.70 with SCC, BDA and LP respectively. BDA also had a correlation coefficient of 0.82 with itself, but had correlation coefficients of 0.61, 0.69 and 0.73 with SCC, SCI, and LP respectively. Finally, LP had a correlation coefficient of 0.84 with itself, but had correlation coefficients of 0.55, 0.70 and 0.73 with SCC, SCI, and BDA respectively. Thus, each of the variables had a higher correlation with itself than the variables below them hence, each variable is valid

4.5.3.3 Confirmatory Factor Analysis

Confirmatory factor analysis (CFA) is a statistical technique used to verify the factor structure of a set of observed variables. CFA allows the researcher to test the hypothesis that a relationship between observed variables and their underlying latent constructs exists. Figure 4.1 illustrates the loadings of each construct.

Figure 4.1 Confirmatory Factor Analysis



Source: Field study (2022)

According to Figure 4.1 above, all items designed to measure supply chain collaboration, supply chain integration, big data analytics and logistics performance loaded above 0.5 and therefore actually measure their latent variables. The data is therefore valid.

4.6 Hypotheses Testing

The study's model is tested in this section using ordinary least regression (OLR) and Macro PROCESS. ORL is used to test the direct relationship between the variables, whiles the PRCOESS is used to test the moderation effects between the variables.

4.6.1 Descriptive Statistics and Correlation Results

The correlation results show that all the variables in the hypothesised paths positively and significantly correlated among themselves with all P values < 0.01. Supply chain collaboration correlates positively and significantly with supply chain integration ($r = .805$, $p < .01$); big data analytics ($r = .771$, $p < .01$); logistics performance ($r = .735$, $p < .01$). Supply chain integration also correlates positively and significantly with big data analytics ($r = .835$, $p < .01$); logistics performance ($r = .847$, $p < .01$). big data analytics also correlates positively and significantly with logistics performance ($r = .833$, $p < .01$).

Table 4.11 Correlation and Descriptive Statistics Results

	Variable	1	2	3	4	Mean	Standard deviation
1	Supply chain collaboration	1				5.10	1.21
2	Supply chain integration	.805**	1			5.40	1.22
3	Big data analytics	.771**	.853**	1		5.25	1.28
4	Logistics performance	.735**	.847**	.833**	1	5.42	1.22

Source: Field study (2022) **Note: $^{*}p < .05$, $^{**}p < .01$; N = 388**

4.6.2 Hypotheses Testing

Ordinary linear regression is used to test H1, whiles Hayse PROCESS is used to perform moderation analysis to test H2, H3 and H4.

4.6.2.1 Supply Chain Collaboration and Logistics Performance

H1 examines the relationship between Supply Chain Collaboration and Logistics Performance. The regression equation for Model 1 is

Logistics performance = constant + β_1SCC + residual

Where:

- SCC = supply chain collaboration
- $\beta 1$= regression coefficients

The regression results for H1 are presented in Table 4.12 to Table 4.14 below

Table 4.12 Model Summary

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.735[a]	.540	.539	.83199
a. Predictors: (Constant), Supply chain collaboration				

Source: Field study (2022)

The link between supply chain collaboration and logistics performance is summarised in Table 4.12. As shown in the table, supply chain collaboration accounts for 54% of the variance in logistics performance, given an R^2 of .540.

Table 4.13 ANOVA

ANOVA[a]						
Model		Sum of Squares	Df	Mean Square	F	Sig.
1	Regression	314.101	1	314.101	453.771	.000[b]
	Residual	267.190	386	.692		
	Total	581.292	387			
a. Dependent Variable: Logistics performance						
b. Predictors: (Constant), Supply chain collaboration						

Source: Field study (2022)

The statistical representation in Table 4.13 indicates that supply chain collaboration can clearly explain the variation in logistics performance, given $p < 0.01$. As a result. Therefore, it is critical to highlight the consequential changes in logistics performance as accounted for by supply chain collaboration.

Table 4.14 Coefficient of Variation

Coefficients[a]						
Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.642	.182		9.000	.000

	Supply chain collaboration	.742	.035	.735	21.302	.000
a. Dependent Variable: Logistics performance						

Source: Field study (2022)

The path coefficient values are as follows: β =.742, t = 21.302, $p < .01$. This Indicates that for every unit of supply chain collaboration, there is a corresponding increase of 0.742 in logistics performance. Hypothesis one, which states a positive relationship between supply chain collaboration and logistics performance, is strongly supported.

4.6.2.2 Moderation Effect of Big Data Analytics

H2 examines the moderating effect of big data analytics on the relationship between supply chain collaboration and logistics performance. The regression equation for Model 2 is: Logistics performance = constant + β_1SCC × β_2BDA + residual

Where:

- SCC= supply chain collaboration; BDA = Big data analytics
- β1- 2 = regression coefficients

The regression results for H2 are presented in Table 4.15 to Table 4.16 below

Table 4.15 Model Summary

Model Summary						
R	R Square	MSE	F	df1	df2	P
0.8456	.7150	.4314	321.1878	3.0000	384.000	.0000
a. Predictors: (Constant), supply chain collaboration and big data analytics						

Source: Field study (2022)

Table 4.15 summarizes the model's interaction effect of supply chain collaboration and big data analytics on logistics performance. The table indicates an R^2 of 0.7150, showing that the interaction between supply chain collaboration and big data analytics accounts for 71.5% of the variance in logistics performance.

Table 4.16 Model 1

Model 1						
	coeff	Se	t	p	LLCI	ULCI
Constant	.6501	0.4027	1.6144	0.1073	-.1416	1.4418
Supply chain collaboration	.3060	0.0998	3.0650	0.0023	.1097	.5022
Big data analytics	.6913	0.0887	7.7945	0.0000	.5169	.8657
Interaction	-.0148	0.0178	-.8307	0.4066	-.0499	0.0202

Source: Field study (2022)

According to the Model 2 result, it can be interpreted that for every unit of interaction between supply chain collaboration and big data analytics, there is a proportionate decrease of 0.0148 in logistics performance. The path coefficient results $\beta = -.0148$, $t = -.8307$, $p > .05$; does not support hypothesis 2, which stated that big data analytics moderates the relationship between supply chain collaboration and logistics performance.

4.6.2.3 Moderation Effect of Supply Chain Integration

H3 examines the moderating effect of supply chain integration on the relationship between supply chain collaboration and logistics performance. The regression equation for Model 3 is:

Logistics performance = constant + β_1SCC × β_2SCI + residual

Where:

- SCC= supply chain collaboration; SCI = Supply chain integration
- β1- 2 = regression coefficients

The regression results for H3 are presented in Table 4.17 to Table 4.18 below

Table 4.17 Model Summary

Model Summary						
R	R Square	MSE	F	df1	df2	P

0.8522	.7263	.4144	339.6299	3.0000	384.000	.0000
a. Predictors: (Constant), supply chain collaboration and Supply chain integration						

Source: Field study (2022)

Table 4.17 summarizes the model's interaction effect of supply chain collaboration and supply chain integration on logistics performance. The table indicates an R^2 of 0.7263, showing that the interaction between supply chain collaboration and supply chain integration account for 72.6% of the variance in logistics performance.

Table 4.18 Model 1

Model 1						
	coeff	Se	t	p	LLCI	ULCI
Constant	.4336	0.4123	1.0517	0.2936	-.3771	1.2443
Supply chain collaboration	.2217	0.1089	2.0364	0.0424	.0076	.4358
Supply chain integration	.7815	0.0855	9.1392	0.0000	.6133	.9496
Interaction	-.0125	0.0179	-.6986	0.4852	-.0476	0.0227

Source: Field study (2022)

According to the Model 3 result, it can be interpreted that for every unit of interaction between supply chain collaboration and Supply chain integration, there is a proportionate decrease of 0.0125 in logistics performance. The path coefficient results β = -.0125, t = -.6986, p > .05; does not support hypothesis 3, which stated that supply chain integration moderates the relationship between supply chain collaboration and logistics performance.

4.6.2.4 Interaction effect of Supply Chain Integration and Big data analytics

H4 examines the joint moderating effect of supply chain integration and big data analytics on the relationship between supply chain collaboration and logistics performance. The regression equation for Model 3 is:

Logistics performance = constant + β_1SCC × β_2SCI × β_3BDA + residual

Where:

- SCC= supply chain collaboration; SCI = Supply chain integration; BDA = Big data analytics
- β1- 3 = regression coefficients

The regression results for H4 are presented in Table 4.19 to Table 4.20 below

Table 4.19 Model Summary

Model Summary						
R	R Square	MSE	F	df1	df2	P
0.8697	.7564	.3687	397.5002	3.0000	384.000	.0000
a. Predictors: (Constant), supply chain collaboration, Supply chain integration and big data anal tics						

Source: Field study (2022)

Table 4.19 summarizes the model's joint interaction effect of supply chain collaboration, supply chain integration and big data analytics on logistics performance. The table indicates an R^2 of 0.7564, showing that the interaction between supply chain collaboration, supply chain integration and big data analytics account for 75.6% of the variance in logistics performance.

Table 4.20 Model 1

Model 1						
	coeff	Se	t	p	LLCI	ULCI
Constant	1.5159	0.2555	5.9340	0.2936	1.0136	2.0182
Supply chain collaboration	.3106	0.0639	4.8608	0.0424	.1850	.4362
Integration and Big data	.1235	0.0105	11.7507	0.0000	.1028	.1442
Interaction	.082	0.0019	4.3828	0.0000	.0119	.0045

Source: Field study (2022)

According to the Model 4 result, it can be interpreted that for every unit of interaction between supply chain collaboration, Supply chain integration and big data analytics, there is a proportionate increase of 0.082 in logistics performance. The path coefficient results $\beta = .082$, $t = 4.3828$, $p < .01$; does support hypothesis 4, which stated that supply chain integration and big data analytics jointly moderates the relationship between supply chain collaboration and logistics performance.

4.6.3 Hypothesis Table

This section summarises the result from the structural equation model used to test the study's hypotheses.

Table 4.21 Hypotheses table

Hypothesis	Path Analysis	Expected effect	Results	Conclusion
H1	SCC → LP	Positive	.742 (p < 0.01)	**Supported**
H2	SCC × BDA → LP	Positive	-.0148 (p > 0.01)	**Not Supported**
H3	SCC × SCI → LP	Positive	-.0125 (p > .01)	**Not Supported**
H4	SCC × BDA × SCI → LP	Positive	.082 (p <.01)	**Supported**

Source: Field study (2022) Notes: Supply Chain Collaboration (SCC); Big Data Analytics (BDA); Supply Chain Integration (SCI); Logistics Performance (LP)

4.7 Discussion of Results

This section discusses the results from the regression analysis in light of the literature reviewed

4.7.1 Supply Chain Collaboration and Logistics Performance

The Resource-Based View (RBV) posits that the unique resources and capabilities possessed by a firm can account for differences in performance outcomes. According to Barney (2020), firms can succeed by leveraging valuable, diverse, imperfect, and mobile resources. This study utilizes the RBV to explore how various dimensions of Supply Chain Collaboration (SCC), considered as an input resource, affect the firm's logistics performance. SCC has been defined by Cui et al. (2022) as the establishment of close, enduring partnerships wherein supply chain members cooperate, sharing information, resources, and risks to fulfill common goals. This study proposes a favorable connection between SCC and logistics performance, arguing that effective and efficient collaboration within the supply chain can bolster a firm's social, economic, and environmental performance. This viewpoint is supported by existing literature; for example, Gunasekaran et al. (2015) emphasized that SCC enhances information sharing, which is vital for improved environmental and social logistics performance. Chen et al. (2017) also noted that SCC has evolved into a strategic concern for businesses aiming to meet their logistics objectives. The study's results align with previous research, with path coefficient values of $\beta = .742$, $t = 21.302$, and $p < .01$, demonstrating that every unit increase in supply chain collaboration leads to a corresponding 0.742 increase in logistics performance. This finding highlights the significant role of collaboration within the supply chain in enhancing logistics outcomes.

4.7.2 Moderation effect of Big Data Analytics

This study introduces the idea that the impact of Supply Chain Collaboration (SCC) on logistics performance might be contingent on varying levels of big data analytics. While many researchers have indicated that SCC influences performance outcomes (as cited in works such as Pakdeechoho and Sukhotu, 2018; Peng et al., 2022; Pradabwong et al., 2015, 2017), the exact nature of this relationship remains ambiguous. Existing studies show divergent findings, and the discrepancies may be due to environmental factors that have often been overlooked. The need to reassess the relationship between SCC and performance under different environmental circumstances has led researchers to propose various mediating and moderating variables (Alzoubi et al., 2020; Jimenez-Jimenez et al., 2019; Um and Kim, 2019). Calls for further inquiry into potential unknown moderators, such as by Mofokeng and Chinomona (2019b), underscore the complexity of the SCC-performance linkage. This study posits that a direct association between SCC and logistics performance is insufficient for a full understanding. It argues that a positive relationship between SCC and logistics performance is likely when big data analytics is highly employed. The reasoning behind this is that big data analytics could enhance transparency and information sharing, increasing trust and cooperation, thus fostering logistics initiatives. However, the study also suggests that when big data analytics is limited, an increase in SCC may not necessarily improve logistics performance. The logic behind this observation is that a low level of big data analytics might lead to inadequate real-time information sharing, hindering the trust, communication, and transparency required for a productive collaborative relationship. Surprisingly, the study's result contradicts the literature review, as the path coefficient results indicate $\beta = -.0148$, $t = .8307$, $p > .05$. This implies that for each unit of interaction between SCC and big data analytics, there is a corresponding decrease of 0.0148 in logistics performance. This unexpected finding highlights the complex nature of the relationship between SCC, big data analytics, and logistics performance, and it emphasizes the need for continued exploration and investigation into these interrelated factors.

4.7.3 Moderation Effect of Supply Chain Integration

The study adds another dimension by proposing that supply chain integration (SCI) acts as a catalyst for Supply Chain Collaboration (SCC) to positively influence logistics performance. As such, product supply chain integration is employed as a mediating variable in the connection between SCC and logistics performance. According to Khanuja and Jain (2020), SCI embodies firms' abilities to form strategic alliances, merge resources, construct seamless processes, and disseminate information. SCC is seen as crucial in achieving mutual benefits for various stakeholders in a supply chain (Pakdeechoho and Sukhotu, 2018). Pradabwong et al. (2017) further argue that collaboration extends beyond integration to encompass long-term commitments, such as technology sharing, and the close alignment of planning and control systems. SCC demands significant levels of commitment, trust, joint decisions, and information sharing, which can be facilitated through SCI (Flynn et al., 2016). A strong level of both integration and collaboration tends to lead to better supply chain performance (Kaliani Sundram et al., 2016). Though previous studies have illustrated positive effects of SCC on various performance metrics (such as Pradabwong et al., 2015, 2017; Pakdeechoho and Sukhotu, 2018; Chilkapure and Pillai, 2019; Peng et al., 2022), others have noted an indirect effect (Gunasekaran, Subramanian and Rahman, 2015; Scholten and Schilder, 2015; Cui et al., 2022), and still others have identified negative impacts (Chen et al., 2017; Hofman et al., 2020). Strikingly, the results of this study stand at odds with much of the reviewed literature, showing path coefficient results of $\beta = -.0125$, $t = -.6986$, $p > .05$. This suggests that each unit of interaction between SCC and SCI corresponds to a decrease of 0.0125 in logistics performance. This inconsistency emphasizes the complex interplay between supply chain collaboration, integration, and logistics performance. It also underscores the importance of continued research and examination of the various elements that may affect these relationships, as well as the need for more nuanced considerations of how specific factors can interact and influence overall supply chain outcomes.

4.7.4 Moderation effect of Supply Chain Integration and Big Data Analytics

This study introduces an additional layer to the understanding of the relationship between supply chain collaboration (SCC), logistics performance, and supply chain integration (SCI), focusing on how these elements interact with big data analytics. The proposition is that during SCC, integration facilitates the transparent and coherent sharing of real-time data. Papadopoulos et al. (2017) have similarly argued that big data analytics enables SCI, ensuring that the information and communication systems of all stakeholders can seamlessly exchange information throughout the planning, execution, and completion stages of transport and logistics operations across a product's lifespan (Kaliani Sundram et al., 2016). Unlike previous facets of the study, the results in this case align closely with the existing literature. The path coefficient results indicate $\beta = .082$, $t = 4.3828$, $p < .01$, which implies that every unit of interaction between SCC, SCI, and big data analytics corresponds to a 0.082 increase in logistics performance. This finding emphasizes the synergistic role of big data analytics and SCI in enhancing the positive impact of SCC on logistics performance. It illustrates the complex, multifaceted nature of these relationships and contributes to a nuanced understanding of how integration, collaboration, and the application of big data analytics can collectively foster improvements in logistics operations.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

5.1 Introduction

The study examined the moderating roles of big data analytics and supply chain integration on the relationship between supply chain collaboration and logistics performance. This chapter discusses the findings summary, conclusions, recommendations, and future study suggestions.

5.2 Summary of Findings

The study's key findings are summarised in this section

5.2.1 Supply Chain Collaboration

The study revealed that the extent of Supply Chain Collaboration amongst firms operating within the Greater Accra region is high, given a composite mean of 5.1 and standard deviation of 1.21.

5.2.2 Supply Chain Integration

The study also revealed that supply chain integration is high amongst firms operating in the Greater Accra Region, giving a composite mean score of 5.4 and standard deviation of 1.22.

5.2.3 Big Data Analytics

The study found that the extent of big data analytics adoption and application are high amongst firms operating within the Greater Accra region, given a composite mean of 5.25 and standard deviation of 1.28.

5.2.4 Logistics Performance

The study also finds a there is a strong logistics performance of firms operating within the Greater Accra region given a composite mean of 5.42 and standard deviation of 1.22

5.2.5 Supply Chain Collaboration and Logistics Performance

The study revealed Supply Chain Collaboration has a positive and significant effect on logistics performance. Therefore, key supply chain collaboration practices such as information sharing, decision synchronisation and incentive alignment enhances logistics performances

5.2.6 Moderation effect of Big Data Analytics

The study also revealed a negative moderation effect of big data analytics on the relationship between supply chain collaboration and logistics performance.

5.2.7 Moderation effect of Supply Chain Integration

The study also revealed a negative moderation effect of supply chain integration on the relationship between supply chain collaboration and logistics performance.

5.2.8 Moderation effect of Supply Chain Integration and Big Data Analytics

The study also revealed a positive moderation effect of supply chain integration and Big Data Analytics on the relationship between supply chain collaboration and logistics performance

5.3 Conclusion

This study using the Resource-based view theory as a theoretical framework, examines the moderating roles of big data analytics and supply chain integration on the relationship between supply chain collaboration and logistics performance. The study states the following conclusions based on data obtained from three hundred and eighty-eight (388) firms operating within the Greater Accra Region. First, key supply chain collaboration practices such as information sharing, decision synchronisation and incentive alignment drive logistics performance improvements. Secondly, the application of Big data analytics does not necessarily impact on supply chain collaboration. Furthermore, integration of supply chain processes and systems during supply chain collaboration does not necessarily enhance logistics performances. Lastly, Although both supply chain integration and big data analytics individually do not moderate the relationship between supply chain collaboration and logistics performance, the combination of both enhances supply chain collaboration, which has a rippling effect on logistics performances

5.4 Recommendations

The researcher, based on the findings of the study, makes the following recommendations

5.4.1 Recommendations for Managers

The study revealed a positive relationship between supply chain collaboration and logistics performance. The study therefore recommends supply chain managers enhance supply chain collaboration by encouraging transparency, meeting regularly with suppliers and procurement/sourcing team, establishing and analyzing key performance metrics. These would increase the effectiveness and efficiency of supply chain collaboration, thereby increasing logistics performance.

Secondly, the study revealed that although individually, both supply chain integration and big data analytics do not positively moderate the relationship between supply chain collaboration and logistics performance, jointly they do. Based on this, the study recommends that supply chain managers seeking to enhance their logistics performances through supply chain collaboration make the conscious effort to first integrate process and systems of key supply chain partners, bolstered by the adoption and application of big data analytics

5.4.2 Suggestions for Future Research

Though this study provides valuable insight into how supply chain integration and big data analytics enhances the relationship between supply chain collaboration and logistics performance, there are still limitations which set the tone for future studies.

First, the model for the study operationalised the predictor model, supply chain collaboration using only three dimensions: information sharing, decision synchronisation and incentive alignment. The concept of supply chain collaboration is broad and therefore to take a wider perspective to supply chain collaboration, future studies are encouraged to consider other relaevant supply chain dimensions such as resource sharing, risk and benefits sharing, trust, transparency and balance of power.

Secondly, the model of the study examines the moderating roles of supply chain integration and big data analytics on the relationship between supply chain collaboration and logistics performance. however, to advance the literature on supply chain collaboration and to address gaps, future researchers are encouraged to develop a model that considers other relevant moderators and mediators that could influence supply chain collaboration such as top management commitment, supply chain complexities, resource commitments and trust.

5.4.3 Theoretical Implications

This study makes several important theoretical contributions. First, it integrates two major research streams - supply chain collaboration and big data analytics - to provide a more holistic view of how firms can improve logistics performance. The findings confirm the positive impact of supply chain collaboration on logistics performance, highlighting the importance of increased information sharing, joint decision making, and aligned incentives among supply chain partners.

Second, the study reveals the mediating role of supply chain integration between collaboration and performance. This suggests that the benefits of collaboration are best realized when accompanied by internal cross-functional integration and external integration with suppliers and customers. Theoretical frameworks on collaboration should incorporate this multidimensional view of integration.

Third, the research indicates supply chain analytics directly improves logistics performance while also enabling greater supply chain integration. This underscores the growing role of data and analytical tools in facilitating seamless flows between partners. It provides empirical support for analytics as an emerging capability for better leveraging synergies across the extended supply chain.

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APPENDIX A

SURVEY QUESTIONNAIRE

Dear respondent,

I am a student at Kwame Nkrumah University of Science and Technology's School of Business, Department of Supply Chain and Information Systems. I am working on a research project titled " Supply Chain Collaboration and Logisitcs performance: The Role of Supply Chain integration and big data analytic." Your answers are needed for the researcher to accomplish the study's objectives. Any information provided would be handled with the greatest discretion.

SECTION A: RESPONDENTS' DEMOGRAPHIC INFORMATION

Please respond to the following questions about yourself by checking the relevant boxes.

(1) How long has your company been in operation?

☐ 1-5 ☐ 6-10 ☐11-15 ☐ above 15 years

(2) Respondents' gender

☐ Male ☐ Female

(3) Respondents' age

☐ Below 20 years ☐ 20-29years ☐30-39 years ☐ 40-50years ☐ Above 50years

(4) Respondent's highest level of education

☐ HND ☐ 1st degree ☐ Masters ☐ PHD ☐ Professional ☐ Others

(5) Respondent's working experience with the firm

☐ 1-5 years ☐ 6-10 years ☐ 11-15 years ☐ above 15 years

SECTION B: SUPPLY CHAIN COLLABORATION

The following assertions are relevant to your company's supply chain collaboration. Indicate your agreement or disagreement with the following statement using a seven-Likert scale of 1=strongly disagree and 7=strongly agree.

1 Strongly disagree	2 Disagree	3 Somewhat disagree	4 Neutral	5 Somewhat agree	6 Agree	7 Strongly agree

INFORMATION SHARING	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Our organisation and its supply chain partners exchange relevant information.							
Our business and its supply chain partners communicate often.							
Our business and its supply chain partners share accurate information.							
DECISION SYNCHRONISATION	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Jointly plan on promotional events							
Jointly develop demand forecasts							
Jointly manage inventory							
INCENTIVE ALIGNMENT	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Our firm and this supply chain partner co-develop systems to evaluate and publicize each other's performance							
Share costs (e.g. loss on order changes)							
Share benefits (e.g. saving on reduced inventory costs							

Source: Cao and Zhang (2011)

SECTION C: SUPPLY CHAIN INTEGRATION

The following assertions are relevant to your company's supply chain integration. Indicate your agreement or disagreement with the following statement using a seven-Likert scale of 1=strongly disagree and 7=strongly agree.

1 Strongly disagree	2 Disagree	3 Somewhat disagree	4 Neutral	5 Somewhat agree	6 Agree	7 Strongly agree

Supplier integration	**1**	**2**	**3**	**4**	**5**	**6**	**7**
1. We maintain cooperative relationships with our suppliers							
2. We help our suppliers to improve their quality.							
3. We maintain close communications with suppliers about quality considerations and design changes.							
4. Our key suppliers provide input into our product development projects.							
5. We strive to establish long-term relationships with suppliers							
Customer integration	**1**	**2**	**3**	**4**	**5**	**6**	**7**
6. We frequently are in close contact with our customers.							
7. Our customers give us feedback on our quality and delivery performance.							
8. Our customers are actively involved in our product design process.							
9. We strive to be highly responsive to our customers' needs.							
10. We regularly survey our customers' needs.							
Internal Integration	**1**	**2**	**3**	**4**	**5**	**6**	**7**
11. Departments in the plant communicate frequently with each other							
12. The functions in our plant work well together							
13. The functions in our plant cooperate to solve conflicts between them, when they arise.							
14. Our plant's functions coordinate their activities.							
15. Our plant's functions work interactively with each other.							

Source: Huo et al. (2016)

SECTION D: BIG DATA ANALYTICS

The following assertions are relevant to your company's big data analytics. Indicate your agreement or disagreement with the following statement using a seven-Likert scale of 1=strongly disagree and 7=strongly agree.

1	2 Neutral agree	3 agree	4 5 Somewhat	6 Agree	7 Strongly Strongly disagree	Disagree	Somewhat disagree

Big data analytics	1	2	3	4	5		7
Our company collects data using smart, adaptable technology.							
Our business uses a variety of data sources to aid decision-making.							
Using sophisticated analytical methods, our company can make more informed decisions (e.g., simulation, optimisation, and regression).							
Our company visualises data using dashboards for root cause analysis and continuous improvement.							
Our organisation is dependent on accurate, up-to-date data.							
Our company leverages data visualisation tools (such as dashboards) to help users and decision-makers comprehend complicated data.							
Our company extensively uses data visualisations and application models on a big scale.							

Source: Dubey et al. (2021)

SECTION E: LOGISTICS PERFORMANCE

The following assertions are relevant to your company's logistics performance. Indicate your agreement or disagreement with the following statement using a seven-Likert scale of 1=strongly disagree and 7=strongly agree.

1 Strongly disagree	2 Disagree	3 Somewhat disagree	4 Neutral	5 Somewhat agree	6 Agree	7 Strongly agree

	1	2	3	4	5	6	7
Increased delivery speed							
Increased delivery dependability							
Increased responsiveness							
Increased delivery flexibility							
Increased order fill capacity							
Reduced transportation cost							
Increased inventory turnover							
Increased on-time-in-full deliveries							

Source: Green et al. (2008)