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DEPARTMENT OF PROCUREMENT AND SUPPLY CHAIN

MANAGEMENT

BIG DATA ANALYTICS AND SUPPLY CHAIN PERFORMANCE: THE ROLES OF SUPPLY CHAIN VISIBILITY AND INFORMATION QUALITY.

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A thesis submitted to the School of Graduate Studies in partial fulfilment of the requirement for the award of the degree of Master of Philosophy
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DECLARATION

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SUPERVISOR'S DECLARATION

I formally affirm that the development and submission of this study took place under proper academic supervision and strictly adhered to the thesis supervision regulations established by the University of Education, Winneba.

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Mr. Alhassan Salifu Bawah ....

(Head of Department, PSCM) Signature Date

DEDICATION

I devote this dissertation to my family, and in loving memory of my late wife, Mrs Mary Adowa Ewur, and my daughter, Miss Josephine Ama Ewur. I also dedicate this work to the inner drive, resilience, and personal discipline that sustained me and enabled me to persevere throughout this journey.

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May God shower blessings upon every one of you.

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ABBREVIATIONS

AfDB	African Development Bank
AGI	Association of Ghana Industries
AVE	Average Variance Extracted
BDA	Big Data Analytics
CR	Composite Reliability
CSV	Comma-Separated Values
HTMT	Heterotrait-Monotrait
PLS-SEM	Partial Least Squares Structural Equation Modeling
RBV	Resources Based View
IQ	Information Quality
SC	Supply Chain
SCD	Supply Chain Digitalization
SCI	Supply Chain Innovation
SCP	Supply Chain Performance
SSCP	Sustainability Supply Chain Performance
SCV	Supply Chain Visibility
SCS	Supply Chain Survivability
SCMP	Supply Chain Management Practices
SEM	Structural Equation Modeling
SPSS	Statistical Package for the Social Sciences
SU	Second University
VIF	Variance Inflation Factor.

ABSTRACT

Manufacturing operations in Ghana continue to struggle with ongoing interruptions across their supply networks, issues that consistently chip away at their operational effectiveness and erode their ability to stay competitive. Even as digital tools become more widespread and the volume of operational information grows exponentially, most companies still haven't managed to properly harness big data analytics for better supply chain coordination and smarter management choices. This investigation set out to examine how big data analytics shapes supply chain results within Ghana's manufacturing landscape, paying special attention to how visibility throughout the supply chain acts as a bridge and how information quality influences that relationship's strength. Drawing on dynamic capabilities theory, information processing theory, and contingency theory as its foundation, the researchers adopted a quantitative methodology. They gathered responses through structured surveys from 272 manufacturing businesses operating in the Greater Accra Region, then processed the information using Partial Least Squares Structural Equation Modelling. What emerged from the analysis shows that big data analytics delivers a measurable and beneficial effect on how supply chains perform. Beyond this direct connection, the study uncovered that visibility across the supply chain serves as a crucial link between analytics efforts and performance gains, primarily because it enables quicker information exchange between partners, smooths out coordination challenges, and sharpens the organization's ability to respond to changing conditions. The evidence further suggests that when information meets high standards for accuracy, timeliness, and relevance, it amplifies the positive impact analytics has on supply chain visibility. From a practical standpoint, the message here is clear: simply pouring resources into analytics technology won't automatically translate into better outcomes unless companies simultaneously build robust systems for seeing across their supply chains and maintain rigorous information standards. By bringing fresh empirical evidence to the table, this work enriches academic conversations while offering concrete direction for manufacturing leaders and policy architects working to strengthen analytical capacities, shore up data integrity, and ultimately push supply chain results and market standing to higher levels.

CHAPTER ONE

INTRODUCTION

1.0 Overview

Ghana's manufacturing sector is currently facing persistent supply chain disruptions driven by macroeconomic volatility, rising production costs, infrastructure constraints, and heightened market uncertainty, all of which undermine operational efficiency and competitiveness. At the same time, organizations operating in this industry are producing substantial amounts of operational and transactional information as digital systems continue to proliferate. Here is a fully rewritten version with original wording, preserved meaning, and a natural academic tone: Despite the explosion in available data over recent years, there is surprisingly little concrete proof regarding how companies might methodically weave big data analytics into their high-level operational planning to boost supply chain results, particularly within local settings. With this gap in mind, the current study sets out to explore how big data analytics influences the effectiveness of supply chains. More specifically, it investigates whether supply chain visibility acts as a bridge in this connection, and it also looks at the specific scenarios where the caliber of information serves to amplify these dynamics. The timing of this investigation is especially relevant, as Ghana pushes forward with its ambitions for industrial growth and digital change. To support smoother coordination, quicker reactions, and smarter choices throughout its manufacturing supply networks, the country needs insights grounded in solid evidence.

1.1 Background of the Study

In today's highly interconnected and rapidly changing global economy, marked by uncertainty and growing operational complexity, supply chain effectiveness has become a critical determinant of organizational success. Supply chain performance involves the intentional alignment and management of relationships among organizations within the network to ensure fairness, dependability, responsible practices, and financial sustainability (Mirii-Lavassani & Movehedi, 2018). Its relevance is particularly pronounced for companies navigating unpredictable conditions, adapting to evolving customer demands, and seeking to preserve a lasting competitive advantage. Modern enterprises no longer operate in isolation; instead, they function within interdependent systems where outcomes are shaped by the overall strength and coordination of the entire chain. Consequently, close collaboration among partners and a commitment to ongoing enhancement across all connected entities have gained strategic importance (Baah et al., 2020; Reddy et al., 2019).

This shift underscores the fundamental role of supply chain integration in strengthening organizational resilience, responsiveness, and value creation in environments defined by swift transformations and heightened customer expectations.Again, the growing complexity of global supply chains, coupled with challenges such as shorter product lifecycles, fluctuating demand, and the need for faster response times, has further emphasized the importance of robust supply chain management (Lee, 2002; Hernández-Espallardo et al., 2010). Effective SC improves operational efficiency and promotes alignment among partners, enabling organizations to react quickly to disruptions, take advantage of new opportunities, and cultivate lasting relationships with stakeholders (Laihonen & Pekkola, 2016; Handfield et al., 2014). As customer satisfaction and sustainability become central to business success, SCP has evolved from an operational concern to a strategic priority, driving organizational growth and competitiveness in an interconnected global marketplace (Ahi & Searcy, 2015; Christopher & Gaudenzi, 2009).

To strengthen supply chain performance (SCP), researchers contend that firms should adopt sophisticated digital tools, particularly big data analytics (BDA), to better understand customer expectations and streamline supply chain activities for enhanced outcomes. Companies face continuous demands to respond to shifting consumer demands while simultaneously upholding environmentally responsible operations (Genovese et al., 2017; Gunasekaran et al., 2017). At the same time, heightened market rivalry pushes organizations to refine durability, accelerate delivery, improve quality standards, and reduce operational costs (Barlette & Baillette, 2020). Contemporary manufacturing systems now operate within highly data-driven ecosystems where enormous datasets are generated, transmitted, and analyzed through interconnected digital platforms, ultimately producing practical insights for production management (Fang et al., 2020; Farooqui et al., 2020). Such developments underscore how essential BDA has become in transforming unprocessed information into strategic knowledge. Through this capability, enterprises are better positioned to implement evidence-based decisions that contribute to stronger customer experiences and more efficient internal processes. On a broader scale, big data is commonly characterized by its extensive volume, rapid generation speed, diverse formats, reliability concerns, and the strategic value derived from its application, all of which are reshaping how organizations across sectors approach decision-making and innovation (Lyu et al., 2023).

Through revealing concealed patterns, unfamiliar correlations, and market trends, BDA provides organizations with essential tools for making informed, data-driven decisions, ultimately enhancing financial performance and supply chain results (Razzaq & Yang, 2023; Merendino et al., 2018). As a result, BDA has become indispensable for organizations seeking to enhance competitiveness, optimize supply chain functions, and deliver exceptional customer value in an increasingly data-driven world (Green et al., 2018; Mikalef et al., 2018b). However, Dubey et al. (2020) suggest that to realize these benefits fully, organizations must leverage supply chain visibility (SCV), which enables effective data sharing and real-time decision-making across supply chain networks.

SCV is critical for organizations to leverage data-driven decision-making fully. SCV refers to how effectively supply chain partners can access or share important information for mutual operational benefit (Barratt & Oke, 2007) and is essential for enhancing SCP by providing real-time insights into material and information movements (Al-Khatib, 2022a). Organizations can better monitor and adapt to supply chain fluctuations by combining BDA with SCV, thus reducing uncertainty and improving operational efficiencies (Ben-Daya et al., 2022). Big Data Analytics empowers firms to obtain highly specific, up-to-the-minute, and practical understandings that drive ideal supply chain visibility, according to Busse et al. (2017) and Kembro et al. (2014). This enhancement in decision-making allows businesses to tackle interruptions head-on and fine-tune their approaches to fit broader supply chain ambitions, as noted by Agrawal et al. (2022) and Sodhi & Tang (2019). On top of that, visibility throughout the supply chain encourages teamwork and the free flow of data among partners, which boosts overall value and operational results, as highlighted by Baah et al. (2022) and Bechtsis et al. (2021). Because of this, tapping into supply chain visibility becomes a key move for businesses hoping to streamline their operations and reach top-tier performance in today's world driven by information, as supported by Somapa et al. (2018) and Dubey et al. (2020). Still, how well both visibility and analytics work ultimately comes down to the caliber of facts and intelligence exchanged among all parties involved in the supply chain, a point made by Bahrami & Shokouhyar (2021) and Al-Okaily & Al-Okaily (2024).

Scholars assert that the quality of information encompassing accuracy, relevance, timeliness, and value plays a crucial role in ensuring the reliability of insights gained through BDA (Miller, 1996; Malhotra et al., 2005). Maintaining high-quality information is vital for data integrity throughout its lifecycle, from pre-processing to analysis, as it significantly affects the data's value and relevance (Taleb et al., 2018). Without a strong IQ, BDA's capacity to enhance SCV is compromised, as poor data quality can lead to flawed insights, misguided decisions, and diminished operational performance (Stvilia et al., 2007). Furthermore, IQ dimensions such as completeness, reliability, and timeliness are essential for fostering trust and collaboration among supply chain partners, facilitating effective information sharing, and improving SCV (Naumann & Rolker, 2000; Kankam et al., 2023). Organizations prioritizing IQ can ensure that the data supporting their BDA initiatives is accurate, actionable, and aligned with strategic objectives, enhancing SCV and boosting supply chain efficiency in a data-driven business environment. This study builds its theoretical foundation on three interconnected perspectives: dynamic capabilities theory, information processing theory, and contingency theory. Each lens offers a unique way of understanding how organizations leverage data to improve their supply chain operations.

Starting with dynamic capabilities, this framework sheds light on why big data analytics (BDA) actually moves the needle when it comes to supply chain performance (SCP). Basically, it is about how companies become better at sensing what is happening around them—spotting market shifts before competitors do, jumping on promising opportunities as they appear, and tweaking their internal workflows as circumstances change. This kind of ongoing adaptation ultimately makes organizations nimbler, more efficient day-to-day, and quicker on their feet when responding to whatever comes their way (Teece et al., 1997; Mikalef et al., 2018). BDA does not work its magic in a vacuum.

Information processing theory helps us see the bigger picture by highlighting how supply chain visibility (SCV) acts as a kind of bridge. Without that clear line of sight across the supply chain, all those sophisticated analytics would not translate into meaningful, coordinated action.

When visibility is high, the knowledge produced through BDA can move smoothly across organizational boundaries, supporting shared understanding, lowering ambiguity, and improving the quality of managerial decisions (Galbraith, 1973; Barratt & Oke, 2007). In contrast, limited visibility weakens this pathway. If insights generated from data analysis fail to circulate effectively within the supply chain network, their practical value diminishes, and performance gains may not materialize (Kembro et al., 2014; Dubey et al., 2020).

Moreover, contingency theory suggests that the strength of the relationship between BDA and SCV depends on contextual conditions, particularly information quality (IQ). When information is reliable, current, and relevant, analytical outputs become more dependable and useful for operational decisions. High-quality information therefore enhances the contribution of BDA to improved visibility and coordination within the supply chain (Donaldson, 2001; Miller, 1996).

In contrast, low IQ weakens this relationship, as poor-quality data undermines the reliability and usefulness of BDA outputs (Stvilia et al., 2007; Taleb et al., 2018). Thus, the interplay between BDA, SCV, and IQ is critical for achieving superior SCP. BDA drives innovation and adaptability, SCV facilitates adequate information flow, and IQ ensures the reliability of data-driven insights.

This study is highly valuable for manufacturing companies, which are vital in fostering economic growth, job creation, and industrialization globally, particularly in Africa and

Ghana. Worldwide, the manufacturing industry contributes approximately 16% to global GDP and accounts for 14% of total employment, serving as a cornerstone of economic progress and innovation (World Bank, 2022). In Africa, this sector is increasingly recognized as a key driver of economic transformation, contributing about 10% to the continent's GDP and employing over 15% of the workforce, with significant growth potential as nations emphasize industrialization through initiatives such as the African Union's Agenda 2063 (AfDB, 2023). In Ghana, the manufacturing sector accounts for around 10% of GDP and employs roughly 11% of the labour force, underscoring its significance in the national economy (Ghana Statistical Service, 2023).

1.2 Statement of the Problem

Ghana's manufacturing sector remains a critical pillar for economic growth, industrialisation, and employment creation; however, its supply chains are increasingly constrained by persistent structural, operational, and macroeconomic challenges that undermine performance and competitiveness (African Economic Outlook, 2024; Opoku et al., 2023). Manufacturing firms continue to grapple with rising inflation, currency depreciation, escalating utility tariffs, high taxation, unreliable power supply, transportation bottlenecks, and inconsistent availability of raw materials (AGI Report, 2024; Deloitte, 2023). These challenges heighten supply chain uncertainty, disrupt production schedules, inflate operational costs, and weaken firms' ability to respond efficiently to fluctuating customer demand, thereby eroding customer trust and overall supply chain performance (Cao et al., 2024; Chen & Fei, 2022; Telukdarie et al., 2020).

In response to these pressures, scholars increasingly argue that manufacturing firms must move beyond traditional experience-based and reactive decision-making and adopt data-driven approaches that enhance agility, coordination, and real-time responsiveness (Genovese et al., 2017; Gunasekaran et al., 2017; Barlette & Baillette, 2020). Big data analytics has emerged as a strategic capability that enables firms to process large volumes of structured and unstructured data generated across procurement, production, logistics, inventory management, and customer interfaces, thereby supporting informed and timely decision making (Wamba et al., 2015; Gupta & George, 2016; Mikalef et al., 2018). Through predictive analytics, real-time monitoring, and pattern recognition, big data analytics enables firms to anticipate demand fluctuations, detect supply disruptions, optimise resource allocation, and improve production planning, all of which are essential for maintaining competitiveness in volatile, resource-constrained environments (Dubey et al., 2020; Razzaq & Yang, 2023).

The dynamic capabilities perspective argues that organizations functioning in highly volatile contexts can maintain a competitive edge when they continuously detect shifts in their environment, capitalize on new possibilities, and reorganize their internal assets to cope with uncertainty (Teece et al., 1997; Mikalef et al., 2018). Within this framework, big data analytics plays an enabling role by strengthening a firm's capacity to transform complex data into practical knowledge and by supporting timely, forward-looking responses to interruptions in supply chain operations (Barlette & Baillette, 2020; Ben Daya et al., 2022). Even so, research shows that simply allocating resources to analytics technologies does not guarantee better supply chain outcomes. Performance improvements depend on how well the resulting insights circulate among partners and are actively applied throughout the network (Kembro et al., 2014; Dubey et al., 2020).

Information processing theory emphasises that supply chain visibility is a critical mechanism through which firms reduce uncertainty and improve coordination by ensuring timely access to relevant information across supply chain partners (Galbraith, 1973; Barratt & Oke, 2007). Empirical studies show that when big data analytics enhances supply chain visibility, firms are better positioned to monitor material flows, align decisions, and respond rapidly to disruptions, thereby improving operational efficiency and performance (Busse et al., 2017; Al Khatib, 2022; Ben Daya et al., 2022). Despite this theoretical and empirical relevance, limited studies have explicitly examined supply chain visibility as a mediating mechanism through which big data analytics influences supply chain performance, particularly within manufacturing contexts in developing economies.

According to contingency theory, there is no one-size-fits-all approach to how well a company's managerial know-how and technological tools actually perform. Instead, their real-world impact is heavily shaped by the specific circumstances at play, particularly the reliability of the information that leaders have to work with (Donaldson, 2001; Miller, 1996). Before any insights pulled from big data can genuinely guide smart decisions, you have to consider the trustworthiness of the underlying information itself. This really comes down to whether the data is accurate, timely, relevant, and thorough enough to stand on (Malhotra et al., 2005; Taleb et al., 2018).

When data quality is compromised, analytical results may become misleading, transparency across the supply chain can deteriorate, and managerial choices may miss the mark, regardless of how sophisticated the analytical technologies are (Stvilia et al., 2007; Bahrami & Shokouhyar, 2021). Even so, much of the current empirical literature gives limited attention to information quality as a conditioning element that shapes how big data analytics influences supply chain visibility, thereby overlooking a crucial perspective on the circumstances under which analytics can most effectively enhance visibility outcomes.Within the Ghanaian manufacturing sector specifically, empirical research that jointly examines big data analytics, supply chain visibility, information quality, and supply chain performance remain largely absent. This gap is particularly significant given the sector's exposure to frequent disruptions, infrastructure constraints, and institutional weaknesses, alongside increasing digitalisation and data generation (Ghana Statistical Service, 2023; AGI Report, 2024). Without context-specific evidence, managers and policymakers lack clear guidance on how to structure analytics investments, improve information quality, and enhance visibility to respond effectively to supply chain challenges and remain competitive. Building on these concerns, the research investigates how big data analytics influences supply chain performance within Ghana's manufacturing industry. It also carefully explores how supply chain visibility operates as a pathway through which this influence occurs, and how the quality of information shapes or conditions these relationships. In doing so, the study generates evidence grounded in the local context, showing how firms in the manufacturing space can use data-driven capabilities to improve coordination across operations, limit unpredictability, reinforce organisational resilience, and remain competitive in a rapidly changing, information-rich market environment.

1.3 Research Objective

This study explores the impact that analyzing massive datasets has on how well supply chains function within Ghana's industrial production landscape. A key focus is placed on the contributions made by both the accuracy of information and the clarity with which supply chain activities can be observed. To direct this inquiry, the following specific aims have been established:

i. To evaluate the impact of big data analytics on supply chain performance.
ii. To explore the association between big data analytics and supply chain visibility.
iii. To examine whether information quality shapes the relationship between big data analytics and supply chain visibility in Ghana's manufacturing industry.

iv. To investigate the extent to which supply chain visibility serves as a mediating mechanism in the connection between big data analytics and supply chain performance in the Ghanaian manufacturing context.

1.4 Research Questions

i. How does the use of big data analytics influence the performance of the supply chain?

ii. What connection exists between big data analytics and supply chain visibility?

iii. In what way does information quality shape or influence the relationship between big data analytics and supply chain visibility?

iv. To what extent does supply chain visibility explain the relationship between big data analytics and supply chain performance?

1.5 Significance of the Study

This study offers important insights for policymakers, higher education institutions, and manufacturing firms, particularly in Ghana and other similar developing economies. In terms of public policy, the findings may help demonstrate how big data analytics can be leveraged to enhance sustainability efforts in the manufacturing sector, which remains a key driver of economic growth and broader structural development.. When decision-makers understand the ways in which supply chain visibility and information quality contribute to the effectiveness of big data initiatives, they are better positioned to design focused policies that encourage technological advancement across industries. Such evidence may point to practical priorities, including strengthening digital infrastructure, establishing clear data management standards, and investing in training programs that improve the reliability of information and promote transparency across supply networks.

In turn, these insights can support broader national development plans, including initiatives like Ghana's "One District, One Factory" program, by reinforcing the importance of evidence-based management and coordinated supply chain systems in fostering long-term industrial sustainability.

Within academic circles, the study expands existing discussions on the links among big data analytics, supply chain visibility, and sustainable performance, particularly in regions that have received limited scholarly attention, such as Sub-Saharan Africa. It refines and extends established theoretical perspectives, including dynamic capabilities theory, information processing theory, and contingency theory, by examining how supply chain visibility functions as an intermediary mechanism and how information quality shapes the strength of these relationships. Through this lens, the research offers a more nuanced understanding of how big data initiatives influence sustainable supply chain outcomes. Empirical evidence generated here helps address important gaps in prior studies, especially regarding indirect pathways and contextual factors that condition the impact of analytics on performance. This contribution not only enriches theoretical debate but also lays groundwork for subsequent investigations in comparable environments.

For manufacturing organizations, the study offers practical guidance on improving operational outcomes. It suggests that firms can achieve better results by developing strong big data capabilities while simultaneously ensuring that the information they rely on is accurate, consistent, and accessible, and that their supply chain processes remain transparent. By aligning technology investment with data integrity and system-wide visibility, companies may enhance efficiency, reduce unnecessary costs, and strengthen customer relationships. Over time, these improvements can reinforce competitive advantage and contribute to wider economic progress.

1.6 Scope of the Study

The way big data analytics influences performance outcomes in manufacturing supply chains is the central focus of this research. Particular attention is given to how visibility throughout the supply chain functions in this dynamic, alongside the quality of information sharing that occurs not only within individual companies but also between different organizations operating in the network. It is situated in the Greater Accra region of Ghana, an area widely recognized for its dense industrial presence and its central role in the country's economic expansion, where many manufacturing enterprises operate. By concentrating on this geographical setting, the study captures the practical realities, constraints, and growth possibilities that firms encounter in a fast-paced urban industrial landscape.

The investigation includes manufacturing organizations from different operational scales and industry segments, allowing for a broad and balanced assessment of the ways big data tools can strengthen supply chain outcomes. Special consideration is given to environments where financial, technological, or infrastructural resources may be limited, making efficient data utilization especially critical. Selecting the Greater Accra region also enhances the study's practical significance for local decision-makers and industry practitioners, while at the same time generating findings that may inform comparable industrial contexts within Ghana and other developing economies.

1.7 Limitations of the Study

This research is not without constraints, and it is important to state them clearly. To begin with, the choice of an explanatory design supported by quantitative methods enabled rigorous statistical analysis, yet it does not fully capture the nuanced organisational and environmental dynamics that shape the links between big data analytics, supply chain visibility, information quality, and overall supply chain performance. In other words, the numerical focus may overlook deeper contextual influences that could enrich interpretation.

In addition, reliance on a standardized survey instrument for gathering data may have shaped participants' responses in subtle ways. Since respondents interpret questions through their own experiences and perspectives, their understanding of the items could have influenced how they answered, potentially introducing elements of perception-based bias.

The study was limited to manufacturing firms located in the Greater Accra Region. While this area serves as one of the country's principal centres of industrial activity, the economic conditions and day-to-day operational environments there may not reflect those in other regions of Ghana or in different international contexts. Therefore, the findings derived from this particular sample may not represent the diversity of experiences that exist across wider geographic or economic settings. For this reason, any extension of the results to contexts beyond the scope of the study should be approached carefully.

1.8 Organisation of the Study

This research is organized into five distinct chapters to allow for a clear and logically structured exploration of the subject. The opening chapter sets the stage by presenting the study's context, clarifying the research problem, and identifying shortcomings in existing scholarship. It also articulates the study's aims and guiding questions, while explaining the justification for the investigation, its boundaries, and the overall layout of the work.

The second chapter engages with scholarly sources relevant to the topic. It discusses central ideas and guiding theories, reviews related empirical findings, and develops a conceptual structure that situates the research within broader academic debates.

In Chapter Three, the focus shifts to the research process itself. This section explains the methodological approach, including the overall research design, procedures for gathering data, and techniques used for analysis. It also provides a concise description of the study area within the Greater Accra region to give contextual clarity.

Chapter Four is devoted to the presentation and interpretation of the collected data. The results are examined in detail, with direct reference to the research questions that shaped the inquiry.

The final chapter brings the study to a close by synthesizing the major insights that emerged from the analysis. It outlines the conclusions drawn from the findings and reflects on their implications from theoretical, practical, and policy perspectives.

CHAPTER TWO

LITERATURE REVIEW

2.0 Introduction

This section explores existing scholarly work concerning big data analytics, transparency within supply chains, the standard of information, and overall supply chain outcomes. It also brings together relevant theoretical perspectives, previous empirical findings, and the study's guiding conceptual model as they relate to the variables under investigation.

2.1 Theoretical Review

This study applies the dynamic capabilities, information processing, and contingency theories to explain the variables under study. Specifically, the information-processing and contingency theories were employed to complement the dynamic capabilities theory and to inform the model for the study.

2.1.1 Dynamic Capabilities Theory

Dynamic capabilities theory, introduced by David J. Teece, Gary Pisano, and Amy Shuen in 1997, provides a robust lens for examining how firms remain effective amid swift and continuous environmental shifts. At its core, the perspective explains that organisations sustain advantage by continually reshaping how they use their assets, combining them in new ways, and deploying them strategically when conditions demand it. Firms that develop these capabilities are better positioned to sense emerging possibilities and looming risks, respond through deliberate strategic action, and adjust their internal structures and routines as circumstances evolve. Within supply chain management, this adaptive capacity is especially important because it strengthens operational resilience, supports recovery from unexpected disturbances, and encourages ongoing improvement aligned with customer expectations. In this context, big data analytics functions as a practical expression of dynamic capability, since it allows organisations to process large volumes of information, detect meaningful patterns, and convert those findings into insights that guide strategic choices in complex and uncertain settings (Teece et al., 1997).

The relationship between dynamic capabilities theory and how big data analytics enhances supply chain performance becomes more understandable when the foundational ideas of the theory are considered closely. At its core, the theory posits that firms operate in environments characterised by uncertainty and constant change, requiring them to adapt repeatedly in order to remain viable and competitive (Teece et al., 1997). Big data analytics supports this adaptive process by facilitating real-time tracking of supply chain operations, improving transparency across activities, and equipping decision-makers with early warnings of potential disruptions so that corrective measures can be implemented promptly (Dubey et al., 2020; Kembro et al., 2014). Furthermore, the framework underscores the need for organisations to reorganise and redeploy their resources strategically to sustain and strengthen their competitive advantage. From this standpoint, big data analytics contributes by exposing operational bottlenecks, guiding more efficient distribution of resources, and supporting the development of innovative approaches to supply chain management (Mikalef et al., 2018; Barlette & Baillette, 2020). Finally, the theory stresses that informed strategic judgement is central to exploiting opportunities effectively. Big data analytics strengthens this dimension by generating evidence-based insights that reduce ambiguity and improve the accuracy and confidence of managerial decisions (Razzaq & Yang, 2023; Al-Khatib, 2022a).

Over the years, the dynamic capabilities theory has been extensively utilized in research examining how technology enhances both organizational and supply chain performance. From the lens of dynamic capabilities, big data analytics (BDA) strengthens firms' ability to develop and renew their internal competencies by supporting evidence-based decision-making and stimulating innovative practices (Mikalef et al., 2018). Building on the same theoretical foundation, Dubey et al. (2020) showed that BDA contributes to greater supply chain resilience and responsiveness, thereby helping organizations manage and adapt to operational disruptions more effectively. Additionally, various studies have emphasized BDA's role in restructuring supply chain processes to better respond to evolving market demands, thus enhancing SCP (Ben-Daya et al., 2022; Barlette & Baillette, 2020). These studies highlight the significance of dynamic capabilities theory for understanding the transformative power of BDA in supply chain management.

The theory of dynamic capabilities provides an insightful lens for understanding how BDA enhances SCV and SCP. BDA empowers organizations to pinpoint, gather, and reallocate resources as conditions shift, aligning perfectly with the theory's core principles. The main elements of dynamic capabilities adaptation to fluctuations, resource reconfiguration, and strategic decision-making are directly enhanced by BDA's features, positioning it as an essential resource for boosting supply chain efficiency, resilience, and innovation. Additionally, the extensive application of this theory in current literature highlights its significance in illuminating the link between BDA and SCP, thereby providing a robust theoretical basis for this research.

2.1.2 Information Processing Theory

Galbraith's 1973 introduction of information processing theory provides a helpful lens for grasping how businesses tackle unpredictability and complexity through smart data handling. The core idea positions companies as systems built around handling information, where their capacity to collect, interpret, and distribute data becomes essential for cutting through confusion and reaching smart conclusions (Galbraith, 1973; Barratt & Oke, 2007). When you apply this way of thinking to supply chains, it becomes clear that making information flow more freely among partners strengthens teamwork and coordination (Kembro et al., 2014; Dubey et al., 2020). Supply chain visibility, or SCV for short, essentially means being able to access and share crucial information across the entire network, and it turns out this visibility serves as a key bridge between big data analytics (BDA) and how well the supply chain actually performs (SCP). By making information more transparent and easier to reach, SCV lets companies put the insights from BDA to work improving their day-to-day operations (Barratt & Oke, 2007; Al-Khatib, 2022a).

The theory starts from the premise that companies constantly deal with unpredictability, and smart information handling is what helps them navigate it (Galbraith, 1973). BDA steps in by offering ways to process enormous datasets, yet here is the catch: without proper visibility across the supply chain, those valuable insights risk staying trapped in isolated departments or never reaching their full potential (Dubey et al., 2020; Kembro et al., 2014). What the theory really drives home is that sharing information and working together smoothly cuts through confusion and leads to smarter choices (Barratt & Oke, 2007). This is exactly where SCV proves invaluable; it keeps information flowing in real time across every link in the chain, making sure the discoveries from BDA actually translate into practical steps that move operations forward (Al-Khatib, 2022a; Ben-Daya et al., 2022). The theory also places heavy emphasis on how information quality shapes reliable decision-making (Galbraith, 1973; Malhotra et al., 2005). By guaranteeing that

BDA works with information that's precise, current, and actually useful, SCV multiplies its effect on supply chain results (Taleb et al., 2018; Kankam et al., 2023).

Researchers studying how digital innovations and information systems reshape supply chain management have increasingly turned to information processing theory as their guiding framework. Building on these ideas, Barratt and Oke (2007) showed that when companies can see more deeply into their supply chains, performance naturally improves because information flows more freely and partners face less uncertainty. In a similar vein, Dubey and colleagues (2020) found that weaving big data analytics together with better visibility does not just streamline operations; it also makes companies tougher when disruptions hit. Other studies have hammered home that SCV acts as an essential go-between, connecting cutting-edge technology with real-world supply chain outcomes, essentially making sure data discoveries do not just sit on a shelf but actually guide concrete actions (Kembro et al., 2014; Ben-Daya et al., 2022). Pulling all this research together makes it clear why information processing theory remains so useful for understanding exactly how SCV serves as that crucial link joining BDA with measurable supply chain success.

Seen through this theoretical lens, everything clicks into place. Information processing theory offers a clear roadmap for understanding how SCV strengthens the connection between BDA and supply chain results, spelling out the exact pathways through which data capabilities turn into genuine performance gains. It puts the spotlight squarely on how information travels, how well partners coordinate, and whether that information is any good, showing how SCV squeezes every drop of value from BDA to sharpen supply chain operations. The theory's bedrock principles (cutting through uncertainty, encouraging open information sharing, and building confidence in decisions) map perfectly onto what SCV actually does, which explains why it emerges as such a decisive factor in the BDA-performance equation. Given how widely researchers have applied this framework in previous work, it clearly has the power to illuminate just how transformative SCV can be for managing supply chains, making it the ideal theoretical foundation for this investigation.

2.1.2 Contingency Theory

Contingency theory, developed by scholars such as Lawrence and Lorsch (1967) and expanded by Donaldson (2001), proposes that organizational outcomes rely on how effectively internal processes align with external environmental factors. This theory stresses that there is no one-size-fits-all management solution; instead, the success of strategies and tools depends on the unique context in which they are applied (Donaldson, 2001; Miller, 1996). In the realm of BDA and SCV, contingency theory acts as a crucial framework for exploring how IQ impacts the relationship between these components. The theory suggests that the effectiveness of BDA on SCV depends on the accuracy, timeliness, and relevance of the data (Taleb et al., 2018; Malhotra et al., 2005). High IQ ensures that the insights from BDA are reliable and actionable, thereby amplifying its positive influence on SCV (Stvilia et al., 2007; Naumann & Rolker, 2000).

The contingency theory also suggests that an organization's success depends on aligning its internal capabilities and external demands (Donaldson, 2001). In this context, BDA is considered an internal capability, while SCV is the external demand for transparency and timely decision-making in supply chains. IQ is crucial in determining how effectively BDA can meet these demands, as poor-quality data undermines analytical reliability and obstructs SCV (Taleb et al., 2018; Kankam et al., 2023). Moreover, contingency theory highlights the importance of contextual factors in shaping outcomes. For BDA to successfully enhance SCV, the data must be relevant to the context, comprehensive, and aligned with the specific needs of the supply chain (Malhotra et al., 2005; Stvilia et al., 2007). Thus, IQ functions as a contextual factor, influencing the strength and nature of the relationship between BDA and SCV.

The contingency theory provides a robust framework for explaining how IQ enhances the relationship between BDA and SCV. This theory emphasizes the importance of aligning internal capabilities with external demands and demonstrates how high-quality information enhances BDA's effectiveness in improving SCV. The assumptions of contingency theory contextual relevance, fit, and alignment are highlighted by IQ's role in ensuring the reliability and applicability of data-driven insights. The extensive prior applications of the theory underscore its importance for elucidating the conditional aspects of the BDA-SCV relationship, providing a solid theoretical foundation for this research. This study enhances the understanding of how organizations can optimize their use of BDA to improve SCV by incorporating contingency theory, emphasizing that success depends on the quality of their information.

2.2 Conceptual Review

This part of the research focuses on several key ideas, including the analysis of massive datasets, the degree of transparency within a supply chain, the caliber of information being shared, and how effectively the supply chain actually functions.

2.2.1 Big Data Analytics

Big Data Analytics (BDA) has become a powerful driver of change in contemporary organisations, equipping firms with the capacity to transform extensive and intricate datasets into practical knowledge that supports action. The idea of big data is commonly explained through the "3Vs" (volume, velocity, and variety) which capture the magnitude, rapid generation, and heterogeneous nature of information produced within today's digitally connected environment (Laney, 2001; Chen et al., 2012). As digital ecosystems have evolved, scholars have extended this model by introducing further characteristics, notably veracity (the reliability and precision of data) and value (the potential of data to generate meaningful insight), thereby highlighting the increasing centrality of data integrity in informed decision-making processes (Gandomi & Haider, 2015; Ishwarappa & Anuradha, 2015). In this context, BDA encompasses the structured methods, technological platforms, and analytical approaches applied to massive datasets in order to reveal underlying relationships, recurring patterns, and emerging trends that guide organisational strategy (Wamba et al., 2015; Gupta & George, 2016). This progression reflects a fundamental transition from simply storing and administering data to deliberately exploiting it as a strategic resource capable of generating sustained competitive benefits. Drawing on the conceptualisation advanced by Gupta and George (2016), this study conceptualises BDA as an organised and methodical approach to gathering, transforming, examining, and interpreting large datasets so as to identify significant patterns, associations, and trends that facilitate evidence-based managerial choices.

Understanding BDA requires careful attention to the foundational dimensions of big data, commonly described as volume, velocity, and variety. Volume captures the immense quantities of information produced continuously across digital platforms, often surpassing the processing limits of conventional database systems (Hashem et al., 2015; McAfee & Brynjolfsson, 2012). The rapid escalation of data accumulation has therefore encouraged the adoption of sophisticated infrastructural solutions, including cloud-based architectures and distributed storage frameworks designed to handle large-scale computational demands. Velocity focuses on the rapid pace at which information is generated and transmitted, especially in environments where immediate analysis is essential, such as algorithmic financial markets or logistics coordination systems

(Gandomi & Haider, 2015; Ishwarappa & Anuradha, 2015). Because data flows in continuously, organisations require advanced analytical mechanisms that can process and interpret information almost instantaneously to enable prompt and informed responses. Variety, on the other hand, refers to the wide spectrum of data formats encountered in modern settings, ranging from structured numerical records to semi-structured logs and unstructured content such as text, audio, or images (Lam et al., 2017; Ghasemaghaei & Calic, 2019). Effectively working with such diverse inputs necessitates adaptable integration strategies and versatile analytical techniques capable of synthesising information from multiple and often disparate sources.

The ways in which BDA is assessed have developed in parallel with its theoretical growth. In its early stages, evaluation efforts concentrated primarily on technological strength, including system capacity for handling large datasets and the advancement of analytical applications deployed within organisations (Bharadwaj et al., 2013; Gantz & Reinsel, 2012). Over time, however, researchers recognised that technological infrastructure alone does not guarantee meaningful outcomes. Consequently, greater attention has been directed toward organisational competencies, such as effective data management practices, specialised analytical expertise, and the successful incorporation of analytical findings into everyday strategic planning (Mikalef et al., 2018; Dubey et al., 2019a). Building on this broader perspective, Mikalef et al. (2020) introduced an integrated model for evaluating BDA capability that includes elements of technological infrastructure, leadership competence, and the organisational capacity to convert analytical outputs into implementable initiatives. This reconceptualisation highlights that the true significance of BDA extends beyond computational power; its strategic impact ultimately depends on how effectively organisations mobilise data-driven insights to shape decisions and achieve long-term objectives.

BDA has been widely adopted across various sectors, demonstrating its versatility and impact. In supply chain management, BDA enhances visibility, optimizes inventory levels, and improves demand forecasting, thereby increasing efficiency and resilience (Kamble & Gunasekaran, 2020; Belhadi et al., 2020). In healthcare, it enables early disease diagnosis, personalized treatment plans, and operational efficiency by analyzing patient data and medical records (Mehta et al., 2020). The financial sector leverages BDA for risk assessment, fraud detection, and algorithmic trading, where real-time data analysis is critical for decision-making (Hansen, 2020; Razzaq & Yang, 2023). Additionally, in retail and e-commerce, BDA drives customer insights, personalized marketing, and supply chain optimization, enhancing customer satisfaction and operational performance (LaValle et al., 2011; Tiwari et al., 2018). These applications underscore BDA's role as a cross-industry enabler of innovation and efficiency.

Big data analytics has become valuable because it turns raw information into a core organizational asset that shapes strategy and fuels innovation. When companies are equipped with timely data and forecasting tools, they can detect emerging trends, adjust to shifts in the environment, reduce exposure to potential threats, and capitalize on promising developments (Wamba et al., 2017; Dubey et al., 2019a). In fast-changing contexts, this capability strengthens responsiveness by drawing on extensive datasets collected from diverse channels, which helps lower ambiguity and supports better strategic coherence (Mikalef et al., 2018; Gupta & George, 2016). Beyond operational advantages, it also encourages a mindset in which managerial judgments are reinforced by empirical evidence rather than relying solely on experience or instinct, ultimately improving the precision and reliability of organizational decisions (Merendino et al., 2018; Al-Kofahi et al., 2023). As a result, the way institutions design strategies and address challenges has evolved considerably, reflecting a deeper integration of data into everyday decision processes.

2.2.2 Supply Chain Visibility

Within the field of supply chain management, Supply Chain Visibility (SCV) has emerged as a cornerstone concept, acknowledged for its contribution to smoother operations, more informed strategic choices, and effective teamwork (Brusset, 2016; Sodhi & Tang, 2019). The academic literature provides a range of interpretations for SCV, highlighting its multi-dimensional character. Schoenthaler (2003), for example, frames SCV as the accessibility of data required to supervise, manage, and adapt both the overarching strategy and day-to-day activities of a supply chain, covering everything from initial sourcing to final product delivery. In a related view, McCrea (2005) portrays it as the capacity to get notifications regarding variations in supply chain processes and to take suitable action. Expanding on these ideas, Barratt and Oke (2007) suggest that SCV signifies the degree to which members of a supply chain network are able to obtain or exchange crucial information that offers reciprocal advantages for their respective activities.

Taken together, these perspectives underscore that effective SCV rests on information that is not only correct and current but also immediately useful, cementing its position as a fundamental building block of contemporary supply chain management. Drawing from the conceptualizations offered by Barratt and Oke (2007) and McCrea (2005), this research treats SCV as the continuous, up-to-the-minute observation and exchange of supply chain data, particularly concerning stock levels and customer demand among collaborating entities. This approach is designed to improve oversight, allow for rapid reaction to interruptions, and encourage unified strategic choices.

The core characteristics that define SCV, namely its accessibility, correctness, currency, thoroughness, and significance, are vital in enabling sound judgments and effective process oversight (Somapa et al., 2018; Williams et al., 2013). These qualities guarantee that the data circulated across the supply network holds real value, contributing to heightened operational effectiveness, shorter fulfillment cycles, and superior quality outcomes (Lee & Rammohan, 2017; Swift et al., 2019). Beyond these operational benefits, SCV plays an indispensable part in managing risks, building resilience, and advancing sustainability. It equips companies to more effectively foresee and navigate disturbances, adjust to evolving market conditions, and put eco-conscious methods into practice (Sodhi & Tang, 2019; Bechtsis et al., 2021). By granting firms immediate visibility into their stock positions, patterns in consumer demand, and broader market movements, SCV allows them to steer their supply chains with foresight, ultimately boosting their performance and competitive edge.

Beyond improving day-to-day operations, SCV significantly strengthens coordination and cohesion across supply chain partners. When timely and accurate information flows seamlessly among participants, confidence grows and working relationships become more stable, creating a foundation for long-term effectiveness (Barratt & Oke, 2007; Caridi et al., 2014). Evidence from Baah et al. (2020) and Dubey et al. (2020) indicates that immediate access to critical data helps synchronize partner activities, thereby boosting the speed and adaptability of the entire network. With this level of transparency, organizations are better positioned to respond quickly to shifting customer expectations and unexpected disruptions, leading to stronger overall performance. In the same vein, findings reported by Fawcett et al. (2007) and Brusset (2016) demonstrate that SCV promotes mutual confidence, clearer allocation of responsibilities, and better strategic alignment—elements that play a decisive role in achieving effective integration across supply chains.

2.2.3 Information Quality

Information Quality (IQ) is a critical concept in data management and analytics, reflecting the degree to which information meets its users' needs in terms of accuracy, relevance, timeliness, and completeness. Defined by Wang and Strong (1996) as "fitness for use," IQ emphasizes the importance of data being not only technically sound but also contextually appropriate for decision-making. Over the years, IQ has been further elaborated to include dimensions such as consistency, reliability, and interpretability, highlighting its multifaceted nature (Naumann & Rolker, 2000; Stvilia et al., 2007). These definitions collectively underscore the role of IQ as a foundational element for effective data-driven decision-making, ensuring that the insights derived from data are both trustworthy and actionable.

The measurement of IQ has evolved significantly, reflecting the growing complexity of data environments and the increasing reliance on data for strategic decisions. Early approaches to measuring IQ focused on technical attributes such as accuracy, completeness, and timeliness (Miller, 1996; Malhotra et al., 2005). However, as organizations began to recognize the broader implications of data quality, measurement frameworks expanded to include contextual and representational dimensions. For instance, Wang and Strong (1996) proposed a comprehensive framework categorizing IQ into four dimensions: intrinsic (e.g., accuracy, reliability), contextual (e.g., relevance, timeliness), representational (e.g., interpretability, ease of understanding), and accessibility (e.g., availability, security). This multidimensional approach has been widely adopted and adapted, with recent studies emphasizing the importance of aligning

IQ metrics with organizational goals and user needs (Taleb et al., 2018; Kankam et al., 2023).

The value of information quality (IQ) stems from its capacity to strengthen the dependability and impact of decisions informed by data. When information is accurate, consistent, and relevant, the outcomes derived from analytical processes become more trustworthy and practically useful, enabling sound strategic and day-to-day management choices (Stvilia et al., 2007; Naumann & Rolker, 2000). Conversely, weaknesses in information quality may produce misleading interpretations, poor judgment, and reduced organizational effectiveness, thereby weakening the overall contribution of data analytics efforts (Taleb et al., 2018; Malhotra et al., 2005). In addition, high information quality supports confidence and cooperation among stakeholders, since dependable and timely data underpin clear communication and coordinated action (Kankam et al., 2023; Naumann & Rolker, 2000). This makes IQ a critical enabler of organizational agility, resilience, and competitiveness in a data-driven world.

IQ has been applied across various sectors, demonstrating its universal relevance and impact. In healthcare, high IQ is essential for accurate patient diagnosis, effective treatment planning, and efficient resource allocation, directly impacting patient outcomes and operational efficiency (Stvilia et al., 2007). In finance, IQ ensures the accuracy of financial reports, supports risk assessment, and enhances regulatory compliance, thereby safeguarding organizational integrity and stakeholder trust (Malhotra et al., 2005). The retail sector leverages IQ to optimize inventory management, personalize customer experiences, and improve supply chain visibility, driving customer satisfaction and operational efficiency (Taleb et al., 2018). Additionally, in logistics and transportation, IQ is critical for real-time tracking, route optimization, and demand forecasting, enhancing overall supply chain performance (Kankam et al., 2023). These applications highlight the pivotal role of IQ in enabling data-driven innovation and efficiency across industries.

2.2.4 Supply Chain Performance

Supply Chain Performance (SCP) has increasingly become a central idea in contemporary business practice, capturing how well organizations coordinate and execute supply chain activities to meet their strategic objectives. Mirii-Lavassani and Movehedi (2018) describe it as the deliberate management of relationships within the supply chain in a way that promotes quality, equity, trust, and financial gains. This perspective places strong emphasis on cooperation and strategic alignment among partners across the network.

In recent years, the understanding of SCP has broadened beyond a narrow focus on cost reduction to include dimensions such as responsiveness to customers, operational flexibility, and the capacity for innovation. This broader outlook mirrors the rising intricacy of global supply networks (Sezen, 2008; Baah et al., 2020). The development in thinking reflects a transition from treating SCP purely as an operational measurement to recognizing it as a key strategic resource that supports competitive positioning and enhances value for customers (Christopher & Gaudenzi, 2009; Chand et al., 2020). Inferring from the definitions proposed by Gunasekaran et al., (2001), Beamon, (1999), and Mirii-Lavassani and Movehedi (2018) this study conceptualises SCP as the systematic measurement and optimisation of supply chain activities to achieve cost efficiency, product quality, and timely delivery while maintaining flexibility to meet dynamic consumer demands. The way supply chain performance (SCP) is assessed has evolved considerably over time. Initial evaluation methods were relatively narrow, relying heavily on cost-related indicators and a few operational measures. In those early approaches, emphasis was placed on variables such as cost efficiency, responsiveness to customers, and cycle or activity time as the primary indicators of performance (Arntzen et al., 1995; Pyke & Cohen, 1994). While these measures provided useful insights, they did not fully reflect the complexity of modern supply chains. Their limited scope prompted researchers to design broader and more integrative assessment models.

Responding to these limitations, more comprehensive measurement systems were introduced. For example, Beamon (1999) proposed a multidimensional framework that evaluates SCP across several categories, including resource utilization (such as inventory expenditure and return on investment), outcomes (such as customer satisfaction levels and sales performance), and adaptability (including product flexibility and volume responsiveness). This model has influenced subsequent research and has been refined in various contexts. Contemporary scholarship increasingly combines both numerical indicators and qualitative assessments to achieve a richer and more balanced evaluation of performance (Cai et al., 2009; Gandhi et al., 2017). Alongside conventional indicators like cost efficiency and lead time, newer dimensions such as customer satisfaction, supplier effectiveness, and the quality of information exchange have become central to performance assessment. This shift highlights the growing recognition that SCP should be measured using an integrated and balanced set of criteria (Ahi & Searcy, 2015; Bulsara et al., 2014).

The relevance of SCP extends beyond measurement; it plays a critical role in enhancing organizational competitiveness and long-term success within highly connected and rapidly changing markets. As competitive pressure increasingly operates at the level of entire supply networks rather than individual firms, performance across the chain has become a decisive factor influencing market position, customer loyalty, and financial outcomes (Reddy et al., 2019; Katiyar et al., 2018).

Effective SCP enables organizations to respond swiftly to market fluctuations, reduce operational costs, and deliver customized products and services, thereby enhancing customer value (Lee, 2002; Hernández-Espallardo et al., 2010). Moreover, SCP measurement systems provide critical insights into supply chain efficiency, helping organizations identify bottlenecks, align goals, and implement continuous improvement strategies (Laihonen & Pekkola, 2016; Handfield et al., 2014). This strategic focus on SCP has made it an indispensable tool for achieving sustainable competitive advantage. SCP has been applied across various sectors, demonstrating its versatility and impact.

In the context of production, applying supply chain performance measurements allows companies to streamline their manufacturing workflows, cut down on delays between order and delivery, and handle stock more effectively, all of which boosts how smoothly operations run (Shafiee et al., 2014; Miani et al., 2023). When you look at the retail sector, businesses lean on SCP models to keep their customers happier by responding more quickly to demand and making sure products are actually on the shelf when people want them (Gandhi et al., 2017). The healthcare sector leverages SCP to streamline the supply of medical supplies, ensuring timely delivery and reducing costs (Aramyan et al., 2007). Additionally, in logistics and transportation, SCP metrics are critical for improving delivery accuracy, reducing transportation costs, and enhancing overall supply chain resilience (Cuthbertson & Piotrowicz, 2011; Berrah & Vernadat, 2012). These applications highlight the universal relevance of SCP in driving efficiency and value creation across industries.

2.3 Empirical Review

This section examines the existing empirical literature related to the variables studied in the research, with a specific emphasis on the relationships established by the research model.

2.3.1 Big Data Analytics and Supply Chain Performance

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A comprehensive quantitative study by Bahrami et al. (2022) delved into the relationship between big data analytics (BDA) and its impact on supply chain resilience, innovation, and overall company performance. The core objective was to pinpoint how proficiency in BDA influences the effectiveness of supply chains, focusing specifically on the indirect routes through resilience and creative problem-solving. To test their hypotheses, the team employed a cross-sectional research design, collecting firsthand information via structured surveys completed by 187 individuals. After gathering all the data, they performed an assessment using partial least squares structural equation modeling (PLS-SEM) with SmartPLS3 software, a method particularly effective for examining complex links between unobservable variables. The findings from their analysis revealed a clear pattern: organizations with robust BDA skills tend to see a marked improvement in their supply chain operations. More critically, the research suggested that companies utilizing sophisticated data analysis are more adept at anticipating possible interruptions and reacting quickly to operational hurdles, thereby boosting their flexibility and overall robustness.

Taking a slightly different angle, Bahrami and Shoukouhyar (2021) explored how big data analytics capabilities (BDAC) contribute to strengthening a supply chain's robustness and a company's success, framing their investigation within the dynamic capabilities theory. This work aimed to clarify the mechanism through which BDAC leads to better organizational results, paying special attention to the intermediary function of resilience and the contextual role played by an organization's attitude toward managing risk. For this inquiry, a cross-sectional survey was again the method of choice, with data gathered from 167 high-level IT professionals possessing substantial expertise in data-informed decision-making. The information was then scrutinized with partial least squares structural equation modeling (PLS-SEM) via SmartPLS3, facilitating a comprehensive look at the web of relationships in their theoretical framework. According to their results, BDAC exerts a strong, beneficial influence on supply chain resilience, mainly by fostering greater innovative potential and refining the caliber of internal communications. This increased resilience, in turn, serves as a direct pathway to enhanced company performance. Moreover, the study uncovered that an organization's risk management culture plays a pivotal part in this process; firms with a deeply embedded, proactive approach to risk are considerably more effective at turning their resilient qualities into concrete, improved business outcomes.

Dubey et al. (2018) examined the organizational conditions and strategic processes that enable firms to adopt big data analytics (BDA) in ways that strengthen supply chain agility (SCA) and support sustained competitive advantage. Drawing on the dynamic capabilities perspective alongside contingency theory, the study conceptualized BDA as a capability that interacts with internal and external factors to shape performance outcomes. The authors also assessed how organizational flexibility and environmental uncertainty influence these relationships. To test their hypotheses, they administered a validated survey instrument and obtained 173 usable responses for statistical analysis. The results indicated that BDA contributes positively and significantly to both supply chain agility and competitive advantage, reinforcing its role as a critical dynamic resource within contemporary supply chain systems. Furthermore, the analysis showed that organizational flexibility strengthens the link between BDA and SCA, implying that firms with adaptable structures and processes are better positioned to convert analytics capabilities into enhanced responsiveness.

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Investigating the mechanisms that connect big data analytics capabilities (BDAC) with enhanced supply chain performance (SCP) was the central focus of a study by Al-Khatib and Ramayah (2022). Their research specifically examined the role of supply chain innovation (SCI) as a key link in this relationship, while also considering the impact of a data-driven culture (DDC) as a factor that could strengthen or weaken this connection. The core aim was to shed light on how an organization's ability to analyze data actually produces tangible improvements and to what extent company values influence this process. To conduct their study, the researchers distributed an online questionnaire to manufacturing companies located in Jordan. From this effort, they obtained 420 usable responses. The subsequent analysis was carried out using partial least squares structural equation modeling (PLS-SEM) through the SmartPLS 3.3.9 software package. What the empirical evidence showed was that big data analytics significantly boosts both SCI and SCP. This indicates that possessing sophisticated analytical tools empowers companies to not only refine their innovative practices but also to see better results in their day-to-day operations. Furthermore, the research confirmed that SCI acts as a crucial intermediary. This means that innovation processes are the essential bridge that turns investment in analytics into concrete performance gains. Finally, the study revealed that a deeply embedded data-driven culture serves to amplify the positive effect of SCI on SCP. This finding underscores the significant strategic advantage of fostering workplace norms that champion decisions based on evidence, as this is key to getting the most out of innovation efforts.

In a related study, Fantazy and Tipu (2023) set out to understand how big data analytics (BDA) contributes to stronger sustainable supply chain performance (SSCP), with a special emphasis on the part played by knowledge development (KD). They sought to illuminate the specific pathways through which analytical power leads to sustainability-related achievements, breaking KD down into its four core components: acquiring new knowledge, sharing information across the organization, building a mutual understanding, and retaining what the company has learned over time. Information was collected via a structured questionnaire completed by 300 manufacturing firms. To test their theoretical model, the researchers applied structural equation modeling (SEM). The analysis uncovered significant and positive connections between every dimension of knowledge development and both BDA and SSCP. This points to the unifying role that knowledge-focused activities play in connecting analytical capabilities with sustainability outcomes. Interestingly, the data did not show a direct influence of BDA on SSCP. Instead, the effect of analytics on sustainability performance was entirely channeled through knowledge development. This crucial finding implies that simply having analytical tools is not enough to drive sustainability improvements. For long-term benefits to materialize, businesses must actively work to translate insights gleaned from data into shared knowledge and collective learning throughout the organization.

Adopting a perspective rooted in the relational view of resource-based theory, Fernando et al. (2018) examined the combined influence of big data analytics, data security measures, and the capacity for service supply chain innovation on overall service supply chain performance. The research team gathered data through surveys from 145 companies operating within the service sector. Their analysis explored how technological assets and relational resources interact. The results showed that BDA boosts a firm's ability to handle data security proficiently. At the same time, it was found to reinforce both the company's innovative capacity and its overall performance within the service supply chain. The study also made an interesting observation: many companies appeared to be using BDA mainly for operational purposes. Its application was largely confined to processing large datasets more quickly through standard analytical routines, suggesting that its transformative strategic potential had yet to be fully tapped. Despite this, the findings clearly illustrate the value of analytics for improving efficiency and streamlining processes, while also hinting at its broader promise as a catalyst for performance gains driven by innovation.

Kibe et al. (2020) analyzed the influence of big data analytics on organizational performance within Kenyan technical universities, employing a mixed-methods design. Data were obtained through questionnaires and interviews involving ICT personnel and institutional users from the Technical University of Kenya (TUK) and another university in Nairobi, supplemented by secondary data sources. Descriptive statistical analysis indicated that big data analytics was associated with improvements in indicators such as innovation, creativity, effectiveness, productivity, and operational efficiency across both institutions. However, differences emerged in other performance dimensions. While the second university (SU) demonstrated positive relationships between analytics adoption, competitiveness, and profitability, TUK exhibited negative associations in these areas. Regression analysis further revealed that big data analytics more strongly predicted performance outcomes at SU than at TUK, suggesting variations in institutional readiness, infrastructure, or implementation strategies. These findings emphasize that the impact of analytics is shaped by contextual factors and organizational capacity, leading to differing levels of performance enhancement.

Su et al. (2021) examined the relationship between big data analytics (BDA) and organizational performance, placing particular emphasis on the role of dual innovation namely, product innovation and process innovation as a mediating mechanism. Their analysis was informed by the resource-based view (RBV) and was based on survey responses obtained from 309 participants employed in manufacturing companies in China. jThe analysis examined both the direct effects of BDA on performance and its indirect effects through innovation activities. Results showed that BDA contributes to organizational performance, partly through its role in stimulating product and process innovations, indicating that analytical capability supports competitiveness not only by improving efficiency but also by enabling firms to develop new offerings and refine internal operations. The findings confirmed that BDA significantly enhances organizational performance, with dual innovations acting as a key mediator in this relationship. Specifically, BDAC enables firms to generate actionable insights that strengthen both product and process innovation, which in turn positively influence overall performance. This study advances prior research by distinguishing BDA's direct and indirect effects, demonstrating that while BDA independently improves performance, its full potential is realized when coupled with innovation capabilities. The results emphasise the strategic importance of integrating Big Data analytics with innovation management to maximize organizational outcomes in competitive manufacturing environments.

Kumar and Raj (2024) conducted a meta-analysis of 76 empirical studies, comprising 205 effect sizes, to investigate how the adoption of big data (BD) enhances innovation capability, supply chain integration (SCI), resilience (SCRes), and overall organisational performance, grounded in organisational information processing theory. Their findings demonstrate that BA directly improves innovation capability, as well as SCI and SCRes, all of which contribute to better organisational performance. Innovation capability was identified as a more significant mediator between BA and SCI than BA and SCRes. However, both SCI and SCRes played equal roles in translating innovation benefits into performance outcomes. Meta regression analysis indicated that developing economies derive greater innovation advantages from BA. At the same time, factors such as national culture and digital competitiveness (assessed through DCS and GDP per capita) significantly influenced these relationships. This study underscores the strategic importance of BA in fostering innovation and supply chain agility, particularly in culturally diverse and emerging economic contexts, providing valuable insights for prioritising initiatives driven by BD.

Studies consistently demonstrate that big data analytics significantly enhances supply chain performance across diverse contexts and industries. Prior research shows that big data analytics improves operational efficiency, agility, resilience, innovation, and competitive advantage by enabling data-driven decision making and real-time responsiveness (Dubey et al., 2018; Bahrami et al., 2022; Al Khatib & Ramayah, 2022). Evidence from manufacturing and service sectors indicates that firms with strong analytics capabilities achieve superior cost efficiency, delivery reliability, flexibility, and customer responsiveness. Meta-analytic and cross-country studies further confirm that the performance benefits of big data analytics are particularly pronounced in developing and emerging economies, where information asymmetries and environmental uncertainty are higher. The literature provides robust empirical support for a direct positive relationship between big data analytics and supply chain performance. ***H1: Big data analytics has a positive and significant effect on supply chain performance.***

Table 2.1: Summary of Empirical Review

Author(s) & Year	Topic/Purpose	Theories	Study Area/Context	Key Findings
Bahrami et al. (2022)	Examined the relationship between BDA, supply chain resilience, innovation, and supply chain performance		Supply chain context	BDA significantly enhances supply chain performance by improving resilience and innovation, enabling organisations to respond effectively to disruptions.
Bahrami & Shoukouhyar (2021)	Investigated the effect of BDAC on supply chain resilience and firm performance	Dynamic Capabilities Theory	IT executives across organisations	BDAC improves supply chain resilience and firm performance. Risk management

	with risk management culture as moderator			culture strengthens the relationship between resilience and performance.
Dubey et al. (2018)	Examined how BDA enhances supply chain agility and competitive advantage	Dynamic Capabilities Theory and Contingency Theory	Multi-industry organisational context	BDA positively influences supply chain agility and competitive advantage. Organisational flexibility strengthens the BDA–agility relationship.
Al-Khatib & Ramayah (2022)	Investigated BDA influence on supply chain performance through supply chain innovation and data-driven culture		Manufacturing sector in Jordan	BDA improves supply chain performance both directly and indirectly through supply chain innovation. Data-driven culture strengthens performance outcomes.
Fantazy & Tipu (2023)	Examined BDA and sustainable supply chain performance through knowledge development	Knowledge-Based View / Organisational Learning perspective	Manufacturing organisations	Knowledge development fully mediates the BDA–sustainable supply chain performance relationship. BDA requires knowledge integration to improve sustainability outcomes.
Fernando et al. (2018)	Investigated impact of BDA, data security, and	Relational View of Resource-Based Theory	Service firms	BDA improves service supply chain performance

	innovation capabilities on service supply chain performance			through enhanced data security and innovation capabilities, mainly improving operational efficiency.
Kibe et al. (2020)	Examined the effect of BDA on organisational performance		Kenyan Technical Universities	BDA improves innovation, efficiency, and effectiveness. However, performance outcomes vary depending on institutional capacity to implement analytics.
Su et al. (2021)	Examined BDA influence on organisational performance through dual innovation	Resource-Based View (RBV)	Chinese manufacturing firms	BDA improves organisational performance directly and indirectly through product and process innovation.
Kumar & Raj (2024)	Meta-analysis examining BDA impact on innovation, supply chain integration, resilience, and performance	Organisational Information Processing Theory	Cross-country and multi-industry	BDA enhances innovation capability, supply chain integration, and resilience, leading to improved performance. Effects are stronger in developing economies.

2.3.2 Big Data Analytics and Supply Chain Visibility

A 2023 study by Chatterjee and colleagues explored how leveraging large-scale data analysis reshapes company decision-making, sharpens forecasting, and influences overall corporate success. To build their case, they gathered input from 366 individuals and employed Partial Least Squares Structural Equation Modeling to examine a conceptual model connecting the use of data analytics with tangible business achievements. Their findings reveal that incorporating these analytical tools significantly improves the quality of managerial choices and the precision of future projections. These advancements, in turn, pave the way for superior fiscal returns and smoother operational workflows, ultimately boosting a company's comprehensive performance. The research further clarifies that enhancements in monetary and functional areas act as crucial links, explaining how the adoption of analytics leads to widespread corporate gains. Moreover, the evidence points to data analytics playing a key role in trimming operational costs and facilitating more astute strategic choices. In essence, the study positions sophisticated data analysis as a vital strategic asset, one that solidifies a company's market position and secures enduring benefits (Chatterjee et al., 2023).

Turning to the pharmaceutical industry in Jordan, Al-Khatib (2022) explored the connections between the Internet of Things (IoT), big data analytics, supply chain visibility, and operational efficiency. The research methodology relied on covariance-based structural equation modeling, with data processed using Amos 25 software. Before diving into the main hypothesis tests, the researcher first validated the measurement instruments by checking for reliability and both convergent and discriminant validity. A confirmatory factor analysis was also run to ensure the theoretical model accurately represented the collected data. The outcomes clearly demonstrate that both IoT and big data analytics have a strong, beneficial effect on how visible the supply chain is and how well it performs operationally. Furthermore, the study found that supply chain visibility itself significantly boosts operational results. It also became apparent that visibility acts as a mediating factor; in other words, IoT and big data analytics improve performance not only directly but also indirectly by fostering greater transparency and smoother information exchange across the entire supply chain network. This investigation underscores the strategic necessity of embracing these technologies within pharmaceutical supply chains to boost productivity and cement a competitive edge, all while offering a data-backed model for tech-driven performance gains.

In a separate line of inquiry, Jian et al. (2025) looked into how a company's capacity for big data analytics affects the resilience of its supply chain, paying close attention to the mediating roles of visibility and flexibility. Rooted in dynamic capability and inertia theories, the research carefully distinguishes between two types of resilience—proactive and reactive—and examines how analytical abilities contribute to each. After surveying 277 manufacturing companies in China, the team analyzed the feedback using partial least squares structural equation modeling. The results show that big data analytics capabilities significantly boost a supply chain's reactive resilience, or its ability to bounce back from disruptions. Interestingly, the study found no meaningful statistical link between these analytical capabilities and proactive resilience, which involves anticipating and preparing for future challenges. The research further confirms that both supply chain visibility and flexibility serve as intermediary links in the chain connecting data analytics to resilience. However, the nature of these mediating effects shifts depending on whether the focus is on proactive or reactive resilience. Overall, the evidence paints a picture of a complex relationship, suggesting that the impact of big data analytics on supply chain resilience is highly dependent on specific contextual elements. Consequently, the authors advise businesses to carefully weigh both their internal organizational traits and the external business landscape when crafting data-centric strategies aimed at bolstering resilience.

Shifting focus to the humanitarian sector, Jeble and colleagues (2019) explored how big data, predictive analytics, and social capital work together to boost performance in aid supply chains. Framed by the resource-based view and social capital theory, the team conducted a thorough review of existing literature to propose a conceptual model. This model posits that big data and predictive analytics, when treated as core organizational capabilities, can significantly improve the speed and effectiveness of humanitarian missions. Their analysis highlights the foundational role of social capital, as it forges critical connections among individuals, aid organizations, and local communities. These relational networks are essential for quickly gathering financial support and other necessary resources during a crisis. The study goes on to argue that the real power emerges when this social capital is strategically combined with big data and predictive analytics, leading to dramatically better outcomes. This fusion underscores the absolute necessity of pairing technological tools with strong human networks to achieve faster response times, better coordination, and greater overall impact in managing humanitarian emergencies.

In the context of service industries, Fernando et al. (2018) investigated how big data analytics, information protection methods, and a company's capacity for innovation drive performance. Using a relational perspective within resource-based theory, they crafted a conceptual framework and put it to the test with data from 145 service-based companies. Their analysis shows that adopting big data analytics plays a pivotal role in strengthening data governance and sparking greater innovation within the organization. These improved capabilities then directly lead to better performance across various service supply chain activities. The research also uncovered that many service providers initially use big data analytics mainly to refine existing processes, often by handling larger volumes of data with standard analytical tools. While this certainly leads to operational gains, the authors contend that the truly significant benefits of big data analytics are realized when it's used to foster innovation and fortify data security. They argue these two elements are the real drivers of sustained performance improvement in service-oriented supply chains.

Finally, Shi and his team (2022) delved into the specific mechanisms and contextual factors that influence how big data analytics capability affects green supply chain integration. Grounded in organizational information processing theory, they looked at supply chain visibility as a key mediator and organizational culture as a key moderator. After collecting survey data in two stages from 317 companies operating in China, they applied hierarchical regression analysis along with bootstrapping methods to test their hypotheses. The findings indicate that a strong big data analytics capability not only improves internal coordination within a company but also forges tighter links with both suppliers and customers when it comes to environmentally sustainable supply chain practices. This suggests that the ability to process and analyze large amounts of data is crucial for building the kind of integrated, eco-friendly supply networks that are increasingly vital in today's business world.The results also reveal that supply visibility functions as a mediator across all three dimensions, whereas demand visibility serves as a mediator only for internal and customer integration. These outcomes demonstrate that visibility operates as a critical pathway linking analytics capability to sustainabilityoriented integration, while organizational culture shapes the strength of these relationships.

A growing body of empirical research further confirms that big data analytics enhances supply chain visibility by enabling more timely data capture, smoother information exchange, and greater transparency throughout interconnected networks. Evidence suggests that analytical tools allow firms to monitor inventory levels, demand fluctuations, and logistics activities with improved accuracy, thereby minimizing uncertainty and strengthening coordination among partners (Al Khatib, 2022; Shi et al., 2022; Jian et al., 2025). Studies informed by information processing theory and the dynamic capabilities framework also indicate that insights generated through analytics reinforce visibility structures, which are essential for continuous monitoring and effective disruption management. Overall, the literature consistently identifies a strong positive relationship between the adoption of big data analytics and improvements in supply chain visibility. ***H2: Big data analytics has a positive and significant effect on supply chain visibility.***

Table 2.2: Summary of Empirical Review

Author(s) & Year	Topic/Purpose	Theories Employed	Study Area/Context	Key Findings
Chatterjee et al. (2023)	Examined the effect of big data analytics adoption on decision-making, forecasting, and firm performance		Multi-industry organisational context	BDA improves decision-making and forecasting capabilities, which enhance financial and operational performance. These outcomes mediate overall firm performance and reduce operational costs.

Al-Khatib (2022)	Examined the influence of IoT and BDA on supply chain visibility and operational performance		Pharmaceutical manufacturing sector in Jordan	IoT and BDA significantly improve supply chain visibility and operational performance. Supply chain visibility mediates the relationship between BDA and operational performance.
Jian et al. (2025)	Investigated the influence of BDA capabilities on supply chain resilience through flexibility and visibility	Dynamic Capability Theory and Inertia Theory	Manufacturing firms in China	BDA capabilities significantly enhance reactive supply chain resilience. Supply chain visibility and flexibility mediate the relationship between BDA and resilience but influence proactive and reactive resilience differently.
Jeble et al. (2019)	Examined the role of big data analytics, predictive analytics, and social capital in humanitarian supply chain performance	Resource-Based View and Social Capital Theory	Humanitarian supply chain context	Integration of big data analytics and social capital improves humanitarian supply chain performance by enhancing coordination, responsiveness, and resource mobilisation.
Fernando et al. (2018)	Investigated the influence of BDA, data security management, and innovation capabilities on service supply	Relational View of Resource-Based Theory	Service supply chain sector	BDA enhances service supply chain performance through improved data security and innovation capabilities, mainly improving operational

	chain performance			efficiency and process performance.
Shi et al. (2022)	Examined how BDA capability influences green supply chain integration through supply chain visibility	Organisational Information Processing Theory	Chinese firms	BDA significantly improves green supply chain integration. Supply visibility mediates the relationship between BDA and internal, supplier, and customer integration. Organisational culture moderates these relationships.

2.3.3 Moderating Role of Information Quality

No empirical studies have examined the moderating role of information quality in the nexus between big data analytics and supply chain visibility. However, various studies have employed SCV as an independent variable, a mediator, and a moderator in different relationships. For example Zuo and Lin (2022) investigated the contingent effects of government R&D subsidies on firm innovation by analysing 11,853 firm-year observations from Chinese listed companies (2007-2015). Their study revealed two key findings: First, government subsidies significantly increased both R&D inputs (investment) and outputs (patents). Second, accounting information quality (IQ) served as a critical moderator, with a one standard deviation improvement in IQ amplifying subsidy effectiveness by 16% for R&D investment and 4% for input growth. Notably, the positive effect on patent outputs was particularly pronounced in high-IQ firms. These results demonstrate that transparent financial reporting enhances the innovation impact of public R&D support by reducing information asymmetries, providing empirical evidence that subsidy effectiveness depends on recipient firms' information environments. The study advances innovation policy literature by quantifying how corporate governance characteristics mediate public intervention outcomes.

Hani (2022) investigated the relationship between supply chain management practices (SCMPs) and supply chain performance (SCP), with a specific focus on the moderating role of information quality. Using structural equation modelling (SEM) to analyse causal relationships, the study revealed two key findings: first, both SCMPs and information quality had significant direct effects on SCP; second, and more importantly, information quality served as a positive moderator that strengthened the relationship between SCMPs and SCP. These results suggest that while effective supply chain practices directly enhance performance, their impact is substantially amplified when implemented in conjunction with high-quality information systems. The study contributes to supply chain literature by empirically demonstrating how information quality acts as a critical contingency factor that determines the effectiveness of management practices, highlighting the need for organizations to simultaneously invest in both operational improvements and information infrastructure to maximize supply chain performance.

Sukumana et al. (2021) examined the roles of e-quality, incident management, and quality management in stimulating training among government employees in Indonesia. The investigation of the moderating role of quality information systems among the links of e-quality, incident management, quality management, and training stimulation of government employees is also included in the objectives of the study. The study has used a quantitative method, collecting data through questionnaires and analyzing them using SmartPLS. The results reported that e-quality, incident management and quality management have a positive association with training stimulation of government employees. The findings also reported that a quality information system has positively moderated the links between quality management and training stimulation of government employees, while negatively moderating the links between e-quality and training simulation.

Empirical studies across different domains indicate that information quality significantly conditions the effectiveness of managerial practices and digital technologies. Evidence shows that high-quality information, characterised by accuracy, timeliness, completeness, and relevance, strengthens the impact of analytics and information systems on organisational and supply chain outcomes (Hani, 2022; Zuo & Lin, 2022). Research further suggests that poor information quality weakens decision-making and undermines visibility and coordination, even when advanced analytics tools are available. Although direct evidence on information quality moderating the relationship between big data analytics and supply chain visibility is scarce, related findings strongly support its role as a critical contingency factor. ***H3: Information quality positively moderates the relationship between big data analytics and supply chain visibility.***

Table 2.3: Summary of Empirical Review

Author(s) & Year	Topic/Purpose	Theories	Study Area/Context	Key Findings
Zuo & Lin (2022)	Examined the moderating role of accounting information quality in the relationship between government R&D subsidies and firm innovation	Innovation Policy Perspective / Corporate Governance Perspective	Chinese listed companies	Government R&D subsidies significantly increased innovation inputs and outputs. Information quality strengthened the effectiveness of subsidies by reducing information asymmetry and enhancing innovation outcomes.
Hani (2022)	Investigated the relationship between supply chain management practices and		Supply chain organisational context	Supply chain management practices and information quality both directly improve supply chain performance.

	supply chain performance with information quality as a moderator			Information quality significantly strengthens the relationship between supply chain practices and performance outcomes.
Sukumana et al. (2021)	Examined the moderating role of quality information systems in the relationship between e-quality, incident management, quality management, and employee training stimulation	Information Systems Perspective	Government institutions in Indonesia	Quality information systems positively moderated the relationship between quality management and employee training stimulation but negatively moderated the relationship between e-quality and training outcomes.

2.3.4 Mediating Role of Supply Chain Visibility

No empirical research has specifically explored how supply chain visibility (SCV) mediates the relationship between big data analytics (BDA) and supply chain performance (SCP). Nonetheless, SCV has been applied in various other contexts. For instance, Al-Khatib (2022) investigated the interplay among the Internet of Things (IoT), BDA, SCV, and operational performance (OP) within Jordan's pharmaceutical manufacturing industry. Using covariance-based structural equation modeling (SEM) through Amos 25, the study tested a conceptual framework derived from prior literature, confirming its validity through assessments of convergent and discriminant validity, reliability, and confirmatory factor analysis. The results demonstrated strong positive associations between IoT/BDA, SCV, and OP. Notably, the research highlighted SCV's mediating function, showing that it channels the effects of IoT and BDA into improved operational outcomes. These findings underscore the strategic importance of integrating IoT and BDA in pharmaceutical supply chains, with SCV serving as a vital mechanism that transforms technological inputs into measurable operational benefits. The study provides empirical support for adopting digital integration in sectors where transparency and operational precision are critical.

Riaz and his colleagues (2024) took a closer look at something researchers haven't really dug into yet: how bringing Industry 4.0 into manufacturing actually connects to supply chain performance. Working from the resource-based view theory, they set out to understand not just whether I4.0 tools make a difference, but how that difference actually happens. They built their study around data from 510 managers working in different kinds of manufacturing companies, and they used a technique called partial least squares structural equation modeling, PLS-SEM for short, to run their analysis.

What they found is pretty telling. First off, there's clearly a strong, straight-line connection between adopting I4.0 technologies and seeing better supply chain results. But the story gets more interesting when you look underneath that surface finding. The research team wanted to know if certain factors help explain this link, so they tested three potential mediators: supply chain traceability, visibility, and resilience. It turns out each one of these individually carries some of I4.0's influence forward to performance outcomes.

But here's where it gets really fascinating. Riaz et al. (2024) discovered something beyond these separate effects, a kind of chain reaction. The impact of I4.0 doesn't just travel through one pathway; it flows sequentially. First traceability picks it up, then passes it to visibility, and finally resilience carries it through to supply chain performance. This cascading effect actually makes the whole relationship stronger.

What this reveals, the authors suggest, is that I4.0 adoption isn't just about implementing isolated technologies. Instead, it helps companies build up interconnected capabilities that work together, each layer reinforcing the next, to ultimately strengthen how the whole supply chain functions.In a related vein, Baah et al. (2020) examined the pivotal role of information sharing in bolstering supply chain performance. Through a PLS-SEM analysis of survey responses from supply chain professionals, the study found that information sharing positively and directly influenced SCV, collaboration, agility, and overall supply chain performance, illustrating the multifaceted ways in which information flow strengthens operational outcomes.

Importantly, the research demonstrated a cascading effect: enhanced visibility subsequently strengthened both collaboration and agility, which in turn drove performance improvements. These findings highlight information sharing as a foundational capability that enables visibility, which then facilitates collaborative relationships and agile responses - ultimately leading to superior supply chain outcomes. The study provides empirical validation for the sequential value creation process in supply chains, emphasizing that information sharing serves as the critical first step in building competitive advantage through enhanced visibility and responsive capabilities.

Tera et al. (2024) investigated the effect of supply chain digitalisation (SCD) on performance (SCP) using a moderated mediation model, analysing survey data from 399 Turkish manufacturing firms. Their research revealed that SCD directly enhances SCP and also functions through a mediating role where supply chain visibility (SCV) facilitates this positive impact. Notably, supply chain survivability (SCS) emerged as a critical contingency factor, strengthening both the direct SCD-SCP connection and the indirect pathway through SCV, particularly at higher SCS levels. The study emphasised that the performance advantages of digitalisation, including cost efficiency, improved communication, and resilience to disruptions, are optimised when robust visibility and survivability capabilities are present. By empirically validating this moderated mediation model, the research enriches our understanding of how digital transformation interacts with operational capabilities to drive supply chain success, providing valuable insights for theory and practice in unstable environments.

Although limited studies have directly examined supply chain visibility as a mediator between big data analytics and supply chain performance, related empirical evidence strongly supports its intervening role. Prior research demonstrates that supply chain visibility acts as a critical mechanism through which digital technologies, information sharing, and analytics capabilities translate into improved performance outcomes (Al Khatib, 2022; Baah et al., 2020; Riaz et al., 2024). These studies reveal that enhanced visibility improves coordination, agility, collaboration, and responsiveness, thereby driving performance improvements. The findings imply that analytics investments alone may not yield performance gains unless they are effectively converted into actionable visibility across the supply chain. ***H4: Supply chain visibility mediates the relationship between big data analytics and supply chain performance.***

Table 2.4: Summary of Empirical Review

Author(s) & Year	Topic/Purpose	Theories Employed	Study Area/Context	Key Findings
Al-Khatib (2022)	Examined the relationships among IoT, BDA, supply chain visibility, and operational performance		Pharmaceutical manufacturing sector in Jordan	IoT and BDA significantly improve operational performance. Supply chain visibility mediates the relationship between IoT/BDA and operational performance, highlighting visibility as a mechanism

				translating technological capabilities into performance outcomes.
Riaz et al. (2024)	Investigated the relationship between Industry 4.0 adoption and supply chain performance through traceability, visibility, and resilience	Resource-Based View (RBV)	Manufacturing firms	Industry 4.0 significantly improves supply chain performance directly and indirectly through supply chain traceability, visibility, and resilience. Sequential mediation reveals layered capability development driving performance improvements.
Baah et al. (2020)	Examined the role of information sharing in enhancing supply chain performance through supply chain visibility, collaboration, and agility	Not explicitly stated (Information sharing capability perspective implied)	Supply chain professionals across organisations	Information sharing significantly improves supply chain visibility, which subsequently enhances collaboration, agility, and performance. Visibility acts as a critical link in the performance improvement process.
Tera et al. (2024)	Investigated the effect of supply chain digitalisation on supply chain performance with supply chain visibility as mediator and supply chain survivability as moderator	Digital Transformation / Capability Perspective	Turkish manufacturing firms	Supply chain digitalisation directly and indirectly improves supply chain performance through supply chain visibility. Supply chain survivability strengthens both direct and mediated relationships, particularly in unstable environments.

2.4 Conceptual Framework

A conceptual framework examined the relationships between big data analytics, supply chain visibility, information quality and supply chain performance. The study used four variables: an independent variable (big data analytics), a mediator (supply chain visibility), a moderator (information quality) and a dependent variable (supply chain performance). The relationships between these variables are illustrated in Figure 2.1.

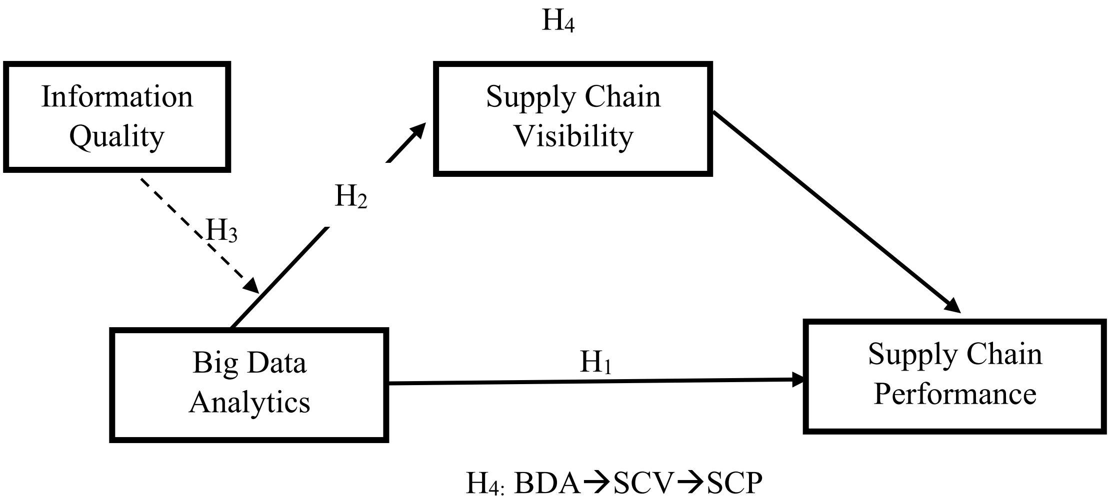

Figure 2.1: Conceptual Framework

2.5 Chapter Summary

This chapter systematically examines the interconnected roles of big data analytics, supply chain visibility, and information quality in enhancing supply chain performance. The review establishes three key theoretical foundations: dynamic capabilities theory explains how organisations leverage analytics for competitive advantage; information processing theory clarifies visibility's role in translating data into actionable insights; and contingency theory demonstrates how information quality determines the effectiveness of these relationships. The conceptual framework positions supply chain visibility as the mediating mechanism between big data analytics and supply chain performance, while information quality serves as a moderating factor that strengthens the relationship between big data analytics and supply chain visibility. Empirical evidence from diverse industries confirms that when supported by robust visibility and high-quality data, analytics initiatives yield significant improvements in supply chain agility, resilience, and efficiency. The chapter concludes with four testable hypotheses.

CHAPTER THREE

RESEARCH METHOD

3.0 Introduction

Chapter Three addresses the research methodology employed in the study. It covers the research philosophy and design, the population, sample size, sampling techniques, data collection methods, and procedures for analysing the data. Consequently, this section clarifies how the entire study was performed. This chapter also discusses reliability and ethical considerations. It concludes with a summary of the different issues presented in the study.

3.1 Research Paradigm

The term "paradigm" was introduced by Kuhn in 1962. Kuhn defined a research paradigm as a collection of scientifically agreed-upon principles for analysing and addressing problems (Kuhn, 1970). The research paradigm guides researchers' decisions. It helps them carefully define a research problem, formulate objectives and research questions, and determine the research's reality, methodological approach, and knowledge base (Kivunja & Kuyini, 2017; Khatri, 2020). The paradigm comprises four components: ontology (our beliefs about the world), axiology (ethical implications to consider when conducting research), methodology (a valid and thorough approach to data collection), and epistemology (the nature of knowledge and how it is obtained and tested) (Kivunja & Kivunja, 2017; Aliyu et al., 2015; Mertens, 2010).

Denzin and Lincoln (2018) categorized the paradigms into seven groups: feminist, positivism/post-positivism, Marxist, ethnic, constructivism, queer theory, and cultural studies.

The positivist research paradigm is adopted in this study because it aligns directly with the study's objective of examining empirically testable relationships among objectively measurable variables. Positivism is grounded in the assumption that reality exists independently of the researcher and is governed by stable, law-like relationships that can be observed and measured (Evered & Louis, 1991). This ontological position is consistent with the study's treatment of constructs such as big data analytics capability, information quality, supply chain visibility, and supply chain performance as observable organisational phenomena rather than subjective interpretations. By adopting this stance, the study is positioned to identify regularities and patterns across organisations and to explain variations in performance through systematic empirical inquiry.

Epistemologically and methodologically, positivism emphasises the generation of objective knowledge through empirical measurement and statistical analysis, enabling theory testing, explanation, and prediction (Benton & Craib, 2010; Sciarra, 1999). Accordingly, the study formulates hypotheses a priori and employs quantitative methods to test causal relationships while ensuring reliability, internal validity, and external validity (Rehman & Alharthi, 2016). The positivist paradigm further supports the study's intention to generalise findings to a broader population, making the results useful for both theoretical advancement and managerial decision-making (Alharahsheh & Pius, 2020). Positivism provides a coherent philosophical foundation that ensures alignment between the study's assumptions about reality, its approach to knowledge generation, and its analytical methods.

3.2 Research Design

A research design serves as a strategic framework that guides the researcher through the process of conducting a study. It functions as a blueprint, detailing the methods and procedures for data collection, analysis, and interpretation to ensure the study's objectives are met (Creswell & Creswell, 2018). Akhtar (2016) defines research design as a structured plan that underpins the entire research process and aligns methodology with the study's goals. Research designs can be categorized into explanatory, descriptive, longitudinal, causal, cohort, case study, and action research designs (Yazdani et al., 2021). A key purpose of research design is to establish relationships between variables, enabling the identification of cause-and-effect dynamics (Maxwell, 2012). The selection of an appropriate research design depends on multiple factors, such as the nature of the research, the study's purpose, and the unit of analysis (Bengtsson, 2016).

This study adopted an explanatory research design to examine the relationship between big data analytics, information quality, supply chain visibility and supply chain performance. Explanatory research is particularly valuable for testing hypotheses and uncovering the underlying reasons behind observed relationships, making it ideal for studies that seek to move beyond description toward prediction and theory-building (Babbie, 2016; Siemsen et al., 2010). Through a systematic analysis of variable interactions, this design promotes the creation of actionable insights useful for both academic literature and practical decision-making (Potwarka et al., 2019). However, critics highlight several limitations, including its reliance on pre-existing data or controlled settings, which may not fully capture real-world complexities (Saunders et al., 2019). Meyer et al. (2017) caution that an overemphasis on causal inference may lead to oversimplification of dynamic, context-dependent phenomena. Despite the challenges, the explanatory design remains a robust choice for this study due to its strong alignment with the research objectives, which prioritize understanding cause-and-effect relationships over mere description. Furthermore, the design's capacity for generalizability when applied with methodological rigor ensures that findings contribute meaningfully to both theory and practice (Bhattacherjee, 2012).

3.3 Research Approach

The term "research approach" refers to processes and procedures involving data collection, analysis, and interpretation. Research approaches are grouped into quantitative, qualitative, and mixed-methods (Levitt et al., 2018**).** The quantitative approach involves the systematic collection and statistical analysis of numerical data to examine relationships between variables and test hypotheses (Creswell & Creswell, 2018). On the other hand, the qualitative approach focuses on exploring meanings, experiences, and social phenomena through non-numerical data such as interviews, observations, or textual analysis to gain an in-depth understanding (Denzin & Lincoln, 2018). The mixed-methods approach integrates both quantitative and qualitative techniques within a single study to provide a more comprehensive analysis by combining statistical trends with contextual insights (Tashakkori & Teddlie, 2010). These approaches differ in their epistemological foundations, data collection methods, and analytical techniques, allowing researchers to select the most appropriate framework based on their research objectives (Levitt et al., 2018).

The study employed a quantitative research design aligned with the positivist paradigm to objectively examine relationships between variables through numerical data and statistical analysis (Creswell & Creswell, 2017). This approach facilitates hypothesis testing by utilizing a deductive methodology, where theories are systematically evaluated through data-driven validation or rejection (Zyphur & Pierides, 2020). Quantitative research is particularly well-suited for large populations, as it enables efficient data collection and analysis while minimizing time constraints (Singer & Couper, 2017). By using inferential and descriptive statistics (Tashakkori & Teddlie, 2003), this method ensures generalizable findings, making it ideal for investigating the relationships between big data analytics, information quality, supply chain visibility, and supply chain performance.

Despite its advantages, the quantitative approach presents challenges, such as the complexity of handling numerical data and ensuring validity and reliability (Stockemer et al., 2019). Additionally, its structured nature restricts respondents' ability to elaborate on their perspectives, potentially excluding important contextual insights. To address these limitations, this study employed rigorous methodological controls, including standardized measurement tools and statistical validation techniques. Ultimately, the quantitative design was selected to minimize bias, test established theories, and provide empirical evidence for decision-making in supply chain management.

3.4 Study Area

The research is centred on the manufacturing industry in the Greater Accra Region. This focus is particularly important as the manufacturing sector plays a vital role in driving economic growth in Ghana. It significantly contributes to GDP, employment, and industrial advancement. The Ghana Statistical Service (2024) reports that the manufacturing sector generated around $8.57 billion in output in 2024, accounting for 11.23% of GDP, and provides jobs to a large part of the workforce, especially in urban centres like Greater Accra. This study zeroes in on manufacturing firms in the Greater Accra region, which hosts the majority of the nation's manufacturers and stands as an economic hub, representing over 40% of the country's manufacturing activities. The region's manufacturing landscape is diverse, encompassing key subsectors such as agro-processing, textiles, chemicals, and construction materials, providing a comprehensive representation of Ghana's industrial ecosystem. Additionally, Greater Accra attracts the majority of domestic and foreign industrial investments, houses critical infrastructure like the Tema Industrial Enclave and the Port of Tema (essential for trade), and serves as a policy testing ground for national economic initiatives. This study targets the region to provide practical insights into productivity issues, supply chain dynamics, and employment trends that can be applied to other areas. The goal is to aid evidence-based policymaking to boost industrialisation, job creation, and GDP growth throughout Ghana.

3.5 Population

The term "population" encompasses all individuals, objects, or elements with shared characteristics that are of interest to the researcher. It represents the complete set from which a study sample may be drawn (Creswell, 2014). Clearly defining the population is essential, as it ensures that the findings are relevant and applicable to the larger group, thereby increasing the validity and generalizability of the research outcomes. In the Greater Accra Region, the total population of registered manufacturing firms stands at 308, accounting for 35% of Ghana's entire manufacturing sector (AGI Report, 2023). This region was chosen for the study because of its notable concentration of these businesses, which enhances the efficiency and relevance of the research. The significant presence of firms in Greater Accra makes it an optimal focus area for a thorough analysis of industry practices, challenges, and opportunities within a key industrial hub. This regional emphasis allows for more precise and detailed insights, which are crucial in developing effective policies and strategies that address the sector's specific needs.

3.6 Sample and Sampling Procedure

Sampling involves selecting a representative portion or percentage of an entire population (Ritchie et al., 2013). Zikmund et al. (2013) define a sample as a subset of the population with shared characteristics. Bambale (2014) observed that a sample refers to the fraction of units selected for study. Sampling methods are divided into probability and non-probability techniques. Probability sampling entails random selection, ensuring every population member has a known and equal chance of being part of the sample. This method enhances the representativeness of the sample and allows for results to be generalized to the whole population, making it commonly used in quantitative research (Creswell, 2014; Bryman & Bell, 2022). In contrast, non-probability sampling does not involve random selection, making it more susceptible to bias. Typically used in exploratory research, it aims to gather deeper insights rather than generalize findings. Although it may lack representativeness, non-probability sampling can be practical and cost-effective, especially when engaging hard-to-reach populations (Etikan, Musa, & Alkassim, 2016; Saunders et al., 2019).

The study employed a probability sampling technique, specifically the ccensus sampling method. The census sampling technique, involves the complete enumeration of all members of the target population (Bryman, 2012; Kothari, 2004). Rather than selecting a sample, data were collected from all 308 registered manufacturing firm in the Greater Accra Region. This approach was deemed appropriate given the relatively small and accessible population of manufacturing firms, as listed by the Association of Ghana Industries (AGI). The census method ensured comprehensive coverage and eliminated sampling error, thereby enhancing the accuracy and generalizability of the findings (Fink, 2009; Cochran, 1977). Additionally, a census approach minimized potential biases that could arise from selective sampling, allowing for precise analysis of sector-wide characteristics and performance indicators.

3.7 Time Horizon

The study employed a cross-sectional research design to collect data from manufacturing firms in the Greater Accra Region at a specific point in time. This method provides a snapshot of the current status of the variables being examined, enabling the analysis of patterns, relationships, and correlations among key factors (Saunders et al., 2019). Unlike longitudinal studies that track changes over extended periods, cross-sectional research is more time- and cost-efficient, making it suitable for studies with limited resources (Zikmund et al., 2013). One of the main strengths of this design is its ability to capture a diverse representation of the population within a specific timeframe, thus enhancing the generalizability of the findings (Bhattacherjee, 2012). Moreover, cross-sectional studies provide the foundation for hypothesis generation, setting the stage for future longitudinal or experimental investigations (Bryman & Bell, 2015). However, a drawback of this approach is its inability to establish causal relationships or monitor changes over time, as data is collected only once. The study implemented standardised data collection methods to enhance rigor and reduce variability in responses.

3.8 Data Collection Instrument

The study employed a structured questionnaire as its primary data collection tool, a choice well-aligned with its explanatory research design and cross-sectional approach. Structured questionnaires offer a systematic and efficient means of collecting standardized, quantitative data from respondents, ensuring consistency and reliability (Malhotra & Birks, 2007). This aligned well with the study's goals of collecting quantifiable insights from various manufacturing firms. The explanatory nature of the research design, which seeks to uncover relationships and patterns, naturally lends itself to structured data collection methods (Maxwell, 2012). A questionnaire, comprising both closed- and open-ended questions, enables researchers to capture respondents' objective perspectives on specific topics (Singer & Couper, 2017). In this case, the questionnaire was carefully designed with items derived from validated literature, ensuring robustness. It included 5 items on big data analytics, 5 on supply chain visibility, 6 on supply chain performance, and 5 on information quality. The questionnaire is divided into five sections: Section A covers respondent demographics; Section B focuses on big data analytics; Section C addresses supply chain visibility; Section D examines information quality; and Section E pertains to supply chain performance. Responses were measured on a 7-point Likert scale (1 = Slightly Agree to 7 = Strongly Agree), providing a nuanced assessment of respondents' views. A structured questionnaire was selected as the preferred tool due to its benefits over other methods. These questionnaires are easy to create, economical, provide consistent results, and ensure high confidentiality.

3.9 Variable and Measurement

The study's measurement items were meticulously selected and adapted from established research to ensure both relevance and robustness. It investigated four primary constructs: big data analytics, information quality, supply chain visibility, and supply chain performance. Items for each construct originated from reputable sources and were tailored to align with the study's specific context and goals. The items for supply chain visibility were modified from Baah et al. (2020), Dubey et al. (2018), and Mubarak et al. (2021). For big data analytics, they were sourced from Bahrami and Shokouhyar (2021), Al-Okaily and Al-Okaily (2024), and Franke and Hiebl (2022). Information quality items were extracted from Bahrami and Shokouhyar (2021) and Al-Okaily and Al-Okaily (2024). Lastly, items for supply chain performance were adapted from Gunasekaran et al. (2001), Hendayani and Fernando (2022), and Ye et al. (2023). To confirm the scales' reliability, all items underwent thorough validation using Cronbach's alpha and composite reliability tests. Both metrics produced results exceeding the 0.70 threshold recommended by Hair et al. (2017), validating the internal consistency and reliability of the scales. This comprehensive selection and validation process strengthens the study's measurement framework, ensuring an accurate and credible assessment of the constructs.

3.10 Reliability and Validity

To ensure the credibility of the study, significant attention was given to the validity and reliability of the structured questionnaire. Validity, as explained by Cook and Reichardt (1979), refers to how well an instrument accurately reflects the truth of a specific inference, while reliability pertains to its ability to produce consistent and precise results when applied repeatedly under the same conditions (Yilmaz, 2013). These concepts guided the evaluation of the questionnaire's effectiveness. Reliability was primarily assessed using Cronbach's alpha, a well-known measure of internal consistency. For it to be deemed reliable, Cronbach's alpha should be greater than 0.7 (Bujang et al., 2018). Additionally, composite reliability, another crucial measure, was evaluated at the construct level, requiring a minimum value of 0.7 (Hair et al., 2017). The reliability of individual items was determined by their outer loadings, which ideally should exceed 0.7. However, items with loadings between 0.6 and 0.7 were retained if supported by composite reliability and convergent validity (Hair et al., 2012; 2017). Convergent validity was confirmed when the average variance extracted (AVE) exceeded 0.5, indicating that the construct sufficiently accounted for the variance in its items (Hair et al., 2017).

Discriminant validity, essential for ensuring that constructs are distinct, was assessed using the Fornell-Larcker criterion and the heterotrait-monotrait ratio (HTMT). According to the Fornell-Larcker standard, the square root of each construct's AVE should exceed its correlations with other constructs (Henseler et al., 2015; Voorhees et al., 2016). Similarly, HTMT values below 0.90 provide evidence of discriminant validity (Henseler et al., 2015). These rigorous statistical criteria confirmed that the constructs within the instrument are both reliable and conceptually separate. Additionally, content validity, which ensures that the questionnaire thoroughly addresses the intended area, was a primary consideration (Almanasreh, 2019). To achieve this, the instrument underwent a pretesting phase aimed at correcting spelling mistakes, vague phrases, and unclear questions. Recognizing that questionnaires require ongoing improvements, the draft was evaluated by procurement specialists, peers, and lecturers, whose feedback guided essential revisions. This collaborative process enhanced the instrument’s clarity and relevance before it was implemented, ultimately improving the study's overall validity and reliability.

3.11 Data Collection Procedures

The data collection process, conducted over two months from May to June 2025, was meticulously organised to ensure efficiency, clarity, and collaboration with the participating manufacturing firms. To create a seamless collection experience, an introductory letter was sent to each firm, clearly outlining the study's objectives and purpose. This initiative-built trust and encouraged respondents to provide accurate and thoughtful responses. Additionally, the researcher offered personal guidance to respondents throughout the questionnaire process, clarifying any requirements. Each questionnaire was designed to take approximately 30-45 minutes, allowing participants sufficient time to read, understand, and respond to questions without feeling rushed. Questionnaires were delivered in person to the firms, with pick-up times arranged at mutually convenient intervals to suit their availability. Furthermore, contact information was exchanged during initial meetings, facilitating effective communication throughout the process. The researcher also proactively followed up with respondents at least once as a reminder of questionnaire deadlines, which helped ensure timely submissions despite their busy schedules. As a result, this efficient approach led to a high response rate and the successful collection of reliable data within the targeted timeframe.

3.12 Data Processing Tools

For processing and analysing data, SPSS (Statistical Package for the Social Sciences) version 27 and SmartPLS-SEM 4 were utilised, capitalising on their complementary advantages. The collected questionnaires underwent systematic coding in SPSS, and the resulting data file was exported as a comma-separated values (CSV) file for seamless integration with SmartPLS-SEM 4 for detailed analysis. SmartPLS-SEM 4 is particularly effective for hypothesis testing and theory development, providing powerful tools for analysing complex models. Hair et al. (2017) suggest that SmartPLS-SEM is adept at managing complex models that include multiple latent variables and pathways, a frequent necessity in research related to social sciences, business, and management. This capability allows researchers to analyse multiple relationships and interactions among variables simultaneously, offering comprehensive insights into the data. Furthermore, Hair et al. (2019) notes that, in contrast to traditional covariance-based SEM, SmartPLS-SEM adopts a variance-based approach that does not require data normality assumptions. This flexibility is advantageous for real-world datasets, which often exhibit non-normal distributions. Additionally, Hair et al. (2017) highlights the strength of SmartPLS-SEM's bootstrapping technique, which facilitates reliable significance testing for path coefficients and factor loadings, thereby enhancing the credibility of the findings. The software's robust predictive accuracy also reinforces its effectiveness in forecasting and hypothesis testing (Hair et al., 2017). This methodology integrated SPSS for data management and SmartPLS-SEM 4 for advanced modeling, resulting in a rigorous, reliable, and insightful analysis that met the study's objectives.

3.13 Data Processing and Data Analysis

In order to ensure data integrity, the questionnaires that were collected were meticulously prepared prior to data entry, accompanied by rigorous checks to eliminate potential errors. Each retrieved questionnaire was assigned a unique identification number to facilitate the tracking and sorting of non-responses. The data were subsequently edited and coded utilising SPSS version 26, with demographic characteristics analyzed through descriptive statistics, including frequencies, means, and standard deviations. For advanced analytical processes, the SPSS data file was exported as a comma-separated values (CSV) file and subsequently imported into SmartPLS-SEM 4, a robust tool for structural equation modeling. In SmartPLS-SEM 4, both reflective and formative measurement models were established to assess the constructs and evaluate the hypotheses posed in the study. Factor loadings were meticulously examined to ascertain construct validity and reliability, ensuring that all indicators exceeded the recommended threshold of 0.7 (Hair et al., 2017).

Composite reliability was evaluated, confirming that the values were above 0.7, while the Average Variance Extracted (AVE) was verified to be greater than 0.5 for each construct (Hair et al., 2017). The confirmation of discriminant validity was achieved through the Fornell-Larcker criterion, wherein the square root of the AVE for each reflective construct surpassed its correlations with other constructs (Henseler et al., 2015; Voorhees et al., 2016). Furthermore, the Heterotrait-Monotrait (HTMT) ratios were scrutinised, ensuring that the values remained below 0.90 (Henseler et al., 2015). In order to investigate the interrelationships among the exogenous variable (big data analytics), mediating variable (supply chain visibility), moderating variable (information quality), and endogenous variable (supply chain performance), a rigorous bootstrapping procedure comprising 5,000 samples was executed. The significance of these relationships was assessed using t-statistics and p-values. Structural equation modelling (SEM) served as the primary inferential analysis tool, consistent with the study's objective, as articulated in the first chapter, which was to examine the interrelationships among the variables. Concurrently, descriptive statistics (percentages, frequencies, means, and standard deviations) provided a comprehensive summary of the demographic data. This methodical approach, combining SPSS for data preparation and descriptive analysis with SmartPLS-SEM 4 for robust hypothesis testing, ensured a comprehensive and reliable examination of the research objectives.

3.14 Common Method Variance

Common method bias was addressed in this study through both procedural and statistical remedies to minimise the risk of measurement errors associated with collecting data from a single source. Procedurally, the study adopted several preventive strategies during the instrument design and data collection stages (Podsakoff et al., 2003). The questionnaire items were adapted from previously validated scales to ensure construct validity and clarity. A pilot test was conducted with a small group of respondents to assess the reliability, wording, and structure of the instrument, leading to refinement of ambiguous items. Additionally, respondents were assured of anonymity and confidentiality to reduce social desirability bias and evaluation apprehension. The questionnaire was also structured to separate independent and dependent variable items to minimise respondents' tendency to provide consistent or patterned responses. These procedural remedies are widely recommended in behavioural and management research as effective approaches to reducing the likelihood of common method variance (Podsakoff et al., 2012). Furthermore, variance inflation factor (VIF) values were examined to detect potential collinearity issues associated with common method variance. All VIF values were found to be within acceptable thresholds, confirming the absence of significant multicollinearity and reinforcing the robustness of the measurement model. The combined use of procedural and statistical controls aligns with recommended best practices for addressing common method bias in survey-based studies (Kock, 2015).

3.15 Ethical Consideration

Ethical considerations are fundamental to conducting credible scientific research, as they establish standards for responsible conduct and interactions (Saunders, Lewis, & Thornhill, 2007). To ensure ethical compliance, an introductory letter was sent to the authorities of the participating firms, formally requesting permission for the data collection process. This letter clearly outlined the study's objectives, its significance, and the intended use of the data, fostering transparency from the outset. A statement in the questionnaire's introduction guaranteed respondents' confidentiality and anonymity prior to distribution. Participants were fully informed about the study's purpose, methodology, and academic nature, ensuring they understood that their responses would be treated with respect and used solely for academic and research purposes. To further protect their privacy, respondents were instructed not to include their names on the questionnaires. The potential benefits of the study for participants and their organisations were also clearly communicated. Additionally, participants were informed that participation was voluntary, with no compensation provided, and they were free to withdraw from the study at any time without consequence. To uphold academic integrity, all literature referenced in the study, whether paraphrased, summarised, or quoted, was meticulously cited, adhering to proper attribution standards and avoiding plagiarism. This rigorous ethical framework ensured that the research was conducted with integrity, respect for participants, and a commitment to scholarly standards.

3.16 Chapter Summary

This chapter provides a comprehensive overview of the research methodology and procedures employed in the study, ensuring a clear and structured approach to achieving the research objectives. It begins by discussing the research philosophy, which adopted a positivist paradigm due to the study's focus on objective, scientific inquiry. Positivism emphasises empirical evidence and objectivity, aligning seamlessly with the study's goals and quantitative nature. The chapter also elaborates on the research design, detailing its framework to address the research questions effectively. It outlines the data collection procedures, including the systematic methods used to gather accurate and relevant data. The research population and sampling strategy are thoroughly described, explaining how the sample was selected to represent the target population appropriately. Furthermore, the research instruments are evaluated for validity and reliability, ensuring robust and credible data collection tools. For data analysis, the study utilised SPSS version 27.0 for descriptive statistics and data preparation, complemented by SmartPLS-SEM 4 for advanced structural equation modeling. These powerful analytical tools were chosen for their ability to handle complex relationships and deliver precise results, directly supporting the study's primary objectives. Finally, the chapter addresses ethical considerations, emphasising the measures taken to uphold integrity, confidentiality, and respect for participants throughout the research process.

CHAPTER FOUR

RESULTS AND DISCUSSION

4.0 Introduction

The study examined the effect of big data analytics on supply chain performance and the roles of supply chain visibility and information quality in Ghana's manufacturing firms. This chapter presents and discusses the findings, which include descriptive statistics of the respondents. The developed hypotheses were tested using Smart PLS-SEM. The analysis first covered the measurement criteria, followed by the structural model. The results and their discussions are provided in this section.

4.1 Response Rate

A total of 308 questionnaires were distributed across the manufacturing firms in the Greater Accra Region, Ghana. Although 278 responses were received, seven were incomplete and subsequently excluded from the analysis. Ultimately, 271 valid questionnaires were prepared for data entry and analysis. These results yielded a response rate of 87.99%, which is considered highly satisfactory for data analysis (Pielsticker & Hiebl, 2020). The high response rate of 87.99% highlights the reliability of the data collected and the robustness of the findings derived from the analysis.

4.2 Demographic Information

This section presents the demographic characteristics of the respondents who participated in the study. The demographic data offers important context for interpreting the findings by highlighting the sample's composition in terms of gender, age, educational background, occupational role, firm experience, workforce size, industry type, and annual revenue. The result is highlighted in Table 4.1.

Table 4.1: Demographic Characteristics

Demographic Characteristics	Frequency	Percentage
Gender		
Male	152	56.09
Female	119	43.91
Age		
23 years and below	30	11.07
24 years - 29 years	70	25.83
30years -35 years	85	31.37
36 years - 40 years	50	18.45
41 years and above	36	13.28
Education		
Secondary	15	5.54
1st Degree	130	47.97
Masters Degree	110	40.59
Ph.D./Doctorate	16	5.9

Position		
CEO	15	5.54
General Manager	25	9.23
Operations Manager	60	22.14
Purchasing Manager	40	14.76
Logistics/Supply Chain Manager	90	33.21
Others	41	15.13
Years of Operation		
Less than 1 year	5	1.85
1-5 years	35	12.92
6-10 years	65	23.99
11-15 years	70	25.83
16-20 years	60	22.14
21 years & above	36	13.28
Number of Employees		
Less than 10	10	3.69
10-50	50	18.45
51-100	65	23.99
101-500	90	33.21
More than 500	56	20.66
Industry		
Industrial machinery	25	9.23
Chemicals	18	6.64
Plastics & rubber	15	5.54
Food, beverages, drinks	50	18.45
Metals, metalworking	20	7.38
Pharmaceuticals	22	8.12
Paper and packaging	16	5.9
Engineering, construction	30	11.07
Textiles and clothing	25	9.23
Electronics	35	12.92
Other	15	5.54
Annual Revenue (GHS)		
Less than 500,000	100	36.9
500,000 - 1,000,000	120	44.28
Above 1,000,000	51	18.82
	271	**100**

Source: Field Survey (2025)

The results in Table 4.1 show the demographic characteristics of the respondents. The gender distribution indicates a moderate male dominance (56.09%) compared to females (43.91%), suggesting a relatively balanced gender representation within the manufacturing supply chain environment. In terms of age, the majority of respondents fall within the productive working age range of 24–40 years, with the highest proportion aged 30–35 years (31.37%), followed by 24–29 years (25.83%) and 36–40 years (18.45%). This age distribution reflects a mature workforce, and likely to be receptive to innovation and digital technologies such as big data analytics. The educational background shows that nearly half of the respondents hold a first degree (47.97%), while a significant proportion (40.59%) possess a master's degree. This suggests that the sample comprises well-educated professionals likely to be familiar with data-driven processes and strategic decision-making frameworks.

The occupational roles reveal that a substantial share of respondents are directly involved in operational and logistics management, with logistics/supply chain managers (33.21%) and operations managers (22.14%) forming the majority. This strengthens the validity of the findings, as these respondents are closely connected to supply chain decisions. Regarding firm characteristics, most firms have been in operation for 6 to 15 years (49.82%), indicating a level of maturity and operational experience that supports meaningful adoption of analytics technologies. A significant proportion of firms also employ between 51 and 500 workers (57.2%), reflecting medium-to-large enterprises with likely access to structured data systems. The dominant industries represented include food and beverages (18.45%), electronics (12.92%), and engineering/construction (11.07%), sectors that typically manage complex supply chains and require high operational efficiency. Lastly, with 44.28% of firms generating annual revenue between GHS 500,000 and GHS 1,000,000, and 36.9% earning less than GHS 500,000, the data shows participation from both lower and mid-tier revenue firms, reflecting a wide range of financial capabilities that could influence the extent to which big data analytics is adopted and integrated into supply chain functions.

4.3 Descriptive Statistics

The descriptive statistics of the indicators were assessed using the mean, standard deviation, kurtosis, and skewness. Each construct was measured with multiple items on a Likert scale ranging from 1 to 5, reflecting the perceptions of manufacturing firms in Ghana. The information is presented in Table 4.2.

Table 4.2: Descriptive Statistics

Indicators	Mean	min	max	SD	kurt	Sk
We use advanced tools to analyse operational and performance data.	3.357	1	5	0.997	0.166	-0.228
We use data visualization techniques to help decision-makers understand complex insights from large datasets	3.33	1	5	1.115	-0.806	-0.009
Data-driven analytics help us make timely financial and operational decisions.	3.17	1	5	1.148	-0.815	0.134
We leverage multiple data sources to generate actionable insights for the business.	3.124	1	5	1.268	1.065	-0.063
We analyse data as soon as it becomes available to support quick decision-making.	3.214	1	5	1.27	-1.079	0.06

The information we generate is available in time to support key business decisions.	3.22	1	5	1.092	-0.884	0.025
The information we produce is precise and error-free, ensuring trustworthy decision-making.	3.357	1	5	1.273	0.88	-0.308
The information we provide covers all the necessary aspects needed for effective decision-making.	3.113	1	5	1.289	-1.11	-0.003
The information we deliver is sufficient in detail and scope for making informed choices.	3.429	1	5	1.215	-0.972	-0.267
The information we supply is consistent and dependable for business decisions.	3.379	1	5	1.275	-1.204	-0.1
Our supply chain consistently delivers products within the promised timeframe.	3.398	1	5	1.15	-0.892	0.104
Our supply chain effectively minimizes waste and cost across all operations.	3.379	1	5	1.102	0.602	-0.211
Our supply chain adapts faster to changes than competitors.	3.288	1	5	1.118	-0.613	-0.006
Our supply chain can rapidly adjust products to meet customer needs.	3.253	1	5	1.203	-0.82	-0.249
Our supply chain maintains an excellent on-time delivery track record.	3.409	1	5	1.198	-0.984	0.137
Our supply chain delivers a superior level of customer service.	3.456	1	5	1.179	0.815	-0.248
We are able to communicate with supply chain partners regarding fluctuations in demand and alterations in customer preferences.	3.261	1	5	1.263	-1.079	0.041
We share performance feedback with our supply chain partners.	3.154	1	5	1.178	0.766	0.083
Our company involves stakeholders in deciding customer preferences and new product requirements.	3.308	1	5	1.024	-0.585	0.003
We consistently monitor inventory levels across the supply chain.	3.283	1	5	1.126	-0.953	-0.053
We gather information from various sources to gauge the market and prepare for seasonal fluctuations.	3.319	1	5	1.18	-0.71	0.175

Source: Field Survey (2025)

The descriptive statistics in Table 4.2 provide valuable insights into respondents' perceptions regarding data utilization and supply chain performance. Most of the mean scores range slightly above the midpoint on a five-point Likert scale, suggesting that while implementing advanced analytics tools and data-driven practices exists, it is not yet highly institutionalised across the sample. For instance, using advanced tools to analyse operational data (mean = 3.357) and relying on multiple data sources for generating insights (mean = 3.124) reflect moderate engagement with analytics capabilities. Similarly, the use of real-time data to support rapid decision-making (mean = 3.214) and the availability of timely information (mean = 3.22) further emphasise that responsiveness is present, though not fully optimised. The standard deviations for these indicators are relatively high (above 1.0), implying varied responses and potential inconsistencies in adopting data analytics practices across organisations. The distribution metrics (skewness and kurtosis) also show moderate deviations from normality, but within acceptable bounds, suggesting the data is suitable for further multivariate analysis.

Furthermore, the supply chain visibility and performance results also reflect moderate effectiveness. Indicators such as consistent product delivery within promised timeframes (mean = 3.398), cost and waste minimisation (mean = 3.379), and superior customer service (mean = 3.456) suggest that operational outcomes are being achieved to a reasonable degree. However, slightly lower scores for adaptability to customer needs (mean = 3.253) and stakeholder involvement in product decisions (mean = 3.308) reveal opportunities for enhancing responsiveness and collaborative innovation. Similarly, visibility indicators such as inventory monitoring (mean = 3.283) and market sensing for seasonal fluctuations (mean = 3.319) indicate some level of strategic information sharing and coordination, although not advanced. These insights point to a developing but not fully mature integration of big data analytics, information quality, and visibility within supply chain management. Therefore, while the foundational elements of an intelligent and responsive supply chain are evident, organisations would benefit from reinforcing analytics culture, improving data reliability, and fostering greater collaboration across stakeholders to enhance decision-making and performance outcomes.

4.4 Model Specification

The model specification in Partial Least Squares Structural Equation Modelling (PLS-SEM) is a crucial step that carefully defines the measurement and structural models within the research framework. The measurement model specifies how latent variables are measured by their indicators, distinguishing between reflective and formative constructs (Garson, 2016). Meanwhile, the structural model explains the nexus between these latent variables, defining the hypothesized paths that represent the causal relationships in the model. Accurate model specification is crucial as it determines how well the data's theoretical concepts are represented and influences the results' reliability and validity. The model specification highlighted in Figure 4.1 represents the specification of the model. Each latent variable, depicted by blue circles, signifies a construct that cannot be directly measured but is inferred through a set of observed indicators, shown as yellow rectangles. The model comprises four main latent variables: big data anlytics, information quality, supply chain visibility and supply chain performance.

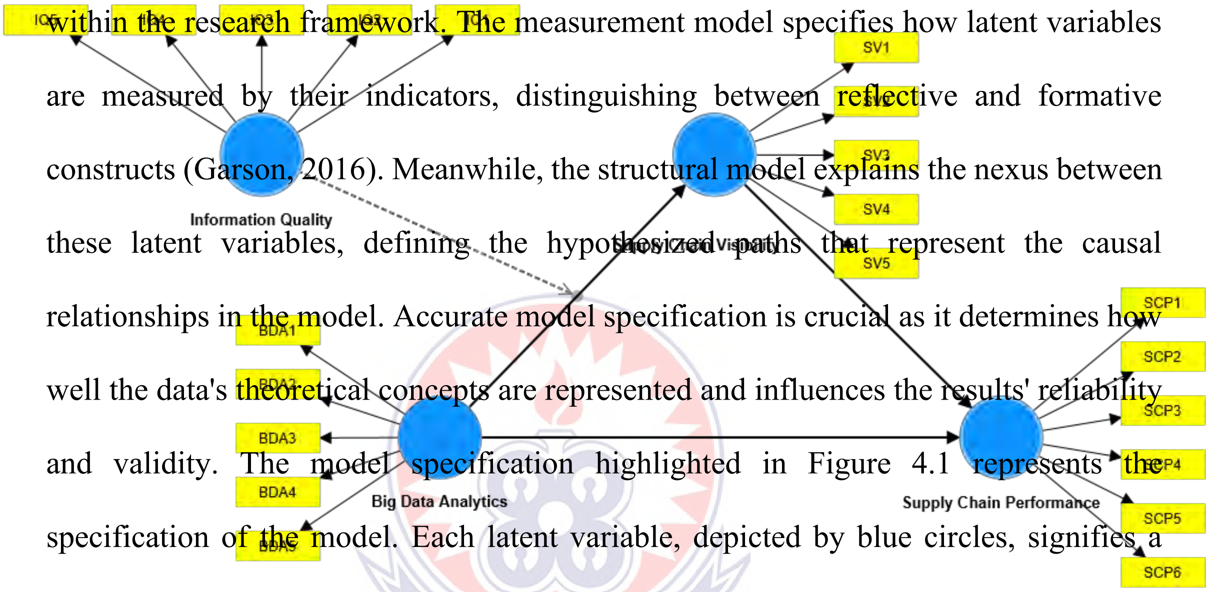

Figure 4.1: Model Specification

4.5 Measurement Model Assessment

Assessing the measurement model in Partial Least Squares Structural Equation Modeling (PLS-SEM) is a critical step that ensures the constructs are accurately measured and valid for subsequent analysis. The primary objective of measurement model assessment is to ensure that the indicators used for measuring latent variables are reliable and valid (Hair et al., 2018). This means verifying that the indicators consistently measure the intended construct (reliability) and accurately capture the construct without overlapping with others (validity). For reflective models, internal consistency is assessed using metrics like Cronbach's alpha or composite reliability (ρC). At the same time, convergent validity is evaluated using the Average Variance Extracted (AVE), which should be greater than 0.50 (Hair et al., 2016). Discriminant validity is also essential to confirm that each construct is distinct from the others, often evaluated using the Fornell-Larcker criterion or the Heterotrait-Monotrait (HTMT) ratio. In formative models, the emphasis is on ensuring that indicators are not collinear and that their weights are significant and relevant to the construct (Henseler et al., 2015; Hair et al., 2016). This thorough assessment process is vital as it forms the basis for producing reliable and valid outcomes in the subsequent structural model analysis (Sarstedt & Cheah, 2024).

4.6 Indicator Loading Assessment

Indicator loading measures the degree to which an observed variable, or indicator, accurately reflects the underlying latent construct it is designed to measure (Hair et al., 2018). Hair et al. (2018) indicates that indicator loadings greater than 0.708 are considered strong, indicating that the indicator shares significant variance with the latent construct, demonstrating robust item reliability. This benchmark is based on the notion that the square of the loading (i.e., the commonality of the item) should account for at least 50% of the variance in the indicator, thereby verifying the indicator's reliability in measuring the construct. Evaluating indicator loadings is fundamental in confirming that the measurement model accurately represents the latent variables, providing a solid foundation for further structural analysis (Cheah et al., 2024; Sarstedt & Cheah, 2024). The result of the indicator loadings are presented in Table 4.3.

Table 4.3: Indicator Loading Assessment

Constructs	Indicator Loadings	T-Values	P-Values	VIF
Big Data Analytics				
BDA1	0.747	26.533	0.000	1.696
BDA2	0.810	49.156	0.000	1.865
BDA3	0.865	65.130	0.000	2.377
BDA4	0.821	45.090	0.000	2.212
BDA5	0.809	41.042	0.000	2.003
Information Quality				
IQ1	0.738	25.448	0.000	1.597
IQ2	0.849	58.120	0.000	2.657
IQ3	0.871	62.340	0.000	3.006
IQ4	0.810	44.043	0.000	2.072
IQ5	0.863	65.632	0.000	2.364
Supply Chain Performance				
SCP1	0.770	42.912	0.000	1.978

SCP2	0.799	49.265	0.000	2.155
SCP3	0.790	38.950	0.000	2.105
SCP4	0.815	43.479	0.000	2.506
SCP5	0.783	31.407	0.000	2.222
SCP6	0.787	34.328	0.000	2.164
Supply Chain Visibility				
SCV1	0.777	30.595	0.000	1.846
SCV2	0.789	33.412	0.000	1.897
SCV3	0.736	26.875	0.000	1.757
SCV4	0.841	53.771	0.000	2.191
SCV5	0.860	49.003	0.000	2.485

Source: Field Survey (2025)

Table 4.3 presents the results of the indicator loading assessment for the four latent constructs: big data analytics, information quality, supply chain performance, and supply chain visibility. The factor loadings are all above the recommended threshold of 0.70, indicating strong validity. For example, BDA3 exhibits the highest loading at 0.865, while SV3 has the lowest at 0.736, within an acceptable range. All t-values are statistically significant ($p < 0.001$), confirming that each indicator contributes meaningfully to its respective construct. Furthermore, Variance Inflation Factor (VIF) values remain below the critical threshold of 3.3, suggesting that multicollinearity is not a concern and that items are sufficiently distinct within each construct.

4.7 Reliability and Validity Assessment

Internal consistency reliability is evaluated to ensure that a group of indicators consistently measures a construct. This assessment has traditionally relied on Cronbach's alpha, which calculates reliability based on the inter correlations among indicators. However, Cronbach's alpha can sometimes underestimate reliability in PLS-SEM due to its assumption of equal indicator reliability. To mitigate this, the study used composite reliability to assess the consistent reliability to account for varying outer loadings of the indicators, offering a more precise reliability estimate. Acceptable composite reliability values should be greater than 0.70. Thus, the combined assessment of indicator loadings and internal consistency reliability is critical for ensuring that constructs within the model are measured accurately and consistently, thereby establishing a strong basis for the validity of the entire model (Cheah et al., 2024; Sarstedt & Cheah, 2024). The consistent reliability and validity results are presented in Table 4.4.

Table 4.4: Constructs Validity and Reliability

Constructs	Cronbach's alpha	rho_a	Composite reliability	Average variance extracted (AVE)
Big Data Analytics	0.870	0.879	0.906	0.658
Information Quality	0.884	0.890	0.915	0.685
Supply Chain Performance	0.880	0.882	0.909	0.625
Supply Chain Visibility	0.861	0.868	0.900	0.643

Source: Field Survey (2025)

The reliability and validity of the four latent constructs are supported by the results presented in Table 4.4. Cronbach's alpha values range from 0.861 to 0.884, all exceeding the commonly accepted threshold of 0.70, indicating strong internal consistency. Similarly, rho_a values range from 0.868 to 0.89, and composite reliability (CR) values fall between 0.90 and 0.915, both above the recommended cutoff of 0.70, further confirming the high reliability of the constructs (Hair et al., 2017). Additionally, the convergent validity of all constructs meet the suggested threshold for average variance extracted (AVE) of 0.50 or higher, with values ranging from 0.625 to 0.685, implying that each construct explains more than 50% of the variance in its indicators. The findings in Table 2 demonstrate that the measurement model exhibits excellent internal consistency, reliability, and convergent validity, supporting its suitability for further structural analysis.

4.8 Discriminant Validity

Discriminant validity is a fundamental component of construct validity that ensures a construct is distinct and separate from other constructs within a model (Hair et al., 2011). It plays a critical role in confirming that the measured constructs are unique and not merely reflections of other variables. By establishing discriminant validity, researchers can mitigate issues related to multicollinearity, thereby enhancing the reliability and validity of study results (Fornell & Larcker, 1981). The present study assessed discriminant validity using the Heterotrait-Monotrait (HTMT) ratio, which addresses the limitations of the Fornell-Larcker criterion. The HTMT method is considered more robust and involves comparing the mean of the item correlations between constructs (heterotrait) with the mean of the correlations within the same construct (monotrait) (Henseler et al., 2015). An HTMT value below the threshold of 0.85 indicates adequate discriminant validity (Hair et al., 2019). The results are indicated in Table 4.5.

Table 4.5: HTMT

	1	2	3	4	5
Big Data Analytics (1)					
Information Quality (2)	0.745				
Supply Chain Performance (3)	0.645	0.568			
Supply Chain Visibility (4)	0.794	0.719	0.66		
Information Quality x Big Data Analytics (5)	0.484	0.262	0.384	0.433	

Source: Field Survey (2025)

The HTMT values presented in Table 4.5 assess discriminant validity among the latent constructs, with a commonly accepted threshold of 0.85. Values below this threshold indicate adequate discriminant validity (Henseler et al., 2015). All HTMT values in the table are well below 0.85, ranging from a minimum of 0.262 (between Information

Quality and the interaction term Information Quality x Big Data Analytics) to a maximum of 0.794 (between Big Data Analytics and Supply Chain Visibility). This suggests that all constructs are empirically distinct, and no excessive collinearity or redundancy exists among them. Even the highest ratio of 0.794 remains under the critical threshold, reinforcing the conclusion that the measurement model exhibits strong discriminant validity. Therefore, the constructs can be confidently used in subsequent structural equation modelling without concerns about overlapping variance or indistinct conceptual boundaries.

4.9 Collinearity Statistics Assessment

Collinearity refers to a statistical phenomenon where two or more predictor variables in a regression model are highly correlated, meaning that one predictor variable can be linearly predicted from the others with a substantial degree of accuracy (Cheah et al., 2023). This issue can distort the estimates of regression coefficients, leading to misleading conclusions about the relationships between variables. Assessing collinearity is thus crucial in regression analysis to ensure the robustness of the model and the validity of the inferences drawn from it (Hair et al., 2017). In PLS-SEM, collinearity assessment is essential to ensure the robustness and reliability of the model's results. One of the primary methods for assessing collinearity is using Variance Inflation Factors (VIF). To assess collinearity, researchers typically examine the Variance Inflation Factor (VIF) values, with a common threshold being a VIF value below 3.3, indicating acceptable collinearity levels (Hair et al., 2018). The results of the VIF values are presented in Table 4.6.

Table 4.6: Multicollinearity Statistics

	VIF
Big Data Analytics -> Supply Chain Performance	1.941
Big Data Analytics -> Supply Chain Visibility	2.071

Information Quality -> Supply Chain Visibility	1.755
Supply Chain Visibility -> Supply Chain Performance	1.941
Information Quality x Big Data Analytics -> Supply Chain Visibility	1.263

Source: Field Survey (2025)

The Variance Inflation Factor values presented in Table 4.6 indicate the extent of multicollinearity among predictor variables in the structural model. According to the commonly accepted threshold of 3.3, VIF values exceeding this level suggest potentially harmful levels of multicollinearity that could distort regression estimates and inflate standard errors (Hair et al., 2019). Results in Table 4 indicate that all VIF values are well below 3.3, ranging from a minimum of 1.263 for the interaction term Information Quality x Big Data Analytics predicting Supply Chain Visibility to a maximum of 2.071 for Big Data Analytics predicting Supply Chain Visibility. This suggests that multicollinearity is not a concern within the model, and the relationships estimated between constructs are likely stable and reliable.

4.10 Coefficient of Determination (R2)

Coefficient of Determination (R^2) measures the proportion of variance in the dependent (endogenous) variables that is explained by the independent (exogenous) variables. It serves as an indicator of the model's explanatory power, reflecting how well the constructs in the structural model are accounted for by the relationships specified between them (Hair et al., 2017). An R^2 value close to 1 indicates that the independent variables in the model explain a large portion of the variance in the dependent variable, suggesting a strong model with high explanatory power (Hair et al., 2017). The results are shown in Table 4.7.

Table 4.7: Coefficient of Determination

	R-square	R-square adjusted
Supply Chain Performance	0.396	0.393
Supply Chain Visibility	0.557	0.553

Source: Field Survey (2025)

Table 4.7 presents the coefficient of determination (R^2) and adjusted R^2 values for the endogenous constructs of supply chain performance and supply chain visibility, indicating the proportion of variance explained by the exogenous variables in the structural model. The R^2 value for Supply Chain Performance is 0.396, meaning that approximately 39.6% of its variance is accounted for by big data analytics, information quality and supply chain visibility. At the same time, the adjusted R^2 of 0.393 reflects a minor penalty for model complexity, suggesting a stable and reasonably explanatory model. For supply chain visibility, the R^2 is notably higher at 0.557, indicating that 55.7% of its variance is explained by big data analytics and information quality, with an adjusted R^2 of 0.553, which confirms that the model maintains strong explanatory power even after adjusting for the number of predictors.

4.11 Predictive Relevance Assessment

PLS Predict provides a more rigorous approach to understanding how well a model can predict future observations that were not part of the model estimation process. This makes PLS Predict particularly valuable in practical applications that forecast outcomes in new data sets (Shmueli et al., 2016). The outputs of PLS Predict, including RMSE and MAE, enable researchers to assess how well their model is likely to perform in real-world scenarios, where new data may exhibit different characteristics from the training data. The output of the PLS predict is highlighted in Table 4.8.

Table 4.8: Predictive Relevance

	Q^2predict	RMSE	MAE
Supply Chain Performance	0.353	0.809	0.627
Supply Chain Visibility	0.541	0.681	0.507

Source: Field Survey (2025)

Table 4.8 presents the results of predictive relevance analysis, including the Q^2predict, Root Mean Square Error (RMSE), and Mean Absolute Error (MAE) for the endogenous constructs Supply Chain Performance and Supply Chain Visibility. The Q^2predict values, which assess the model's out-of-sample predictive power using a blindfolding procedure, are positive: 0.353 for Supply Chain Performance and 0.541 for Supply Chain Visibility. According to Shmueli et al. (2016), Q^2predict values greater than zero indicate the model has predictive relevance; hence, these results suggest that the structural model demonstrates acceptable to strong predictive accuracy, particularly for Supply Chain Visibility. Additionally, the RMSE and MAE values provide insight into the magnitude of prediction errors, with lower values indicating a better fit. The RMSE is 0.809 for Supply Chain Performance and 0.681 for Supply Chain Visibility, while the corresponding MAE values are 0.627 and 0.507, respectively.

4.12 Effect Size (F2) Assessment

Effect size, typically measured by Cohen's f^2, quantifies the impact of an exogenous variable on an endogenous variable by comparing the coefficient of determination (R^2) when the exogenous variable is included and excluded from the model (Hair et al., 2020). This measure goes beyond simply determining whether relationships are statistically significant; it provides insights into their magnitude. For instance, an f^2 value of 0.02, 0.15, and 0.35 typically indicates small, medium, and large effects, respectively, as per Cohen's (1988) guidelines. These thresholds help researchers understand the relative contribution of each predictor variable, enabling them to identify which variables exert the most significant influence on the model's outcomes and which have minimal impact. The output is highlighted in Table 4.9.

Table 4.9: F-square statistics

	f-square
Big Data Analytics -> Supply Chain Performance	0.091
Big Data Analytics -> Supply Chain Visibility	0.193
Information Quality -> Supply Chain Visibility	0.139
Supply Chain Visibility -> Supply Chain Performance	0.108
Information Quality x Big Data Analytics -> Supply Chain Visibility	0.032

Source: Field Survey (2025)

The findings in Table 4.9 indicate that Big Data Analytics has a small to medium effect on both Supply Chain Performance ($f^2 = 0.091$) and Supply Chain Visibility ($f^2 = 0.193$). Similarly, Information Quality exerts a moderate effect on Supply Chain Visibility ($f^2 = 0.139$), while Supply Chain Visibility demonstrates a small to moderate effect on Supply Chain Performance ($f^2 = 0.108$). In contrast, the interaction term Information Quality x Big Data Analytics has a small effect on Supply Chain Visibility ($f^2 = 0.032$). The results suggest that while most predictors contribute meaningfully to the model, their explanatory power varies. Big Data Analytics and Information Quality have a significant influence on shaping supply chain outcomes.

4.13 Assessment of Path Coefficients and Significance Level

Assessing path coefficients is crucial for understanding the relationships between constructs in a model. These coefficients indicate the strength and direction of the links between exogenous and endogenous variables. Similar to regression coefficients, they quantify how much change in the independent variable impacts the dependent variable (Hair et al., 2017). Evaluating these coefficients involves checking their significance levels, usually determined through bootstrapping in PLS-SEM. A p-value below 0.05 typically signifies that the relationship is unlikely due to chance, lending confidence to the findings. Significance was assessed using t-statistics from 10,000 bootstrap samples, following a two-tailed test as recommended by Hair et al. (2014). Generally, a t-statistic over 1.96 and a p-value under 0.05 indicate statistical significance. The detailed results are presented in Table 10 and Figure 4.2.

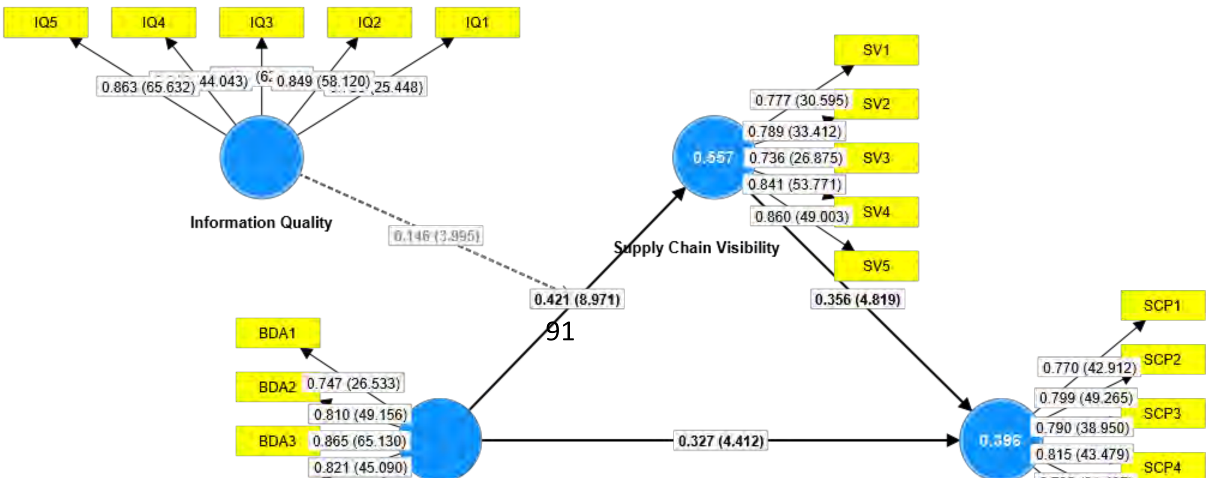

Figure 4.2: Final Model Assessment

Table 4.10: Path Coefficient

	β	Confidence Interval 2.50%	97.50%	T stat	P values	Decision
Direct Effect						
H1: Big Data Analytics -> Supply Chain Performance	0.327	0.182	0.471	4.412	0.000	Accepted
H2: Big Data Analytics -> Supply Chain Visibility	0.421	0.329	0.512	8.971	0.000	Accepted
Information Quality -> Supply Chain Visibility	0.328	0.241	0.416	7.46	0.000	
Supply Chain Visibility -> Supply Chain Performance	0.356	0.215	0.503	4.819	0.000	
Moderating Effect						
H3: Information Quality x Big Data Analytics -> Supply Chain Visibility	0.146	0.071	0.215	3.995	0.000	Accepted
Mediating Effect						
H4: Big Data Analytics -> Supply Chain Visibility -> Supply Chain Performance	0.15	0.085	0.227	4.094	0.000	Accepted

Source: Field Survey (2025)

The results in Table 4.10 provide robust empirical support for the strategic influence of big data analytics on supply chain outcomes, with statistically significant effects across all tested hypotheses. Specifically, big data analytics positively enhances supply chain performance (β = 0.327, t = 4.412, p = 0.000, 95% CI [0.182, 0.471]), indicating that leveraging data analytics enhances operational efficiency, responsiveness, and overall performance. Similarly, the direct effect of big data analytics on supply chain visibility is even more substantial (β = 0.421, t = 8.971, p = 0.000, 95% CI [0.329, 0.512]), suggesting that the application of big data analytics significantly improves the transparency and traceability of supply chain processes. Information quality also shows a notable direct effect on supply chain visibility (β = 0.328, t = 7.460, p = 0.000, 95% CI [0.241, 0.416]), reinforcing the argument that timely, accurate, and relevant information is foundational to achieving effective supply chain performance. Additionally, supply chain visibility significantly enhances supply chain performance (β = 0.356, t = 4.819, p = 0.000, 95% CI [0.215, 0.503]), confirming that visibility is a critical enabler of improved supply chain outcomes.

In terms of moderating effects, information quality significantly moderates the relationship between big data analytics and supply chain visibility (β = 0.146, t = 3.995, p = 0.000, 95% CI [0.071, 0.215]), indicating that the positive effect of big data analytics on visibility is amplified when the quality of information is high. This highlights that big data analytics tools perform more effectively in environments prioritizing data integrity and usability. Finally, the mediating role of supply chain visibility in the relationship between big data analytics and supply chain performance is statistically significant (β = 0.150, t = 4.094, p = 0.000, 95% CI [0.085, 0.227]), illustrating that BDA enhances performance not only directly but also indirectly by improving visibility. The results show that supply chain visibility partially mediates the nexus between big data analytics and supply chain performance. The findings emphasise integrating high-quality data management practices with advanced analytics capabilities to achieve optimal supply chain performance.

Figure 4.3: Slope Analysis

The slope graph in Figure 4.3 illustrates the relationship between big data analytics and supply chain visibility across different levels of information quality. The graph features three lines: the red line representing Information Quality at -1 standard deviation (SD), the blue line at the mean, and the green line at +1 SD. Figure 4.3 shows that as big data analytics increases from -1.1 to 1.1, supply chain visibility shows a positive trend across all levels of information quality, with the steepest increase observed for the +1 SD line (green), followed by the mean (blue), and the least steep for -1 SD (red). This suggests that higher information quality significantly enhances the positive impact of big data analytics on supply chain visibility, indicating a moderating effect where better information quality amplifies the benefits of analytics.

Table 4.11: Summary of findings

	Decision
H1: Big Data Analytics -> Supply Chain Performance	Accepted
H2: Big Data Analytics -> Supply Chain Visibility	Accepted
H3: Information Quality x Big Data Analytics -> Supply Chain Visibility	Accepted
H4: Big Data Analytics -> Supply Chain Visibility -> Supply Chain Performance	Accepted

4.14 Discussion of Results

Hypothesis 1: Big data analytics and supply chain performance

The analysis reveals a statistically significant direct effect of big data analytics on supply chain performance (β = 0.327, t = 4.412, p = 0.000, 95% CI [0.182, 0.471]). This indicates that organisations leveraging BDA are more likely to experience enhanced performance outcomes such as increased efficiency, better customer service, and improved responsiveness to demand changes. The implication is that BDA enables firms to process large volumes of data, generate predictive insights, and optimise decision-making, all of which contribute to superior supply chain performance. This relationship suggests that BDA enables firms to forecast demand accurately, manage inventories effectively, and improve supply chain responsiveness. This result is particularly instructive for manufacturing firms in Ghana, many of which face persistent challenges such as production delays, inefficient logistics, and market unpredictability. It implies that by leveraging big data analytics to detect patterns and trends in supply and demand, these firms can enhance decision-making, reduce wastage, and boost productivity.

This finding is supported by Bahrami et al. (2022), who demonstrated that big data analytics capabilities enable organisations to anticipate disruptions, strengthen supply chain resilience, and drive overall performance. Similarly, Bahrami and Shoukouhyar (2021), adopting a dynamic capability perspective, found that big data analytics improves innovative capabilities and enhances information quality, leading to resilient supply chains and better firm performance. Dubey et al. (2018) further corroborated this, showing that big data analytics enhances supply chain agility and competitiveness, particularly under conditions of environmental uncertainty. These studies converge on the view that, beyond its technical capacity, big data analytics builds adaptive and innovative responses to supply chain challenges, resulting in performance gains. Similarly, Fernando et al. (2018) found that while big data analytics improves performance by enhancing service innovation and data security, many firms only apply it operationally rather than strategically. Additionally, Kibe et al. (2020) highlighted variability in big data analytics outcomes across institutions, with performance improvements being more pronounced in entities with better data infrastructure and analytics capacity. This variability is critical for manufacturing firms in Ghana, where disparities in digital readiness persist. Therefore, while the present study affirms the value of big data analytics for supply chain performance, its successful implementation depends on contextual enablers such as digital infrastructure, data culture, and innovation capability. Ghanaian manufacturers must thus invest in analytics tools to enhance supply chain performance.

The findings aligns with the tenets of the dynamic capability theory, which emphasises an organisation's ability to adapt, reconfigure resources, and make strategic decisions in response to environmental change (Teece et al., 1997). In Ghana's manufacturing sector, where firms often face infrastructural inefficiencies, demand fluctuations, and supply disruptions big data analytics functions as a dynamic capability that enhances organisational agility and responsiveness. Specifically, big data analytics supports the sensing component by enabling real-time monitoring and early detection of supply chain anomalies (Dubey et al., 2020), facilitates resource reconfiguration by identifying operational inefficiencies and opportunities for innovation (Mikalef et al., 2018; Barlette & Baillette, 2020), and strengthens strategic decision-making by offering precise, data-driven insights that reduce uncertainty and support informed planning (Razzaq & Yang, 2023; Al-Khatib, 2022a). The result, therefore, not only confirms empirical findings but also aligns with theoretical expectations that organisations with advanced analytical capabilities are better equipped to build adaptive supply chain systems that improve performance, resilience, and competitiveness in dynamic environments.

Hypothesis 2: Big data analytics and supply chain visibility

In addition to its performance benefits, big data analytics have a positive effect on supply chain visibility ($\beta = 0.421$, $t = 8.971$, $p = 0.000$, 95% CI [0.329, 0.512]), highlighting its transformative potential in fostering transparency across the supply chain. This finding suggests that big data analytics enhances firms' ability to monitor supply chain activities in real-time, detect disruptions, and trace products from origin to endpoint. The implication is that the visibility gained through big data analytics facilitates and enhances proactive management, thereby reducing the risks associated with supply uncertainty. As a result, firms that adopt big data analytics are better positioned to foster transparency, accountability, and trust across the supply chain network. This insight is crucial for Ghanaian manufacturing firms, which often operate within fragmented supply networks and with limited digital infrastructure. Big data analytics can bridge these gaps by enabling firms to monitor supplier performance, anticipate disruptions, and coordinate better with distributors and retailers. Visibility is a support function and a strategic resource that strengthens operational alignment and trust across the supply chain.

The findings aligns with prior studies. For instance, Chatterjee et al. (2023) found that big data analytics significantly strengthens forecasting and decision-making capabilities, which are foundational to achieving visibility in complex supply chain operations. By enabling organisations to track and anticipate demand, monitor supplier behaviour, and identify process inefficiencies in real-time, big data analytics fosters a more responsive and transparent supply chain. Similarly, Fernando et al. (2018) revealed that while many firms currently use big data analytics for operational efficiency, its broader value lies in supporting innovation and real-time data access, two pillars that enhance visibility. These findings validate big data analytics as a strategic enabler of information flow and process transparency.

In addition, other empirical works affirm that big data analytics strengthens visibility not only in commercial supply chains but also in humanitarian and sustainable contexts. Jeble et al. (2019), drawing from the resource-based view and social capital theory, demonstrated that predictive analytics and relational networks improve the responsiveness of humanitarian supply chains by increasing visibility and coordination. Likewise, Shi et al. (2022) highlight that visibility is not merely a by-product of data analysis, but a deliberate outcome of organisational capability, built through effective data capture, interpretation, and dissemination. In alignment with this, Al-Khatib (2022) confirmed that big data analytics significantly improves operational performance through enhanced SCV, particularly in the pharmaceutical manufacturing sector, where real-time visibility into inventory, production, and logistics is essential for efficiency and regulatory compliance. Moreover, Jian et al. (2025) provided further support by showing that big data analytics capabilities influence supply chain resilience through visibility and flexibility, with visibility playing a particularly crucial role in managing reactive resilience. This indicates that big data analytics enables firms to dynamically monitor their supply chains and adjust to disruptions through real-time insights. The cumulative evidence suggests that big data analytics enhances organisational adaptability and control by promoting comprehensive supply chain visibility.

Theoretically, visibility becomes a strategic asset that enables firms to sense disruptions, monitor real-time operations, and respond effectively. Big data analytics directly supports this adaptive capacity by facilitating the continuous collection and analysis of high-volume data, enhancing an organisation’s ability to detect inefficiencies, anticipate risks, and adjust operations accordingly (Dubey et al., 2020; Kembro et al., 2014). Moreover, by improving data accessibility and flow, big data analytics strengthens the firm's capability to reconfigure supply chain resources optimising routes, inventory levels, and supplier coordination to maintain agility and responsiveness (Mikalef et al., 2018; Barlette & Baillette, 2020). Notably, big data analytics enhances strategic decision-making by offering timely, evidence-based insights that reduce uncertainty, allowing firms to align visibility-driven intelligence with broader competitive objectives (Razzaq & Yang, 2023; Al-Khatib, 2022a).

Hypothesis 3: Moderating Effect of Information Quality

The moderating effect indicates that information quality significantly moderates the relationship between big data analytics and supply chain visibility ($\beta = 0.146$, $t = 3.995$, $p = 0.000$, 95% CI [0.071, 0.215]). This finding suggests that the effect of big data analytics on visibility is more substantial when the quality of information is high. In other words, big data analytics tools yield greater value in contexts where data is clean, accurate, and well-structured. The implication is that organisations should adopt BDA technologies and improve their data ecosystems. This includes eliminating silos, automating data collection, and fostering a data-driven culture. This means that the effectiveness of big data analytics in enhancing visibility is contingent upon the quality of information available. Big data analytics tools perform optimally in environments with high-quality, structured, and standardised data. Therefore, to fully benefit from analytics, firms must invest simultaneously in data infrastructure, quality assurance training, and information systems.

This finding aligns with Hani (2022), who established that information quality significantly amplifies the relationship between supply chain management practices and performance. High-quality information systems ensure data accuracy, timeliness, and completeness, which are essential for big data analytics tools to deliver relevant insights and trigger timely visibility-enhancing actions. Without reliable information, even the most advanced analytics tools may produce inaccurate or delayed outputs, reducing their effectiveness in supporting visibility. Additionally, Zuo and Lin (2022) demonstrated that information quality significantly strengthened the impact of government R&D subsidies on innovation outcomes, suggesting that high-quality information environments reduce asymmetries and improve strategic alignment. Similarly, Sukumana et al. (2021) found that quality information systems moderated the effects of various organisational factors on employee training outcomes, further highlighting the cross-sectoral importance of information quality as a catalyst for performance improvement. These findings collectively support the logic that high-quality information improves internal data flows in a supply chain context and conditions the effectiveness of big data analytics tools, thereby reinforcing their impact on visibility. Hence, the current study contributes to the literature by confirming that information quality is not just a support system but a strategic enabler that enhances the performance of big data analytics-driven visibility initiatives.

The findings align with the tenets of the contingency theory, which posits that organisational effectiveness is determined by how well internal processes align with external environmental demands (Donaldson, 2001; Lawrence & Lorsch, 1967). In this context, big data analytics represents an internal capability that enables organisations to process large volumes of data, while supply chain visibility represents an external requirement for timely and transparent decision-making. However, the ability of big data analytics to enhance visibility is contingent on the quality of information being analysed. Contingency theory emphasises that such contextual fit is essential for strategic success. When organisations operate in environments with high-quality information, big data analytics tools can generate insights that directly enhance visibility across supply chain functions. Conversely, in settings with poor data quality, the value of analytics diminishes, undermining their contribution to visibility and responsiveness. Therefore, information quality functions as a contextual variable that shapes the effectiveness of data analytics, offering a robust theoretical explanation for why the impact of big data analytics on supply chain visibility is significantly amplified under conditions of high information quality.

Hypothesis 4: Mediating Effect of Supply Chain Visibility

Finally, the mediation analysis confirms that supply chain visibility partially mediates the relationship between big data analytics and supply chain performance ($\beta = 0.150$, $t = 4.094$, $p = 0.000$, 95% CI [0.085, 0.227]). This result demonstrates that big data analytics contributes to supply chain performance through direct pathways and indirectly through visibility. The implication is that visibility serves as a mechanism through which analytics insights are translated into operational outcomes. Firms that focus solely on analytics without ensuring visibility may miss out on the full performance benefits. Hence, a combined strategy that strengthens big data analytics capabilities and visibility infrastructure is essential for enhancing supply chain performance. Manufacturing firms in Ghana must adopt a dual-focus strategy that combines data analytics with visibility-enhancing processes, such as real-time dashboards, automated reporting, and end-to-end traceability systems, to enhance supply chain performance (Opoku et al., 2024).

The findings corroborate with Al-Khatib (2022), who demonstrated that supply chain visibility mediates the relationship between big data analytics and operational performance in the pharmaceutical manufacturing sector. The ability to access and interpret real-time data enhances the precision and efficiency of supply chain decisions.

This finding reinforces the view that visibility acts as a conduit through which the analytical insights generated by big data tools are operationalised to improve supply chain outcomes. Additionally, Riaz et al. (2024) found that supply chain visibility, traceability, and resilience mediate the effect of Industry 4.0 adoption on supply chain performance. Their study highlights the sequential value of visibility, positioned as a central enabler that links technological adoption to enhanced supply chain responsiveness and strategic alignment. Similarly, Tera et al. (2024) found that the benefits of digitalization are partially transmitted through visibility, with greater performance gains occurring when visibility is combined with supply chain resilience. These studies collectively affirm that visibility is not merely a by-product of digital transformation but a necessary condition for realising the strategic advantages of analytics and digital technologies in volatile supply chain environments.

Additionally, the work of Baah et al. (2020) offers valuable insight into how information sharing initiates a chain reaction that begins with visibility and culminates in performance improvement. Their findings show that visibility enhances collaboration and agility, two capabilities crucial for supply chain resilience and responsiveness, which drive performance. This cascading effect aligns with the current study's findings, suggesting that big data analytics alone does not directly enhance performance unless leveraged to strengthen visibility. Thus, the mediating role of supply chain visibility provides an understanding of how technological capabilities are converted into strategic outcomes, highlighting the need for organisations to invest in analytics tools and visibility-enabling processes and infrastructures.

The findings can be explained through information processing theory, which posits that organisations manage uncertainty and complexity by efficiently acquiring, interpreting, and sharing information (Galbraith, 1973). Big data analytics is an advanced tool for processing large volumes of data to generate strategic insights; however, without supply chain visibility, these insights risk being siloed and underutilised. The structural mechanism facilitates informed decision-making and timely responses to disruption, translating analytics into measurable performance gains (Dubey et al., 2020; Al-Khatib, 2022a). Information processing theory demonstrates that supply chain visibility is not merely a passive outcome but an active enabler that connects analytical capability with performance. The theory's emphasis on reducing uncertainty and promoting coordination further strengthens its relevance. It highlights supply chain visibility as a critical strategic link from data to value.

4.15 Chapter Summary

This chapter presented the results of the structural model analysis, which revealed strong and statistically significant relationships among the core constructs. The findings confirmed that big data analytics have a direct impact on supply chain visibility and performance, indicating its strategic role in enhancing operational transparency and efficiency. Information quality also emerged as a critical factor, significantly improving supply chain visibility and strengthening the effectiveness of analytics applications. Additionally, supply chain visibility has a positive influence on performance, reinforcing its role as a key driver of supply chain success. The analysis further established that information quality moderates the relationship between big data analytics and visibility, highlighting the importance of high-quality information in amplifying the benefits of analytics tools. Moreover, supply chain visibility was a significant mediator between big data analytics and performance. This suggests that visibility is a key mechanism through which analytics capabilities translate into performance improvements.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATION

5.0 Introduction

This chapter summarizes the key findings from the study's analysis, highlights the conclusions related to the research objectives, and provides practical recommendations based on the evidence collected. It provides a concise overview of the main results, highlights key insights, and explains how the findings contribute to addressing the research problem. The chapter also discusses potential areas for future research and suggests policy or practice actions to improve the situation studied.

5.1 Summary of Findings

The study examined how big data analytics affect supply chain performance through the supply chain visibility conditioned by information quality. The study was guided by four specific objectives, including

i. Examine the effect of big data analytics on supply chain performance.
ii. Assess the relationship between big data analytics and supply chain visibility.
iii. Determine whether information quality moderates the nexus between big data analytics and supply chain visibility in the manufacturing industry in Ghana.
iv. Assess the mediating effect of supply chain visibility in the relationship between big data analytics and supply chain performance in the Ghanaian manufacturing industry.

The study was anchored in three interrelated theoretical frameworks: dynamic capabilities theory, information processing theory, and contingency theory. These theories provided a robust conceptual foundation for examining how the use of big data analytics influences supply chain performance and how this relationship is shaped by the visibility of operations across the supply chain and the quality of information exchanged. Dynamic capabilities theory explained how firms develop adaptability, responsiveness, and innovation by leveraging data-driven capabilities. Information processing theory highlights the importance of real-time coordination and communication for managing supply chain complexities, while contingency theory emphasizes that the effectiveness of data analytics depends on the context, particularly the accuracy, relevance, and timeliness of the information available for decision-making.

The study adopted a positivist philosophical stance, reflecting a commitment to objective measurement and hypothesis testing. A quantitative research design was employed, and data were collected through a structured questionnaire administered to selected manufacturing firms within the Greater Accra region of Ghana. The region was chosen for its industrial significance and concentration of diverse manufacturing activities. A census approach was used to capture responses from decision-makers in these firms, ensuring relevance and informed perspectives. The data collection instrument was designed using rigorously validated scales from existing literature, covering key constructs such as data analytics, supply chain visibility, information quality, and supply chain performance. Reliability and validity were established through pilot testing, expert review, and confirmatory factor analysis. The final dataset was analyzed using structural equation modelling via the partial least square's technique, which allowed for a robust assessment of complex relationships among latent variables and testing of mediating and moderating effects.

The findings revealed that the application of big data analytics significantly enhances supply chain performance by improving responsiveness, efficiency, and strategic coordination. In addition, the analysis demonstrated that visibility across the supply chain mediates this relationship, indicating that data-driven insights must be effectively shared and acted upon to yield tangible performance benefits. Furthermore, the quality of information was shown to moderate the link between big data analytics and supply chain visibility, confirming that organisations with accurate, complete, and timely data are better positioned to leverage analytics for enhanced coordination. The study confirmed that integrating advanced data practices, supported by operational transparency and reliable information, and is crucial for achieving competitive supply chain outcomes.

Conclusion

The study examined the effect of big data analytics on supply chain performance and the roles of supply chain visibility and information quality within Ghana's manufacturing sector. The findings provide compelling evidence that big data analytics significantly improves supply chain performance when effectively integrated into operational decision-making. The study established that this relationship is strengthened through enhanced supply chain visibility, which serves as a critical pathway for translating data-driven insights into real-time coordination, agility, and responsiveness. Furthermore, the analysis confirmed that the quality of information moderates the impact of big data analytics on supply chain visibility, highlighting that accurate, relevant, and timely information is essential for maximising the benefits of analytics. These findings suggest that for manufacturing firms to achieve superior supply chain performance, they must not only invest in advanced data analytics capabilities but also ensure transparency across the supply chain and uphold high standards of information quality.

5.2 Managerial Implications

The findings of this study carry significant managerial implications for manufacturing firms in Ghana seeking to enhance their competitiveness and operational performance in a volatile and data-driven market environment. Managers must recognise that big data analytics is not merely a technological investment but a strategic enabler that allows firms to detect supply chain inefficiencies, predict market shifts, and respond with agility and precision. However, the realisation of these benefits is contingent upon the firm's ability to achieve high levels of visibility across the supply chain. Therefore, managers must prioritise the development of integrated systems that facilitate real-time tracking and seamless information sharing among supply chain partners. This requires deliberate investments in digital infrastructure, inter-organisational platforms, and workforce capabilities that promote transparency, collaboration, and timely decision-making. In parallel, ensuring the quality of information, its accuracy, timeliness, relevance, and completeness, must become a central managerial focus. Poor data quality undermines the effectiveness of analytics and visibility efforts, resulting in flawed insights and reactive decision-making. Consequently, managers must implement robust data governance frameworks and quality assurance protocols across the supply chain to guarantee that the insights derived from analytics are both reliable and actionable. By strategically aligning big data analytics initiatives with visibility and information quality priorities, Ghanaian manufacturing firms can strengthen supply chain coordination, reduce operational risks, and deliver greater value to customers and stakeholders in a highly competitive industrial landscape.

5.3 Theoretical Implications

The findings of this study offer strong theoretical implications that extend and enrich existing frameworks within supply chain management literature, particularly the dynamic capabilities theory, information processing theory, and contingency theory. First, the confirmation that big data analytics enhances supply chain performance reinforces the central tenet of dynamic capabilities theory, that organisations must continuously sense, seize, and reconfigure resources to adapt to environmental changes. This study demonstrates that data analytics functions as a dynamic capability, enabling firms to proactively manage supply chain complexities and improve responsiveness. Second, the mediating role of supply chain visibility provides empirical support for information processing theory, underscoring that the value of analytics is maximised only when information flows freely and is effectively utilised across supply chain networks to reduce uncertainty and enable coordinated actions. Lastly, the moderating effect of information quality affirms the contingency theory proposition that the effectiveness of internal capabilities (such as data analytics) is context-dependent. High-quality information enhances the strategic value of analytics and visibility, whereas poor information weakens these linkages.

5.4 Contribution to Knowledge

This study makes a contribution to knowledge through the development and empirical validation of an integrated moderated mediation framework that explains how big data analytics enhances supply chain performance through the mediating role of supply chain visibility and the moderating influence of information quality within the under-researched context of Ghana's manufacturing sector. Unlike prior studies that examine analytics, visibility, or performance relationships in isolation, this research demonstrates that the performance benefits of big data analytics are neither automatic nor linear but occur through enhanced supply chain visibility and are strengthened under conditions of high information quality. The study advances theoretical clarity and provides deeper insight into the mechanisms and boundary conditions shaping analytics effectiveness through the simultaneous examination of direct, mediating, and moderating relationships within a unified model. It further extends dynamic capabilities, information processing, and contingency theories by illustrating how technological capabilities, information flow structures, and contextual quality factors interact to influence operational outcomes in a resource-constrained environment. The study also contributes rare empirical evidence from a developing economy manufacturing context, thereby broadening the geographical and industrial scope of supply chain analytics research. The application of integrated structural modelling to examine layered capability interactions strengthens the methodological originality of the findings. The study reframes big data analytics as part of a broader system of complementary organisational capabilities that must align to achieve sustainable supply chain performance improvements.

5.5 5 Limitations and Recommendations for Future Research

In light of the limitations identified in this study, several avenues for future research are recommended. First, while this study employed a quantitative approach using structured questionnaires, future research could adopt a mixed-methods or qualitative design to explore in greater depth the organisational, behavioural, and cultural factors that influence the implementation and effectiveness of big data analytics, supply chain visibility, and information quality. Second, as the study was limited to manufacturing firms within the Greater Accra Region of Ghana, future studies should consider expanding the geographical scope to include other regions and sectors, thereby enhancing the generalisability and contextual robustness of the findings. Additionally, the use of a cross-sectional design restricts the ability to assess changes over time; thus, longitudinal research is recommended to examine the dynamic evolution of the relationships among the key variables under varying market conditions. Furthermore, future studies could incorporate additional contingency factors, such as leadership commitment, digital readiness, or regulatory frameworks, to provide a more comprehensive understanding of the conditions under which big data analytics influence supply chain performance. Such extensions would enrich the theoretical and practical insights into the contextual enablers that shape data-driven supply chain strategies in developing economies.

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APPENDIX

Questionnaire

I am Robert Ewur a postgraduate student at the University of Education, Winneba, Department of Procurement and Supply Chain Management. This survey instrument has been designed to enable me to research the topic: *"Effect of Big Data Analytics on Supply Chain Performance and the Roles of Supply Chain Visibility and Information Quality"*. The data is solely needed for academic purposes, and its confidentiality is assured. Participation is entirely voluntary. Please tick [√] the most appropriate answer to each of the questions.

Section A: Demographic Information

1. Gender: [ ] Male [ ] Female

2. Age: [ ] 23 years and below [ ] 24–29 years [ ] 30–35 years

[ ] 36–40 years [ ] 41 years and above

3. Educational Background:

[ ] Secondary [ ] 1st Degree [ ] Master's Degree [ ] Ph.D./Doctorate

4. Please indicate your position in the firm [ ] CEO [ ] General Manager [ ] Operations Manager [ ] Purchasing Manager [ ] Logistics/Supply Chain Manager [ ] Others

5. Number of years the firm has been in operation:

[ ] Less than 1 year [ ] 1-5 years [ ] 6-10 years
[ ] 11-15 years [ ] 16-20 years [ ] 21 years & above

6. Number of employees in the firm:

[ ] Less than 10 employees [ ] 11-50 employees [ ] 51-100 employees
[ ] 101-500 employees [ ] More than 500 employees

7. Please, indicate the industry your firm belongs (tick only the dominant one)

[ ] Industrial machinery, machine, tools [ ] Chemicals [ ] Plastics & rubber [ ] Food, beverages, drinks [ ] Metals, metal working [ ] Pharmaceuticals, health care [ ] Paper and packaging [ ] Engineering, construction [ ] Textiles and clothing [ ] Electronics

Other (please specify): ____

8. Firm's annual revenue (in Ghana Cedis)?

[ ] Less than 500,000 [ ] 500,000 – 1,000,000 [ ] Above 1,000,000

Section B: Big Data Analytics

Please indicate by ticking [√] the appropriate column using the scale: 1= Strongly Disagree – 7= Strongly Agree

	Statements	1	2	3	4	5	6	7
BDA1	We use advanced tools to analyse operational and performance data.							
BDA2	We use data visualization techniques to help decision-makers understand complex insights from large datasets							
BDA3	Data-driven analytics help us make timely financial and operational decisions.							
BDA4	We leverage multiple data sources to generate actionable insights for the business.							
BDA5	We analyse data as soon as it becomes available to support quick decision-making.							

Section B: Supply Chain Visibility

Please indicate by ticking [√] the appropriate column using the scale: 1= Strongly Disagree – 7= Strongly Agree

	Statements	1	2	3	4	5	6	7
SCV1	We are able to communicate with supply chain partners regarding fluctuations in demand and alterations in customer preferences.							
SCV2	We share performance feedback with our supply chain partners.							
SCV3	Our company involves stakeholders in making decisions about customer preferences and new product requirements.							
SCV4	We consistently monitor inventory levels across the supply chain.							
SCV5	We gather information from various sources to gauge the market and prepare for seasonal fluctuations.							

Section D: Information Quality

Please indicate by ticking [√] the appropriate column using the scale: 1= Strongly Disagree – 7= Strongly Agree

	Statements	1	2	3	4	5	6	7
IQ1	The information we generate is available in time to support key business decisions.							
IQ2	The information we produce is precise and error-free, ensuring trustworthy decision-making.							
IQ3	The information we provide covers all the necessary aspects needed for effective decision-making.							
IQ4	The information we deliver is sufficient in detail and scope for making informed choices.							
IQ5	The information we supply is consistent and dependable for business decisions.							

Section E: Supply Chain Performance

Please indicate by ticking [√] the appropriate column using the scale: 1= Strongly Disagree – 7= Strongly Agree

	Statements	1	2	3	4	5	6	7
SCP1	Our supply chain consistently delivers products within the promised timeframe.							
SCP2	Our supply chain effectively minimizes waste and cost across all operations.							
SCP3	Our supply chain adapts faster to changes than competitors.							
SCP4	Our supply chain can rapidly adjust products to meet customer needs.							
SCP5	Our supply chain maintains an excellent on-time delivery track record.							
SCP6	Our supply chain delivers a superior level of customer service.							

Thank you for your time and participation.