KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI

Impact of industry 4.0 capabilities in achieving supply chain innovation. The mediating role of data-driven decision making in Ghana

by

Faisa Achaab

A Thesis submitted to the Department of Supply Chain and Information Systems, School of Business, in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE IN

LOGISTICS AND SUPPLY CHAIN MANAGEMENT

JANUARY, 2023

DECLARATION

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

FAISA ACHAAB ……………………….. ………………..

(PG9247121) Signature Date

Certified by:

Prof. Kwame Owusu Kwateng ………………... …………………

(Supervisor) Signature Date

Prof. David Asamoah ……………….. ………………..

(Head of Department, SCIS) Signature Date

DEDICATION

I dedicate this work to my lovely husband, Stephen Elvis Ajowiak, my mother, Mrs. Francisco Tindaan, and my Children. Also, to all you who indirectly supported me in this journey.

ACKNOWLEDGEMENT

Working on this research project was a great learning experience for me. I would like to sincerely thank Professor Kwame Owusu Kwarteng, for his valuable and continued guidance throughout this project that allowed me to delve deeper into this subject beyond my perceived capacity. I thank Jesus Christ for His amazing grace and love that kept me going, even when the demands of the project became tough. I am also forever indebted to my wonderful husband, Mr. Stephen Elvis Ajowiak, for offering unwavering support especially when I had to burn the midnight oil working on this project. To my children, accept my heartfelt gratitude for the many moments of humour. All those times have contributed to this success. Finally, I wish to say thank you to Patrick Agyei (a.k.a. Nana) for the encouragements as a course mate. Your effort has paid off.

ABSTRACT

The main objective is to examine the mediating role of data-driven decision-making and the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. The study employed a cross-sectional research design. This survey was conducted using a quantitative approach. Stratified sampling was used to choose 381 participants. A prepared questionnaire was the main tool used for data collection. Both SPSS v26 and SmartPls v4 were used for the statistical analysis. Both descriptive and inferential approaches were used to analyse the data. The result reveals that industry 4.0 had a significant direct influence on SC innovation and data-driven decision-making. The result also concludes that data-driven decision making has a direct effect on SC innovation. The results indicate that data-driven decision making positively and fully mediates interactions between industry 4.0 and SC innovation. The study, therefore, concluded that managements should constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose to reason over instinct when presented with actual data that contradicts their beliefs to gather data and draw conclusions, have the real-time capacity, and makes decisions virtually and decentralised to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically.

TABLE OF CONTENT

CONTENTS **PAGE**

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

IoT	Internet Of Things
SEM	Structural Equation Modelling
ECS	Electronic Components and Systems
EECA	Eastern Europe and Central Asia
EECA	Eastern Europe and Central Asia
BEEPS	Business Environment Enterprise Performance Surveys
DDSCO	Data-Driven Supply Chain Orientation
AI	Artificial Intelligence,
SCRes	Supply Chain Resilience
SCP	Supply Chain Performance
OIPT	Organizational Information Processing Theory
SCP	Supply Chain Performance
CMV	Common Method Variance
KMO	Kaiser-Meyer-Olkin
HTMT	Heterotrait-Monotrait Ratio
KNUST	Kwame Nkrumah University of Science and Technology

CHAPTER ONE

INTRODUCTION

1.1 Background of the study

Technological breakthroughs often have the potential to affect all industries, resulting in structural changes (Wang et al., 2020; Hahn, 2020). Technological changes have led to industrial changes that have had significant effects on production processes, value chains, and social organizations (Fatorachian and Kazemi, 2021; Hopkins, 2021). In the last decade, digital technologies such as cloud computing (Liu and De Giovanni, 2019), the Internet of Things (Hahn, 2020), and artificial intelligence have combined our physical and digital worlds,' therefore they are entering the fourth revolution, even normal business changes lead to industrial revolution 4.0 (Fatorachian and Kazemi, 2021; Pfohl et al., 2017). Products are now increasingly added to digital services (Wamba and Queiroz, 2022; Yuan et al., 2022), which has caused a change in the way businesses to develop, produce and change their delivery (Tiwari, 2022; Bousdekis et al., 2021). Both academics and experts believe Industry 4.0 to transform all businesses in fundamental ways that can improve their results and efficiency (Kusi-Sarpong et al., 2021; Donkor, et al., 2021). Examples of applications include machine learning (Momeni and Martinsuo, 2018), human monitoring (Kumar et al., 2021), and smart management projects (Marinakis et al., 2020; Zhai, 2021).

Regardless of the tremendous potential, few businesses have successfully transformed through the full use of 4.0 technologies and their applications for digital product solutions (da Rocha Torres et al., 2022). This rate of change is low in small and medium-sized companies in the industrial sector (Kohnová et al., 2019). It should be noted that the realization of the potential of Industry 4.0 requires changes in the industrial sector (Frank et al., 2019), as their production strengths are linked to the core capabilities to be equipped with new information technology capabilities (Frank et al., 2019; da Rocha Torres et al., 2022). The major challenges related to this are caused by the lack of knowledge and understanding of the potential of information technology systems in the Industry 4.0 transition (Salimova et al., 2020). On this basis, the decision to be taken by the business players will be good with a completely specialized vision for them to make good (Ludbrook et al., 2019), informed decisions for long-distance organizations (Hyers, 2020), management, and employees on the capabilities of Industry 4.0 (Duft and Durana,2020). Instead of focusing more on the usual 'why' and 'what' of Industry 4.0, this study focuses on the neglected 'how' (Grant, 2021). This study aims to provide a specific perspective on the technological system capabilities needed by industries that want to use Industry 4.0 (Tseng et al., 2021).

Theoretically so far, the literature on Industry 4.0 can be considered mature because it provides important knowledge to define and organize aspects of technology in terms of supply chain innovation (Ramirez-Peña et al., 2020; Yadav et al., 2020). For example, researchers have found many success factors (Rad et al., 2022) and employee needs (Bhagawati et al., 2019; Luthra and Mangla, 2018). Current knowledge also includes important changes, such as studies on the readiness of Industry 4.0 (Lassnig et al., 2021) or aging models (Manavalan and Jayakrishna, 2019). Although this study provides a good understanding of the Industry 4.0 revolution, it does not cover all the capabilities or dimensions of information systems required for successful business operations in the Industry 4.0 era.

Similarly, firms are using digital technologies to change their supply management models (Sony and Naik, 2019), implement supply chain strategies, and identify key factors for delivering value to customers (Castelo-Branco et al., 2019). These expectations have benefited greatly from the technical and technological developments that followed the Fourth Industrial Revolution (Xing et al., 2021). This phenomenon is caused by 'Industry 4.0' or Industrial 4.0, also known as 'The

Internet of Things', which has attracted a lot of interest in the professional community (Fernando et al., 2022; Nick et al., 2021). Industry 4.0 shows the vision of virtual and connected assets, that is, smart products and devices that are independent and can create coordinated systems such as smart stores and supply chains (Shayganmehr et al., 2021; Harmoko, 2020).

In addition, these technologies can enable the use of new models of the supply chain to supplement or replace traditional practices (Ramanathan and Samaranayake, 2021; Sarı et al., 2020). Inspired by these published studies, this study examines the impact of industry 4.0 on supply chain innovation through the theoretical model of supply chain management (Nica, 2019). The importance of information and communication technology for the management of the supply chain (Felstead, 2019) and its positive effect on performance (Dallasega et al., 2018) has been widely confirmed. Recent advances in computer technology have promised major changes in the supply chain of many industries and sectors (Kayikci et al., 2022). Such innovations affect supply chain operational models (Yu et al., 2021) and require the use of new (digital) delivery methods for supply chain management (Ardito et al., 2019).

By distinguishing the outcomes of innovation from the process of innovation and the specifics of innovation (Luthra and Mangla, 2018), this study examines the content of innovation and its formation as a measure of innovation results in terms of elements analysed to achieve supply chain (Chalmeta and Santos-deLeón, 2020). This study uses a fixed perspective and differentiates from firms to reflect the innovative new ways of showing companies in these sectors, which is especially determined by the use of technology (Patrucco et al., 2020). Therefore, this study tries to answer two questions: What is the status and future of industry 4.0 that drives the use of supply chains and what is the fundamental level of the Industry 4.0 that drives the use of innovation and how they are related. Both questions are analyzed specifically on the similarities and differences of companies based in the Ghanaian economy. Following a theoretical model (Luthra and Mangla, 2018), this study improves the experimental design model described by Corallo et al. (2028) to ensure that the industry 4.0 help supply chain achieve its innovation process.

The current system of devices and information communication between industries can be improved by the development of new technologies such as the Internet of Things (IoT), cloud computing, and cyber-physical systems. This situation is often referred to as Industry 4.0, smart manufacturing, and digital factories (Da Silva et al., 2019). The amount of information generated by special machines and special machines and machines has been described in various evaluations of business networks and data sources, for example (Ding, 2018), Especially special attention to the reduction of costs and the improvement of business is playing an important role (Hossain and Thakur, 2020). Urgent care uses a variety of information to assess abnormal behaviour (diagnosis), predict the future (prognosis), and provide immediate support for decision making in the era of Industry 4.0, which also need to support decision-making using the development of new methods and algorithms aimed at helping firms make the best decisions about maintenance and performance (Dalmarco and Barros, 2018), This research emphasizes the popularity of data-driven decision making for industry, starting with a research area and analyse the results of the situations using real-time statistical data.

Ability to generate automated system data; specialized, internet of things enabled devices; and multiple devices that challenge existing decision-making tools in Industry 4.0 improvement applications (Krykavskyy et al., 2019). Literature has shown the increasing exposure of data-based policies that are used to make the most of the information collected in the context of Industry 4.0. With the rise of cyber-technology as well as cloud technologies for data processing and storage, next generation care decision making will be more responsive and able to be understood and forward decisions on the supply chain innovation achievement (Matthyssens, 2019).

Today, the ability to collect and process information has increased with the rapid development of computer technology (Hofmann et al., 2019), for example, big data analysis, business intelligence and information processing. A comprehensive analysis can improve the decision-making process (Manavalan and Jayakrishna, 2019). Therefore, the practice of information-based strategies has increased (Tiwari, 2020). This model states that decision making is based on data analysis and not just based on knowledge (Preindl et al., 2020). This decision-making process for supply chain optimization, focusing on supply chain network problems, analyses for businesses using data in specific decision areas to develop solutions (Ludbrook et al., 2019). The information required by this model is found in the implementation of new communication methods, which accurately describe the beginning and development of the communication paradigm (Duft and Durana, 2020). Therefore, experimental models are suitable for the study of complex systems such as supply chains (Davidson, 2020). Data-driven decision making can include business-specific and multi-level analysis for supply chain management without assumptions or limitations (Tseng et al., 2018). Therefore, data-based decision-making has clear advantages over experimental decision-making in the creative process of the supply chain (Fernández-Caramés et al., 2019).

Currently, data related to supply chain decisions is still in its infancy and some potential gaps still need to be explored (Tseng et al., 2021). As a new paradigm, the decision-making process is focused on understanding the state of supply development that needs to be re-evaluated based on research and identification (Riley et al., 2021). Data collection for specific business analysis and decision-making data still requires careful consideration (Hyers, 2020). Unique data-driven business analysis is required for supply chain optimization (Yu et al., 2019). Specific and comprehensive formats or information-based data methods for supply chain innovation are neglected in the existing literature (Nica, 2019). To bridge this gap, this study aims to examine the decision-making process based on data on the placement of supply chain innovation. This study proposes a data-based decision-making model for supply chain innovation. In this model, supply chain data granularity is created to validate the data form for decision -making, this current study aims to examine the impact of Industry 4.0 capabilities in achieving supply chain innovation, through its mediating role in data-based decision-making.

1.2 Problem statement

Industry 4.0 uses a variety of tools and technologies to help redefine traditional business processes. Supply chains are increasingly computerized, automated, and efficient in their operations (Zheng et al., 2021). At the moment of digital communication, many different technologies are used to create efficient, transparent, flexible, and improved systems at different stages of the supply chain, including the development of new products, production, sales including planning, logistics, and marketing (Chae and Olson, 2022). The impact of Industry 4.0 can be felt at different levels of supply and in management strategies (Papakostas et al., 2022); thus, more accurate information and planning by integrating and increasing the tracking of materials and products (Pires et al., 2019), sharing real-time information and coordinating with suppliers and improving the performance of the business through the warehouse and motor vehicles (Javaid and Haleem, 2019).

The sudden disruption due to digitalization is forcing companies to rethink how they organize their supply chain (Mastos, et al., 2021). The clarity and ease of access to many choices of where to buy and what to buy, allowed by e-commerce platforms, has strengthened competition in terms of supply chain innovation process development (Ivanov et al., 2019). In particular, the update has an important role in the change of the supply, providing remote and real-time monitoring of the condition of the vehicle and the speed (Hofmann et al., 2019), the level of corrosion through thermal sensors, the condition of the machines and operations, etc (Ghadge et al., 2020). The increased communication of supply chain partners and the increasing importance of collaboration requires an assessment of decision-making on the performance of Industry 4.0 in supply chain innovation (Koh et al., 2019).

Frank et al. (2019) identified the supply chain as part of Industry 4.0, including digital data and sales, suppliers, customers, and partners. Improving information sharing and coordination activities between supply chain partners helps reduce costs and helps improve supply chain efficiency and effectiveness (Frank et al., 2019; Ghobakhloo and Fathi, 2021). Better transparency and collaboration in supply chain innovation also led to stronger trust and relationships between supply chain members. Industry 4.0 has the potential for structured communication, maintenance and management of goods, materials, and supply chains to increase the number of sales activities, and reduce risk (Luthra and Mangla, 2018). The integration of 4.0 technology has also led to changes in business models and production management system strategies (Müller, 2019). In addition to the requirements and processes to manage digital transformation in the supply chain, new challenges and risks arise due to business process transformation and digital transformation. Some of these issues include a lack of information, information security problems, and lack of skilled workers (Simic and Nedelko, 2019). Therefore, there is a need for a basic model and special studies to guide the industry in the development of a successful and sustainable Industry 4.0 that can be adapted to the supply chain and quickly adapt to changes in technology and markets (Fathi and Ghobakhloo, 2020).

Hahn (2020) in his study on Industry 4.0; a supply chain innovation perspective, shows supply chain innovation through industry 4.0 presented in three dimensions; such as process (Mosser et a., 2022), technology (Bai et al., 2020), and business structure (Haseeb et al., 2019). It also shows that the modernization of supply chains enabled by Industry 4.0 has broadened the initial focus on improvement in the production process of the supply chain in expansion and adaptation (Telukdarie et al., 2018). Most of the industry 4.0 solutions rely heavily on analytics and smart things while abandoning the technology experts and human processes associated with the industry 4.0 paradigm (Hallioui et al., 2022). This has caused companies adopting industry 4.0 to simply maintain their current business structures and drastically change their operating models, heavily dependent on statistical data and economic conditions (Topleva, 2018). Therefore, the industry pursues a problem-solving, engineering-based approach to supply chain innovation while following an asset-aware, and strategic approach in business.

Bousdekis et al. (2021) show that industries make decisions for the production and maintenance of work because they benefit from the use of the technologies of Industry 4.0, which analysed the data, predict trends, and enable the use of algorithms to recommend mitigation actions. Bousdekis et al. (2021) analysed data-based outcomes of care and outlined directions for future research into decision-making for Industry 4.0 maintenance data. Their main areas of research include fuzzy information and applications rather than Internet of Things (IoT) devices that combine the real world with the world of industries for slow communication and decision making and augmented reality, integrating care decisions with other activities such as scheduling and planning; the use of continuous cloud computing to optimize decision-making services; ability to make decisions when dealing with big data; integration of security mechanisms; and integrate decision-making with virtualization software, autonomous robots, and other advanced technologies to improve the supply chain innovation process.

Studies on Industry 4.0 in achieving supply chain innovation have been shown in the literature to be conducted in developed countries (Pfohl et al., 2017; Hahn, 2020; Wang et al., 2020; Hopkins, 2021; Liu and De Giovanni, 2019; Fatorachian and Kazemi, 2021; Yuan et al., 2022; Tiwari, 2022) such as UK, USA, Canada, Australia and Malaysia. The findings from these studies have proven that the presence's Industry 4.0; capabilities in supply chain can only be improved through innovation to meet the demand of industries for the satisfaction of their customers. Industry 4.0 can never be achieved without the support of data-driven decision-making (Bousdekis et al., 2021). But the gap identified in the literature was that have failed to look at how data-driven decision-making can impact industry 4.0 in achieving supply chain innovation. It can been seen that good data-driven decision-making will supply chain use industry 4.0 models to bring out new things to improve the supply chain with the procurement curtains. The aspect of industry 4.0 capabilities towards supply chain innovation has not been given the needed attention in developing countries, especially Ghana. Studies such as (Kusi-Sarpong et al., 2021; Donkor et al., 2021), have looked at industry 4.0 but has not to look it impact on supply chain innovation or even talked about the mediating role of data-driven decision-making. This study attempts to bridge the gap by examining the mediating role of data-driven decision-making on the effect of industry 4.0 capabilities on supply chain innovation in Ghana.

1.3 Objectives of the study

The main objective is to examine the mediating role of data-driven decision-making on the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. The specific objectives are as follows:

i. To examine the effect of Industry 4.0 capabilities on supply chain innovation in Ghana.
ii. To investigate the influence of Industry 4.0 capabilities on data-driven decision-making in Ghana.
iii. To assess the effect of data-driven decision-making on supply chain innovation in Ghana.
iv. To investigate the mediating role of data-driven decision-making in the relationship between Industry 4.0 capabilities and supply chain innovation in Ghana.

1.4 Research questions

i. What is the effect of Industry 4.0 capabilities on supply chain innovation in Ghana?
ii. Does data-driven decision-making have significant positive influence on supply chain innovation?
iii. What is the relationship between data-driven decision-making and supply chain innovation in Ghana?
iv. Can data-driven decision-making mediate the relationship between Industry 4.0 capabilities and supply chain innovation?

1.5 Significance of the study

For organizations, policy makers and educators, Industry 4.0, also known as the fourth industrial revolution, will have a major impact on business, society and supply chains. In Industry 4.0, supply chains will be digitized, opening up new opportunities for competitive advantage through new supply chain structures, new processes, and the ability to use technology to deliver four sessions. Supply chain management and packaging processes, with the aim of reducing the amount of data in the supply chain (Meherishi et al., 2022). Supply chain management has shown great importance in improving supply chain performance and promoting organizational performance through innovation. It continues to improve the assembly process in response to social and technological change (Hofmann et al., 2019). This will increase the efficiency of supply chain systems, businesses, and help them operate at a higher level (Shao et al., 2021).

Economic activity in an organization can be measured by its ability to generate value from new ideas. It makes a great contribution to the success and competitiveness of the organization, but it also has important problems (De Giovanni and Cariola, 2021). Companies are investing in new technologies to improve supply chain performance, which help create better information between supply chain members, and communication and collaboration have also helped (Chauhan et al., 2021). It has become very important for many businesses in the era of Industry 4.0. Supply chain integration facilitated by Industry 4.0 reduces implementation time and cost while allowing for new ideas and faster response times (Chauhan et al., 2021).

Supply chain innovation will help improve operational efficiency and service quality through new sales and marketing methods that integrate information and communication from Industry 4.0 (Díaz-Chao et al., 2021). One of the biggest challenges for organizations is the impact of technology, Industry 4.0 helps improve operational efficiency, as well as make informed decisions (Gupta et al., 2021). Supply chain management and its implications for the supply chain are discussed by Manavalan and Jayakrishna (2019) on the impact of Industry 4.0 and the role of the Internet of Things. As a process that combines knowledge, organization, technology, and market forces, the innovation process is multifaceted. The company's network usage model has changed by identifying factors that help to implement supply strategies and provide value to customers (Manavalan and Jayakrishna, 2019). The technical and technological development of Industry 4.0 has contributed to this effort (De Giovanni and Cariola, 2021). Many research studies have proven the importance of innovation in supply chain management (Kusi-Sarpong et al., 2021; Donkor et al., 2021). Finally, the results of this study will encourage the creation of effective policies and programs for governments to encourage firms to adopt Industry 4.0 technologies to improve supply chain innovation in their production settings. Therefore, the findings of this study will be useful for both firms, consumers and other stakeholders involved in the implementation of Industry 4.0 capabilities in supply chain innovation with the help of data-driven decision making.

1.6 Brief Methodology

The study employed the descriptive research design and quantitative approaches in examine the mediating role of data-driven decision-making of the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. Data will be collected through the administering of questionnaires. Close and open-ended questions will be categorized into sections. The study respondents will be top managers and procurement officers of the sampled firms in Ghana. Three hundred and sixty-nine (369) firms will be selected using a simple random sampling technique with the help of Cochran's (1977) formula of sample size determination. For the data analysis, the data was analysed in SPSS which will include missing values, validity, explanatory statistics, and hypothesis testing for multi-dimensional analysis. Subsequently, the data was transferred to version 3 of SmartPLS (Sarstedt and Cheah, 2019; Hair et al., 2020) to perform predictive calculations through multivariate data analysis. Which will help examine the mediating role of data-driven decision-making of the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. The results will be displayed using tables, graphs, and charts.

1.7 Scope of the study

The study aims to examine the mediating role of data-driven decision-making in the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. In this context, the study focused on all firms involved in supply chain innovation activities in Ghana. Geographically, firms ready to use Industry 4.0 technologies to improve supply chain innovation in Ghana are the main target for this current study. This will cover all firms located in the urban and rural environment in Ghana.

1.8 Organization of the study

The study was structured into five chapters, the first chapter (chapter one) will introduce and describe the study, the problem statement, the objectives, and the research questions about the significance and scope of the study. The second section, reviews literature-related definitions and concepts, research theory and theoretical frameworks, and other authors' empirical evidence. The third part discussed the research design, descriptions of study sites, target populations, sampling and sampling methods, sample sizes, questionnaires, collection procedures, data sources, data analysis, reliability, and validity from the source. The fourth section contains data analysis and discussion, and the fifth section finds a summary of the research, conclusions, and recommendations.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

Chapter two of this thesis is organized into four main sub-headings. The chapter provides information organized under conceptual review, theoretical review, empirical review, and finally the research model and hypotheses development. The Conceptual review section provides definitions, operationalizations, and how the constructs have been used in this study. The theoretical review section also provides the theoretical underpinnings of the study. The various prepositions proposed in this study were depicted using a conceptual framework and various relationships were well discussed. The Chapter ends with a summary that also highlights the gap explored in this study.

2.2 Conceptual Review

This section provided definitions, operationalizations, and how the constructs have been used in this study. The model had three main constructs (industry 4.0 capabilities, supply chain innovation, and data-drivenn decision making). These constructs had been operationalized in subsequent sections below (see 2.2.1-2.2.3).

2.2.1 Industry 4.0 Capabilities

Industry 4.0 is a paradigm change in manufacturing that is driven by technology and will digitally link manufacturing systems in both a horizontal and vertical manner (Yao, Lin, 2016; Lasi, et al., 2014; Klingenberg, and Antunes, 2017; Liao, et al., 2017). Industry 4.0 has an impact on the whole company as well as every business unit's desired strategy (Galati and Bigliardi 2019; Schrauf and Berttram 2016). On a tactical as well as an operational level, new technology breakthroughs or solutions might alter organizational culture or have an impact on the broader business strategy.

Industry 4.0, as defined by (OECD, 2016), is the fusion of several technologies that is causing industrial output to undergo a digital transition. Additionally, industry 4.0 is described as a new paradigm that enables businesses to advance their competences by fusing the physical and digital worlds into a holistic setting (Zhou, Liu, and Zhou 2016). It has emerged as a crucial idea in contemporary production settings (Galati and Bigliardi 2019). Industry 4.0, according to (Oesterreich and Teuteberg 2016), is the method of expanding the digitalization and automation of manufacturing environments as well as the growth of the digital supply chain. This enables better communication, transparency, and traceability for all involved goods, services, and business partners. Operations and supply chain management might be revolutionized by these technologies. Erboz, 2017; Lin, et al., 2019; Devi et al., 2021; Klovien, and Uosyt, 2019). According to (Rennung, et al., 2016), Industry 4.0 is a concept that describes how future consumer needs, resources, and data will be shared, used, managed, and recycled to produce goods and offer services more quickly, cheaply, effectively, and sustainably. Additionally, Kusiak (2018) pointed out that digitization increases corporate processes' transparency, efficiency, and sustainability by aiming for the dynamic integration of people and machines throughout the whole supply chain. According to (Constantiou and Kallinikos 2015; Wamba and Queiroz, 2022; Mikalef et al. 2019), one of the key elements of changes in technology (Industry 4.0) is the generation of large amounts of data and its analysis, known as big data analytics, for developing crucial insight that has a positive impact on the dynamic capabilities of firms as well as the ultimate benefit of achieving competitive advantage. Additionally, Industry 4.0 has enormous potential for adopting sustainability, which is an increasing concern for international manufacturing businesses, according to Felsberger, et al., (2022). Industry 4.0 refers to the horizontal and vertical integration of production environments driven by real-time data exchange and flexible manufacturing to enable customized production. Its other synonyms are smart manufacturing, smart production, or smart factories (Jabbour et al., 2018). The Internet of Things, cloud computing, big data, and analytics are among the most commonly referenced advanced digital technologies in the era of Industry 4.0. (Jabbour et al., 2018). To ensure better communication, transparency, and traceability for all products, processes, and business partners involved, this study will adopt the definition of industry 4.0 provided by (Oesterreich and Teuteberg 2016), which defines it as the one that comprises the increasing digitalization and automation of manufacturing environments as well as the expansion of the digital supply chain.

2.2.2 Supply Chain Innovation

A supply chain innovation is described as a change (radical or incremental) in the supply chain network, supply chain technology, or supply chain processes (or combinations of these), which can occur in a business function, within a business, in an industry, or a supply chain, to improve new value creation for the stakeholder (Stentoft, and Rajkumar, 2018). The outbound supply chain's technologically enhanced processes and procedures as well as modifications to the product, process, or service that either increase efficiency or raise end customer satisfaction are all examples of supply chain innovation Wong and Ngai, (2019; Shamout (2019). Shamout (2019) asserts that the ability of logistics companies to adapt innovations that improve shippers' bottom lines is a critical component of their competitiveness. Supply chain innovation places a focus on market demands, which can improve value propositions for consumers downstream (Yasmin, 2022). According to Stoji et al. (2019), supply chain stakeholders will become more successful at delivering on commitments, meeting standards, and resolving issues as they embrace new procedures, operational and practices, and invest in new technology systems. Technology innovation and process innovation are two subcategories of the multifaceted concept of supply chain innovation (Heaslip et al., 2018; Yasmin (2022; Gao, and Paton, 2018). Olajide, et al. (2019) made a case that technological innovation intends to improve the reale tracking technology, integrated information system, and innovative logistics equipment throughout global supply chains. In addition, according to Papadonikolaki (2020), technological innovation enables businesses to increase labour and capital productivity and provide real-time visibility into the flow of goods, information, and sales data. This enables businesses to improve inventory management and broaden their value proposition for end users. Process innovation on the other hand, is the use of new, better techniques, processes, and procedures with the aim of continuously improving a service quality or lowering its cost, according to Wagner (2008). The successful redesign and reengineering of the supply chain is a focus of process innovation. Olajide, et al., (2019). Meaningful process innovations and final value for improved services may be encouraged by understanding how the supply chain transfers innovation as well as knowledge, according to (Gao and Paton, 2018). It focuses on operational problems and procedures that improve networking, distribution, procurement, and other management techniques (Jimenez-Jimenez, et al., 2018). The definition of supply chain innovation used in this study will be taken from Shamout, 2019; Wong, and Ngai, (2019) which states that supply chain innovation includes technologically enhanced outbound supply chain processes and procedures as well as modifications to products, processes, or services that either increase efficiency or raise customer satisfaction.

2.2.3 Data-driven Decision Making

Data-driven decision-making refers to the practice of utilizing data to support decision-making and to confirm a course of action before committing to it (Söderlund, 2022). Several variables, including the organization's goals and the types and quality of data it has access to, will determine exactly how data may be incorporated into the decision-making process (Varvne, et al., 2020).

Data is used to benchmark what is already in place, according to Karabacak (2019), so that companies may better comprehend the effects of whatever decisions they make. Additionally, Chigoba, 2021 defines data-driven decision-making as the practice of leveraging data to create well-researched conclusions. Organizations may overcome prejudices and make the finest managerial decisions that are in line with corporate strategy with the aid of contemporary analytics tools like interactive dashboards. Fundamentally, using verified, studied data to make decisions rather than winging it is what is meant by data driven decision making (Söderlund, 2022). However, in order to truly benefit from the data, it must be accurate and pertinent to business objectives. It used to be a time-consuming process to gather, extract, prepare, and analyse insights for better data-driven decision making in business. This naturally caused the process to take longer overall. However, today's customers may evaluate and draw insights from their data even without extensive technical experience thanks to the development and democratization of business intelligence tools. The production of reports, trends, visualizations, and insights that aid in the data decision-making process thus requires less internet technological assistance. (Mukherjee, Ilebode, 2019). Information is treated as a real asset more by businesses that approach decision-making jointly than by businesses that use alternative, less clear-cut ways (Confrey, and Shah, 2021). According to Pollard (2018), making decisions based on data can result in the identification of brand-new, exciting business prospects. According to Lim et al. (2020), data-driven decision-making tools will enable organizations to connect with new trends and patterns that affect both their internal operations and the industry in which they operate. Any business may make decisions that will guarantee they always stay competitive, relevant, and lucrative if they can comprehend these trends or patterns on a deeper level. Data-driven decision making (DDM) is a new method of making decisions that are mostly based on verifiable data in a systematic and organized process.

It has been produced and established as a result of the availability of data and the opportunities that it provides (Kumar, et al., 2019; Wilton, et al., 2022; Parra et al, 2019). Companies that effectively use large amounts of data by analysing and presenting information in a way that adds value will enable managers to make better decisions (Comuzzi and Patel, 2016; Parra et al, 2019). According to (Cai and Zhu, 2015), organizations need to invest in or make technical breakthroughs if they want to use data to their advantage and base decisions on it. This study will use Chigoba, (2021) concept of data driven decision making, which says that it is the process of using data to create decisions that are well-informed and supported by evidence.

2.3 Theoretical Review

To focus the research direction, two underpinning theories were used as a research foundation in supporting and addressing the gap, and as a guide to align this research into an appropriate direction. In this section, the researcher discusses underpinning theories that form the basis to investigate and study the phenomenon of industry 4.0 capabilities, supply chain innovation, and data driven decision making. The driving theories of this study are the information processing theory and systems theory. Theoretical frameworks provide a clear prism or context through which a subject is studied; it explains the context and the connections between the various factors and dimensions.

2.3.1 Information Processing Theory (IPT)

The idea of IPT was made to assist with the creation of organizational structures (Galbraith, 1973, 1974). In order to get the best innovation performance, information processing demands and capabilities should be matched (Premkumar et al., 2005). Information processing requirements are determined by the various environmental contexts in which the organization is located, whereas information processing capabilities refer to the configurations of resources, technology architecture, and other work units that make it easier to collect, process, and distribute information (Galbraith, 1973; Tushman and Nadler, 1978). Organizations can use two strategies to support decision-making and boost performance to deal with environmental dynamism or the frequency of changes in environmental factors: (1) increase the amount of high-quality information that they collect to lessen the impact of dynamism; and (2) focus more on enhancing their information processing capabilities (Fan et al., 2017). IPT has received a recent attention in supply chain management, technology integration, production management systems, information systems (Wong et al., 2015), maintenance management (Swanson, 2003), and production control systems (Cegielski et al., 2012; Fan et al., 2017). Digital technology has frequently been named as the main component of an organization's information processing capability in earlier research. Premkumar et al. (2005) propose using information technology support to gain access to information processing skills based on IPT. Investments in technology-based process enhancement can boost information processing capacities, according to Melville and Ramirez (2008) (e.g., the adoption of information technology). According to Cegielski et al. (2012), an organization's information processing capabilities are its capacity to use and organize information in a way that promotes decision-making. They view cloud-based infrastructure as a stand-in for these organizational information processing capabilities. The Internet of Things, cloud computing, big data analytics, and other industry 4.0 technologies are organized and linked in this research to handle the necessary amounts of information and so reflect the organization's information processing capabilities. Additionally, digital supply chain platforms offer avenues for information sharing to acquire outside information. In other words, supply chain platforms are driven by digital technology to meet information needs.

2.3.2 Systems Theory

A systems approach enables comprehension of sociotechnical advancements (Waldman and Schargel 2006). As a result, it enables analysis of how the technical application affects business operations. Technology-wise, the proper operation of a supra-system depends on the alignment and integration of the information systems and technological advancements of its subsystems (processes/firms). Ensuring efficient connectivity and coordinated information flow, this can ultimately boost creativity. In other words, it is crucial to take into account the technological integration of constituent processes (in this case, supply chain activities) to enable harmonic interactions between processes within the supra system (Mele, Pels, and Polese 2010). Systems theory can analyse the effects of industry 4.0 enabling technologies on subsystems (individual supply chain processes/involved firms) and can enable investigating the impact of their potential capabilities on supply chain (supra system) innovation improvement by highlighting the impact of connectivity and interrelationships on supply chain innovation. To put it another way, this theory may be used to analyse how new technology enable substantial integration between specific supply chain operations and throughout the supply chain (supra system), which may increase supply chain innovation (Wiengarten and Longoni 2015; Blome, Paulraj and Schuetz 2014; Liu, et al., 2011).

2.4 Empirical Review

This section provided the relationship between the constructs by reviewing the literature on the findings from earlier related studies. The relationships included industry 4.0 capabilities and supply chain innovation, and the mediating effect of data driven making on the relationship between industry 4.0 and supply chain innovation.

2.4.1 Industry 4.0 Capabilities and Supply Chain Innovation

Hopkins, (2021) did research to examine how supply chain practitioners' experience with industry 4.0 technology drives supply chain innovation. The study made use of primary data from a descriptive survey of supply chain professionals operating in Australians various industry sectors and supply chain stages. The research revealed that Australian supply chain businesses are only just starting to use several Industry 4.0 technologies. The results also revealed a number of notable disparities between predicted effect and expected investment, with bigger organizations being deemed to be more digitally prepared than smaller firms.

Fatorachian and Kazemi (2021) investigated how Industry 4.0 might affect SC performance and conceptualized and developed their results into a practical framework supported by systems theory. Inductive reasoning was employed to guide the study's exploratory research methodology. An organized review of the literature was used in the investigation. According to the findings, Industry 4.0 signifies a significant paradigm shift in supply chain management. Future research should concentrate on examining organizational and cultural aspects that affect the adoption of the operational viewpoint of Industry 4.0 in supply chain management.

De Giovanni and Cariola (2021) looked at the effects of process innovation strategies on lean practices and green supply chains. These strategies are implemented by businesses using Industry 4.0 (I4.0) technology. Data was gathered from 172 enterprises made up of four production managers from European organizations and faculty members in the field of SCM. To assess the data, structural equation modeling (SEM) was employed. The research results showed that adopting a process innovation strategy built on I4.0 technologies enhances the impact of leanness on operational performance, which also boosts economic results. Future studies might focus on finding more innovation tactics that could boost the impacts of leanness, GSCM, and performance.

Wamba and Queiroz (2022) used a block chain technique to study the influence of Industry 4.0 on supply chain digitization. A questionnaire was employed to collect data from India and the United States. PLS-SEM was used to validate the model. The data indicated that there are significant disparities across countries in the variables that impact block chain innovation and the stage of dissemination. The study proposed that future studies include additional emerging and developed nations in order to generalize our findings.

Da Silva et al. (2018) undertook a study to contextualize the problem of technology transfer directed to the supply chain in the Brazilian Industrial 4.0 Scenario. To create the bibliographic portfolio, a review of the literature was conducted using a systematic process and criteria. According to the findings, the supply chain will undergo major changes in the Industrial 4.0 Scenario, including real-time visibility throughout the whole supply chain and continuous communication between the stages of the chain, among other important changes.

2.4.2 Industry 4.0 Capabilities and Data-driven Decision Making

Bousdekis et al. (2021) did a study that reviewed the literature on data-driven decision-making in maintenance and outlined future research goals in Greece for data-driven decision-making for Industry 4.0 maintenance applications. The approach of the literature review was adopted in the investigation. The findings indicated that, in conjunction with the rise of cyber-physical systems and cloud technologies for data processing and storage, next-generation maintenance decision-making would become increasingly responsive and capable of allowing correct and proactive judgments.

Tripathi et al. (2022) investigated the construction of a data-driven decision-making system in Industry 4.0 utilizing lean and smart manufacturing concepts. The Taguchi L9 orthogonal array approach of experimental sign was used. The outcome demonstrated that the created system may improve production efficiency and financial profitability while working within constrained limits. The study found that the efficacy of the created decision-making system may be increased by combining the lean principle with other process optimization strategies for shop floor management under various production settings, such as Industry 4.0.

Felsberger et al. (2022) looked at how Industry 4.0 deployment affected the sustainability facets of European manufacturing industries with a focus on digital transformation. The study employed a multiple case research approach to examine six European manufacturing firms, including those involved in the production of electronic components and systems (ECS) and aerospace manufacturing (AM). The research revealed that the mediation of Industry 4.0 effects on economic, environmental, and social aspects is provided by the reconciliation of dynamic capacities. The study made the suggestion that further research should look at how digital process improvement might lessen variability in manufacturing processes within facilities.

Li et al. (2020) investigated how digital technologies impact economic and environmental performance in the new era of Industry 4.0. The mediating role of digital supply chain platforms Data was obtained from 188 Chinese industrial businesses. The data was evaluated using regression analysis. The findings demonstrated that digital supply chain platforms mediate the impacts of digital technologies on both economic and environmental performance that the mediating effects are exacerbated when there is a high degree of environmental dynamism. Future study may put the concept to the test in developed economies to assess possible disparities in the use of digital technology and supply chain platforms.

2.4.3 Data-Driven Decision-Making and Supply Chain Innovation

Karaman et al. (2020) performed a study to investigate organizational and environmental (competition, capital scarcity, and labour organization) aspects that influence enterprises' supply chain innovation activities in Eastern Europe and Central Asia (EECA. Firm-level data from Business Environment Enterprise Performance Surveys (BEEPS) were used in the study. The data was evaluated using regression analysis. The findings revealed that the drivers of innovation differ depending on the kind of innovation activity; as a result, supply chain innovation activities should target strategic resources that will produce competitive advantages. The research suggested that future studies use longitudinal data to improve the validity of the results.

Yu et al. (2021) investigated the link between data-driven supply chain orientation (DDSCO) and company financial performance a moderating influence of innovation oriented complementary assets (CA-I). A moderated regression analysis was used to evaluate survey data from 329 Chinese manufacturing enterprises. According to the findings, DDSCO has a considerable financial impact. Future study should identify and experimentally analyse whether supplementary assets associated with a DDSCO are also necessary to improve business success, as well as which industries they are most effective

Bhatti et al. (2022) investigated the influence of organizations' big data analytic capability on supply chain innovation. Data was acquired from 386 Pakistan industrial enterprises and tested using structural equation modelling. The findings revealed that big data analytics has a substantial impact on supply chain innovation. The study suggested that future studies include other stakeholders in the interaction and investigate how the big data analytic capability of enterprises from any sector might influence the inventive capacities of buyers or suppliers.

Belhadi et al., (2021) study the direct and indirect impacts of artificial intelligence (AI), supply chain resilience (SCRes), and supply chain performance (SCP) in the setting of supply chain dynamics and uncertainties. Data was obtained from 279 firms of varying sizes working in diverse industries in North Africa, South Europe, and Southern Asia. Data was analysed using a structural equation modelling (SEM) technique. The findings revealed that, while AI has a direct influence on SCP in the near term, it is advised that it be used to develop SCRes for long-term SCP. To get deeper insights, future research should investigate additional linkages and phenomena using a combination of qualitative and quantitative approaches.

Rodriguez and Da Cunha (2018) performed research to determine the characteristics of big data and predictive analytics used in sustainable supply chain innovation, as well as to investigate the impact of absorptive capacity. The study used a literature review technique. The findings demonstrated that big data and predictive analytics have an impact on long-term supply chain innovation. The study suggested that more research be conducted to either expand the sample dimension or establish an action research approach for thoroughly testing the framework inside a real firm.

2.4.4 The mediating Role of Data Driven Decision Making

Ghasemaghaei et al. (2019) investigated the influence of each big data feature (data volume, data velocity, data variety, and data veracity) on firm innovation competency (exploitation competency and exploration competency), as mediated through data-driven insight creation (i.e., descriptive insight, predictive insight, and prescriptive insight). Data was gathered from 280 middle and upper-level executives at national market research organizations in the United States. The Structural equation modelling technique was used to analyse the data. The findings revealed that while data-driven insight (descriptive and predictive insights) improves innovation capability, prescriptive insight does not. Future study should take into account not just the beneficial benefits of big data on business results, but also their potential non-significant consequences.

Chaudhuri et al. (2021) explored how a data-driven culture influences process performance and product innovation, resulting in improved organizational overall performance and increased commercial value. The study used a survey with 513 usable replies from workers of the Bombay Stock Exchange in India. The data was analysed using the PLS-SEM method. The results showed that an organizational data-driven culture has a significant moderating effect on product innovation and process improvement. Further research might be conducted on different organizations throughout the typological, geographical, and industry spectrums, allowing for comparisons and more generalization.

Usama Awan et al. (2021) looked at the link between big data analytic competence and circular economy performance and the mediating function of data-driven insights in the relationship between big data analytic capability and decision-making. Partial least squares structural equation modelling was used to examine data from 109 Czech manufacturing companies. The findings showed that decision-making quality in businesses is driven by big data analytic capacity and is not mediated by data-driven insights. The association between big data analytic capabilities and environmental and innovation performance may be studied further in future research to examine the mediating role of circular economy performance.

El Hilali et al. (2021) investigated the mediating function of big data analytics in increasing organizations' commitment to sustainability. The research used a quantitative method with 41 Moroccan enterprises from various industries. Using a method known as Partial Least Squares-Structural Equation Modelling (PLS-SEM). The findings revealed that technical abilities such as big data analytics do not play a significant impact and do not enhance the mediating role of big data in terms of sustainability. Future research might include widening the scope of the study by seeking firms from different industries and regions to participate in our poll.

2.5 Conceptual Framework

The section explains the conceptual framework and underlying assumptions that relate the industry 4.0 and supply chain innovation as well as how data driven decision making affect the relationship. The study examined the direct effect of industry 4.0 on supply chain innovation and the indirect role of data driven decision making in the industry 4.0 and supply chain innovation link.

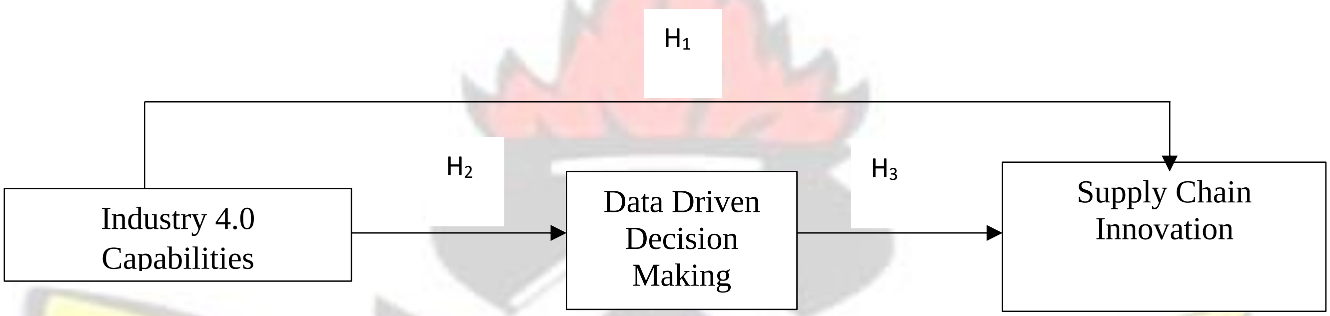

Figure 2.1 Conceptual Framework

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

2.5.1 Effect of Industry 4.0 Capabilities on Supply Chain Innovation

Multiple cutting-edge tools and technologies are used by Industry 4.0, helping to reinvent traditional industrial processes (Ghadge, et al., 2020). In order to become more digital, automated, and flexible in their operations, supply chains are making significant progress. In order to create effective, transparent, adaptable, and robust systems at many phases of the supply chain, including new product development, production, procurement, planning, logistics, and marketing, today's digital supply chain innovation uses a variety of technologies (Ghadge, et al., 2020). The value chain's entire performance is improved, and risks are decreased, thanks to Industry 4.0-enabled features including highly structured interconnections and real-time monitoring and management of materials, equipment, and supply chain parameters (Luthra and Mangla, 2018). The adoption of Industry 4.0 technology also caused these networks' business models and management approaches to change (Kiel, et al., 2020; Ghobakhloo, 2018). According to Luo, Shi, and Venkatesh (2018), many organizations are already using information technologies through E-Business solutions to improve their operational excellence and supply chain innovation. They are also searching for the application of novel and innovative technologies to improve their process innovation and analytic capabilities. As these technologies are predicted to transform supply chain management by bringing about advanced levels of connectivity and comprehensive innovation, they are seen as a promising strategy for addressing the innovation challenge (Kache and Seuring 2017). This will result in significant performance improvements for the supply chain (Shrivastava, Ivanaj and Ivanaj 2016). In light of the aforementioned literature, this study proposed that:

H_1. Industry 4.0 capabilities has a positive and significant effect on supply chain innovation.

2.5.2 Effect of Industry 4.0 on Data Driven Decision Making

Industry 4.0 is a vision of the future of manufacturing and industry in which information technologies will increase efficiency and competitiveness by integrating every resource (people, data, and equipment) in the Value Chain (Politecnico di Milano 2017). One of the primary foundations of Industry 4.0, the fourth generation of manufacturing, which employs ideas like decentralized decision-making, virtual replicas of actual equipment and processes, and cyber-physical systems to build a smart factory or "Factory 4.0," is data (Miragliotta, et al., 2018). Industry 4.0's six Cs—connection (sensors and networks); cloud (computing and on-demand); cyber (model and memory); content/Context (meaning and correlation); community (sharing and cooperation); and customization can be used to highlight the influence of big data (personalization and value). The Industrial Internet of Things is essential to this new paradigm (IoT). IoT enables businesses to more quickly collect data about processes and goods, to have global awareness of the whole supply chain, to work with more intelligent operations that enable quick decision-making, and more (IDC Digital Universe 2014). According to a number of studies by McKinsey, the next frontier for fostering innovation, competitiveness, and development in manufacturing is the efficient extraction and exploitation of the information encoded in data (McKinsey, 2011, 2015). Consequently, this study hypothesizes that:

H_2. Industry 4.0 capabilities have positive and significant effect on data-driven decision making.

2.5.3 Effect of Data-Driven Decision-Making on Supply Chain Innovation

By identifying trends in past data, such as variances in sales of various items and client purchasing preferences, supply chains may get data-driven insights. For instance, businesses can utilize straight-forward methods like plotting data to find trends, regression analysis to determine the relationship between various factors, or data visualization to make the data easier to grasp (Pusala, Salehi, Katukuri, Xie, and Raghavan, 2016). The capacity of a supplier to effectively develop new items or expand existing product lines may be improved by these descriptive data creation processes. Supply chain companies may also combine vast volumes of data from several sources to forecast upcoming occurrences and trends (Ghasemaghaei et al., 2016). This predictive information enables businesses to anticipate their sales patterns and overall performance, which may result in the creation of new items or the improvement of current ones (Ghasemaghaei, and Calic, 2019). Online retailers, for instance, can estimate consumer behaviour when designing new items by using customer online activity, customer purchase history, such as page visits and time spent on each page, to produce predictive data (Dawson, 2021). Additionally, by producing prescriptive data and knowing the optimum course of action, businesses may optimize their exploration or exploitation operations (Ghasemaghaei, and Calic, 2019). For instance, businesses may utilize simulations to evaluate various situations and identify the best answers for improving their present goods (Selvan, and Balasundaram, 2021). As a result, supply chain companies that collect business data successfully are able to enhance their innovation capability. In this perspective, the study suggests that:

H_3. Data-driven decision-making has a positive and significant effect on supply chain innovation.

2.5.4 The Mediating Role of Data-Driven Decision Making

Data-driven decision making is working toward major business objectives by employing verified, evaluated data rather than just guessing (Söderlund, 2022). Firms, for example, analyse data to comprehend current occurrences, examine why something happened in the past, and discover accurate predictions of future events. According to a recent survey, 49 percent of organizations believe that the greatest benefit of using big data is to improve corporate decision quality (Al Kuwaiti et al., 2018). Firms claimed that processing and analysing big data has greatly improved their outcomes, according to Henke et al. (2016). Credit-card companies, for example, can use large data warehouses to select prospects who are most likely to become customers, or they can use a "ready-to-market" database that allows a system to analyse an issue and make a personalized offer in milliseconds, or they can optimize offers over time by tracking responses to predict future decisions (Camilleri, 2019). According to Henke et al. (2016), technological improvements have enabled most businesses to gather and process data in high volume, velocity, and diversity. Furthermore, Davenport et al. (2001) discovered that data and information are components of an intrinsic value system that rewards data-driven decision making. Furthermore, Chatterjee et al., (2021) said that data-driven decision making enables a company to efficiently shift its business model toward product innovation. Based on the literature reviewed, the study proposes the following hypothesis:

H_4. Data-driven decision making mediates the industry 4.0 capabilities and supply chain innovation relationship.

Author/Year	Country	Purpose	Theory	Method	Findings	Future Studies
Fatorachian and Kazemi (2021)	England	To investigate how Industry 4.0 might affect SC performance	Systems Theory	Exploratory research (Qualitative)	Industry 4.0 signifies a significant paradigm shift in supply chain management	Future research examines organizational and cultural aspects that affect the adoption of the operational viewpoint of Industry 4.0 in supply chain management.
Hopkins, (2021)	Australia	To examine how supply chain practitioners' experience with industry 4.0		Quantitative	Australian supply chain businesses are only just starting to use several Industry 4.0 technologies	

		technology drives supply chain innovation.				
De Giovanni and Cariola (2021)	Europe	To look at the effects of process innovation strategies on lean practices and green supply chains through industry 4.0.		Quantitative	Adopting a process innovation strategy built on I4.0 technologies enhances the impact of leanness on operational performance	Future studies might focus on finding more innovation tactics that could boost the impacts of leanness, GSCM, and performance
Wamba, S.F., and Queiroz (2022)	India and United States	To study the influence of Industry 4.0 on supply chain digitization.	Innovations theory, the resource-based view, and dynamic capability.	Quantitative	There are significant disparities across countries in the variables that	Future studies can include additional emerging and developed nations in order to

					impact block chain innovation and the stage of dissemination	generalize our findings.
Da Silva et al. (2018)	Brazil	To contextualize the problem of technology transfer directed to the supply chain in the Brazilian Industrial 4.0 Scenario.	Technology transfer (TT) Theory	Qualitative	the supply chain will undergo major changes in the Industrial 4.0 Scenario, including real-time visibility	
Bousdekis et al., (2021)	Greece	To review the literature on data-driven decision-making in Industry		Qualitative	Next-generation maintenance decision-making would become	

		4.0 maintenance applications			increasingly responsive	
Felsberger, et al. (2022) l	Europe	To look at how Industry 4.0 deployment affected the sustainability facets of European manufacturing industries with a focus on digital transformation		Qualitative	mediation of Industry 4.0 effects on economic, environmental, and social aspects is provided by the reconciliation of dynamic capacities	Further research should look at how digital process improvement might lessen variability in manufacturing processes within facilities.
Li et al. (2020)	China	To investigate how digital technologies impact economic and environmental performance in the	Information processing theory	Quantitative	Digital supply chain platforms mediate the impacts of digital technologies on both economic	Future studies may put the concept to the test in developed economies.

		new era of Industry 4.0			and environmental performance	
Karaman et al. (2020)	Eastern Europe and Central Asia (EECA	To investigate organizational and environmental aspects that influence enterprises' supply chain innovation.	Resource advantage theory	Quantitative	Drivers of innovation differ depending on the kind of innovation activity	Future studies can use longitudinal data to improve the validity of the results.
Yu et al. (2021)	China	To investigate the link between data-driven supply chain orientation (DDSCO) and company financial performance.		Quantitative	DDSCO has a considerable financial impact.	Future studies should experimentally analyse whether supplementary assets associated with a DDSCO are

						also necessary to improve business success.
Bhatti et al. (2022)	Pakistan	To investigate the influence of organizations' big data analytic capability on supply chain innovation.	RBV and dynamic capabilities theory.	Quantitative	Big data analytics has a substantial impact on supply chain innovation.	Future studies should include other stakeholders and investigate how the big data analytic capability of enterprises from any sector might influence the inventive capacities of buyers or suppliers.

Belhadi et al., (2021)	North Africa, South Europe, and Southern Asia	To investigate the effect of artificial intelligence (AI), supply chain resilience (SCRes), and supply chain performance (SCP) in the setting of supply chain dynamics and uncertainties.	Organizational Information Processing Theory (OIPT)	Quantitative	Artificial intelligence has a direct influence on supply chain performance.	Future research should investigate additional linkages and phenomena using a combination of qualitative and quantitative approaches
Ghasemaghaei et al. (2019)	United States	To investigate the influence of each big data on firm innovation competency as	Organizational learning theory and Gestalt insight learning theory	Quantitative	Data-driven insight (descriptive and predictive insights) improves innovation capability.	Future study should take into account the non-significant consequences of big data analytics.

		mediated through data-driven insight creation.				
Chaudhuri et al. (2021)	India	To explore how a data-driven culture influences process performance and product innovation.	RBV	Quantitative	An organizational data-driven culture has a significant moderating effect on product innovation and process improvement.	Further research might be conducted on different organizations throughout the typological, geographical, and industry spectrums.
Usama Awan et al., (2021)	Czech	To look at the mediating function of data-driven insights in the relationship		Quantitative	Big data analytic capacity is not mediated by data-driven insights.	

		between big data analytic capability and decision-making.				
El Hilali et al., (2021)	Morocco	To investigate the mediating function of big data analytics in increasing organizations' commitment to sustainability.		Quantitative	Technical abilities such as big data analytics do not play a significant impact and do not enhance the mediating role of big data in terms of sustainability.	Future research might include widening the scope of the study by seeking firms from different industries and regions

.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

The study examines the mediating role of data-driven decision-making in the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. This chapter provides details of the research methodologies used to solve the research topic and accomplish the study's objectives. Consequently, this section of the study deals with the research design and approach, study population, sample size, sampling technique, source of data, research instrumentation and data collection procedure, validity and reliability, and ethical consideration.

3.2 Research Design

The positivism research philosophy is the underpinning philosophy for this study. The choice of the positivist approach is justified by the fact that the study examined the mediating role of data-driven decision-making of the impact of Industry 4.0 capabilities on supply chain innovation in Ghana, all the variables are measurable and can be overserved numerically and hence is considered to fit well with the objectives of the research study. Subsequently, the study employed quantitative methods of data collection in a single study according to the nature of the study.

The quantitative research approach was chosen on the basis that it produces accurate and measurable data that can be generalized to a broader population (Goertzen, 2017). Aside from that, it is ideal for evaluating and verifying already known concepts about how and why events occur by testing hypotheses developed before data collection. In general, quantitative research is regarded as a deductive approach to the investigation (Ragab and Arisha, 2018). The study combines both descriptive and explanatory research types. While the descriptive provides a description of the constructs in the model. The explanatory research will also aid in examining the mediating role of data-driven decision-making of the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. Finally, the study employs the cross-sectional survey design where deductive reasoning is applied to the quantitative data (Cohen, Manion, and Morrison, 2017). The survey design allows the collection of data from different units over a specific period. Since the study is conducted over a limited time period, the cross-sectional survey is deemed more appropriate to examine the mediating role of data-driven decision-making of the impact of Industry 4.0 capabilities on supply chain innovation in Ghana.

3.3 Population of the Study

Etikan, Musa, and Alkassim (2016) defined population as the range of the instances, persons, or objects that are the focus of a study. The population consists of a diverse variety of persons from whom a sample should be drawn (Shamsuddin et al., 2017). The study's population comprised all senior managers of manufacturing firms in Ghana.

3.3 Sample and Sampling Techniques

The nature of the study and the research design, according to Kothari (2012), determine the number of study participants who should be included in the sample. In obtaining the sample size in a given population, three main methods for estimating a sample size can be identified. Firstly, the sample size can be calculated by using formulas (Israel, 1992). Secondly the use of a published statistical table to estimate the sample size, for instance, the published statistical table of Krejcie and Morgan (1970) and Cohen et al., (2013, 2009). Lastly, a researcher can decide to utilize census methods by collecting data from the entire population. The nature of the study and the research design, according to Kothari (2012), determine the number of study participants who should be included in the sample. In obtaining the sample size in a given population, three main methods for estimating a sample size can be identified. For this study, sample size determination will be established from Singh andMasuk u’s (2014) formula of sample size determination.

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

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

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

C=Confidence interval

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

n=384.16

n~384

Based on the formula, 384 managers of firms in Ghana are drawn for the study. The processes used to choose a sample for a research endeavour are referred to as sampling techniques. Probability procedures and non-probability procedures are the two types of sampling procedures (Taherdoost, 2016). For this investigation, a purposive sampling strategy is used. This approach was selected because the target population included senior managers of firms in Ghana.

3.4 Data and Data Collection

This study dwelled on the use of primary data that was collected using primary data. The data was gathered using a questionnaire. The questionnaire was designed in two parts. The first part contained the demographic information of the respondents. The second part contains questions on variables. A five-point Likert scale was used to code the responses, with 1 denoting "strongly agree," 2 denoting "agree," 3 denoting "uncertain," 4 denoting "disagree," and 5 denoting "strongly disagree."

In the survey, participants were asked to choose a number from 1 to 5 that best represented their thoughts on each statement. The items used to measure the constructs are included in the appendix. Though the items were already validated and tested in previous studies, this study will also conduct different types of validity and reliability of the items to ensure the final results are reliable. To encourage participation, each questionnaire was accompanied by a cover note from the researcher clarifying the aim of the study as well as soliciting respondent involvement in the study; it as well assured confidentiality y of the selected participants and briefly introduce the research work.

3.5 Validity and Reliability

To ensure external validity, the participants were randomly selected to avoid selection bias. The selected participants were assured of the benefits of the study to the organization to ensure a minimum dropout rate. Both the content and the construct validity of this study were also ensured. The validity and reliability of a research study are two research criteria for consistency (Straus, 2017). An alpha coefficient of 0.70 is used as a cut-off point for assessing the internal consistency of the research item and scales to guarantee study reliability (Singh, 2017; Hair, Biasutti, and Frate, 2017)). To eliminate logical flaws and biases in the study, the researcher emphasizes the validity and reliability of the results. This was done by adopting all of the constructs and conducting a pilot study using ten employees from the company.

3.6 Method of Data Analysis

The method of data analysis forms an essential component of any research such that the choice of the method of analysing data plays important role in the quality of findings, conclusions, and recommendations that are drawn from the data. Being a quantitative study, this study employed multiple quantitative techniques in analysing the data to fulfill the goal outlined in chapter one. After gathered was gathered, all the data was compiled in excel for scrutiny. After the scrutiny, a few questionnaires that were found incomplete were discarded. The analysis employed Statistical Package for Social Sciences (SPSS) version 26.0. The Statistical Package for Social Sciences (SPSS) was used for the analysis such as frequencies, means, standard deviations, independent sample t-test, and correlation analysis. Smart PLS SEM was used for the inferential analysis to test the various hypotheses proposed in the model.

3.7 Ethical Consideration

A consent form was presented to the authorities of all respondents to inform them of all benefits and risks involved in the participation and further sought their consent for their inclusion in the study. Selected farmers had the right to decline their participation in the study. The researcher indicated in the consent form that all forms of anonymity and confidentiality would be observed. Privacy of farmers in terms of freedom to define the time, extent, and conditions of sharing information was also observed. The researcher avoided any form of action in their relation with participants that amounts to deception. All forms of plagiarism and falsification of data were also avoided by the researcher.

3.8 Profile of Organization

Given that developed as well as developing nations manufacturing sector accounts for the largest share of the industrial sector (Haraguchi, Cheng, and Smeets, 2017). The manufacturing industries refer to those industries which involve the manufacture and processing of articles and indulge in either creating new commodities or adding value (Pfeiffer, 2017). Dangelico and Vocalelli (2017) describe the term as a manufacturing and marketing segment focused on the manufacture, processing, or preparation of raw material and commodity products, the finished products could be used both as a finished good of production or for sale to customers (Xu, Serrano, and Lin, 2017). Whereas, as per Hitomi (2017), a manufacturing sector could be seen as an economic activity wherein, on a large scale, the material is converted into finished products (Kayanula and Quartey 2000). Added to that, the National Manufacturing Association (USA) proposed the term as the firms engaged in the manufacturing and processing of products.

In its industry report, the Ghana Statistical Service (GSS) proposed the term as a collection of activities associated with goods and services. The Ghana Enterprise Development Commission (GEDC) has described the manufacturing sector in aspects of their machinery and plants. However, Kayanula and Quartey (2000) brought up the underlying potential risk of prioritizing a fixed asset and the potential impact of inflation on valuation, in specific by adopting criteria for fixed assets. The indigenous manufacturing industry supports local businesses and employs a major section of the increasing workforce. Manufacturing, food processing, construction, a small glass industry, textiles and clothing, chemicals and pharmaceuticals, metal processing, furniture and wood products, and leather and footwear are among Ghana's most important manufacturing industries (Addo, 2017).

Among the issues that have plagued this industry is that most manufacturers have not kept up with technological advancements and have failed to invest in new and modernized equipment, resulting in higher electricity usage (Abor and Quartey, 2010). Inadequacies in terms of innovation, knowledge inadequacies, financial constraints and the quality of locally produced items, as well as operational inefficiencies, and insufficient knowledge are just a few of the identified constraints faced by small and medium scale enterprises (Abor, 2015; Oppong et al., 2014; Quartey et al., 2017; Sitharam and Hoque, 2016)

CHAPTER FOUR

DATA ANALYSIS, RESULTS, AND DISCUSSION

4.0 Introduction

The fourth chapter provides an analysis of the data presented in the third chapter. This chapter is divided into four parts. The first chapter presents the findings from the exploratory data analysis, while the second presents demographic data. Research variables were analysed both descriptively and correlational. The final portion contains the Confirmatory Factor Analysis and the model fit index. The research hypotheses are put to the test using a regression model. Most importantly, the outcomes are discussed at the end.

4.1 Exploratory Data Analysis

The first analysis of the data was purely exploratory. Initial data quality was evaluated by exploratory factor analysis. The most common software was SPSS. Subsections include response rate, non-response bias, and normal procedure bias or variance. The sections below detail the tests and interpretations used to first evaluate data quality.

4.1.1 Response Rate

In most cases, the survey response rate is represented as a percentage. It is calculated by dividing the total number of surveys distributed by the total number of respondents. In most cases, a survey response rate of 50% or above should be considered exceptional. Data collection lasted more than one month, from 20th October 2022 to 20th November 2022. From the study, the sample estimated was 384, but 400 questionnaires were administered to check for response rate. After evaluating the individual questionnaires for acceptability, 326 were deemed to be useable, yielding an 81.5% response rate, which is adequate for analysis, according to prior research (Sun et al., 2022; López, 2022; Lavidas et al., 2022), as shown in Table 4.1 below.

Table 4.1: Data Response Rate

Distributed	Collected	Percentage of Usable
Response	326	81.5
Non-Response	74	18.5
Total	**400**	**100.0%**

Source: Field Data, 2022

4.1.2 Test for Common Method Bias and Sampling Adequacy

Due to the potential for a change in the relationship among predictors and the dependent variable if just one participant is used in a survey, CMB testing is required (Podsakoff and Organ, 1986; Bahrami et al., 2022). Consequently, inaccurate assumptions. Consistency and social acceptance were identified as CMB by Podsakoff et al. (2003). CMB data output might be lowered using a variety of techniques. Exploratory Factor analysis verified Harman's single component technique by demonstrating that fewer than 50% of the variance could be accounted for by a single factor. A 49.3% variance was accounted for by the principal components.

Table 4.2: Test for Common Method Variance (CMV)

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	**Total**	**% Of Variance**	**Cumulative %**	**Total**	**% Of Variance**	**Cumulative %**
1	7.886	49.290	49.290	7.886	49.290	49.290
2	1.788	11.173	60.462	1.788	11.173	60.462
3	1.393	8.704	69.166	1.393	8.704	69.166
4	.880	5.498	74.665			
5	.586	3.664	78.329			
6	.509	3.179	81.508			
7	.439	2.742	84.250			
8	.424	2.652	86.902			
9	.376	2.351	89.253			

10	.345	2.156	91.408
11	.312	1.949	93.357
12	.263	1.643	95.000
13	.243	1.521	96.522
14	.213	1.331	97.853
15	.179	1.117	98.969
16	.165	1.031	100.000
Extraction Method: Principal Component Analysis.			

Source: Field Data, 2023

4.1.3 Bartlett's Test of Sphericity and KMO Test

Bartlett and Kaiser-Meyer-Olkin (KMO) test determined sphericity. As demonstrated in Table 4.3, Bartlett's test suggests statistical significance (Approx. Chi-Square = 3241.636, df: 120, Sig. = 0.000), and Kaiser-Meyer-Olkin sampling accuracy is 91.7%. The results confirm sample validity.

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

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.917
Bartlett's Test of Sphericity	Approx. Chi-Square	3241.636
	df	120
	Sig.	.000

Source: Field Data, 2023

4.1.3 Non-Response Bias

Non-response bias was investigated. Non-response bias results from fewer survey responders than population members. If survey response rates are poor, non-response bias may affect sample validity and generalizability. Early and late replies were compared to reduce non-response bias. Oppenheim (2001) required that "early responders" and "late responders" have identical input variables to use the same model. This shows the sample was representative of the population. Both early and late responses scored 163. T-tests assessed non-response bias. Inconclusive t-test findings (see Table 4.4). First- and last-month construct data were identical.

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

			Levene's Test for Equality of Variances		
	Group	**Mean**	**F**	**Sig.**	**t**
Green Design Sustainability	1	14.53	0.042	0.838	-0.144
	2	14.61			-0.144
Green Innovation	1	26.93	0.004	0.95	-0.038
	2	26.96			-0.038
Environmental Performance	1	34.52	0.138	0.71	-0.276
	2	34.79			-0.276

Source: Field Survey (2023)

4.2 Profile of the Respondents

This section includes the demographics of the respondents in order to provide information about the persons and companies that participated in the study. The respondent's gender, age, educational background, position, experience, number of employees, number of products, and age of organizations are the most important information collected.

Table 4.2: Profile of the Respondents

Variables	Categories	Frequency	Percent
Gender	Female	156	47.9
	Male	170	52.1
Age	18 - 30 Years	86	26.4
	31 - 40 Years	127	39.0
	41 - 50 Years	89	27.3
	Above 50 Years	24	7.4
Education	Bachelor Degree	78	23.9
	Diploma	90	27.6

	Graduate Studies (Master / Ph.D)	33	10.1
	HND	1	0.3
	Junior High School	38	11.7
	Senior High School	86	26.4
Position	Business Owner	83	25.5
	Business Owner and Manager	151	46.3
	Employee (proxy)	13	4.0
	Manager	45	13.8
	Production Manager	33	10.1
	Sales executive	1	0.3
Experience	1-5 Years	95	29.1
	11-15 Years	86	26.4
	16 Years and Above	44	13.5
	6-10 Years	101	31.0
Employees	30-99 employees	33	10.1
	6-29 employees	160	49.1
	Less than 5 employees	124	38.0
	More than 100	9	2.8
Products	1-2 Products	94	28.8
	3-5 Products	99	30.4
	More than 5 Products	133	40.8
Operations	1-5 Years	95	29.1
	6-10 Years	105	32.2
	More than 10 Years	126	38.7
	Total	326	100.0

Source: Field Data, 2022

Table 4.2 reveals that 47.9% of the 326 respondents were female, 52.1 were male. Males outnumbered females in the research. 26.4% were 18–30, 39.0% were 31–40, 27.3% were 41–50, and 7.4% were above 50. Most respondents were 31–40 years old. 23.9% held a bachelor's degree, 27.6% a diploma, 10.1% a master's or doctorate, 0.3% HND, 11.7% JHS, and 26.4% SHS. Most respondents had degrees. 25.5 percent were company owners, 46.3% business owners and managers, 4.0% employee (proxy), 13.8% managers, and 10.1% production managers. Results showed that most respondents were company owners and managers. 29.1 percent of 326 respondents said 1–5 years, 26.4 percent said 11–15 years, 13.5 percent said 16+ years, and 31.0 percent said 6–10 years. Most questionnaire respondents were 6–10 years experienced. 10% had 30–99 personnel, 49.1% had 6–29, 38.0 percent had fewer than 5, and 2.8 percent had more than 100. Most responding organizations had 6–29 workers. 28.8% operate 1–2 products, 30.4% operate 3–5, and 40.8% operate more than 5. The data reveals that most businesses have more than 5 products. 29.1% have been in business 1–5 years, 32.2 percent 6–10 years, and 38.7% 10+ years. Most of the responding firms have been operational for more than 10 years.

4.3 Correlation Analysis

The correlation coefficients between data-driven decision making and industry 4.0 ($r = 0.461$, $P < 0.05$), data-driven decision making and SC innovation ($r = 0.668$, $P < 0.05$), and industry 4.0 and SC innovation ($r = 0.516$, $P < 0.05$) are all very high in Table 4.3. A correlation value of 0–0.30 indicates a weak link, 0.30–0.70 a moderate correlation, and 0.70–1.0 a strong correlation. The variables are strongly correlated.

Table 4.3: Descriptive and Correlation Analysis

Construct	1	2	3
Data-Driven Decision-Making	1.000		
Industry 4.0	0.461	1.000	
Supply Chain Innovation	0.668	0.516	1.000

Source: Field Data, 2023

4.4 Confirmatory Factor Analysis

Validity assessment of research models is crucial. The study's authors utilised Cronbach's alpha and the Composite reliability test to evaluate the model's consistency. To test the reliability of the model, we employed AVE and indication loadings. Cronbach's alpha was calculated to be 0.7, and a composite reliability score was utilised to examine the degree to which the various constructs in this research were consistent with one another. Table 4.7 shows that both Cronbach's alpha and the composite reliability index are higher than .80 (Hair, et al., 2016). The properties of the measurement model are supported by these results. There was no sign with loading below 0.7. Convergent validity may be established. For AVE values over 0.5, convergent validity was established. (Take a look at Table 4.7.) Table 4.7 shows that the T T-testound all of the variables to be statistically significant at the 1.96-percentile level and Sig. < 0.05. Check out Table 4.7 for more descriptive statistics. Calculated as: (Mean and Standard Deviation). The average in the table ranges from 3.512 to 4.016. The range of standard deviations was 1.066-1.389.

Table 4.7: Confirmatory Factor Analysis

Scales	Codes	Outer Loadings	Mean	Std. Dev.	Skewness	T statistics (|O/STDEV|)	P values	VIF
Data-Driven Decision-Making (CA = 0.922; CR = 0.926; AVE = 0.763)	DDDM1	0.810	3.873	0.926	-0.733	22.416	0.000	2.198
	DDDM2	0.884	4.01	0.881	-0.842	58.833	0.000	3.266
	DDDM3	0.880	4.09	0.861	-0.804	43.821	0.000	2.965
	DDDM4	0.891	4.063	0.875	-0.963	60.778	0.000	3.530
	DDDM5	0.900	4.083	0.858	-0.925	66.137	0.000	3.343
Industry 4.0 (CA = 0.854; CR = 0.868; AVE = 0.694)	I4.01	0.794	3.973	0.852	-0.956	20.691	0.000	1.875
	I4.02	0.856	3.987	0.783	-0.521	43.286	0.000	2.213
	I4.03	0.840	3.867	0.873	-0.643	40.124	0.000	1.795
	I4.04	0.841	3.95	0.817	-0.645	34.685	0.000	1.989
Supply Chain Innovation (CA = 0.900; CR = 0.901; AVE = 0.626)	SCIN1	0.820	3.92	0.872	-0.693	27.082	0.000	2.821
	SCIN2	0.809	3.937	0.808	-0.799	27.996	0.000	2.761
	SCIN3	0.772	4.043	0.776	-0.506	22.366	0.000	2.126
	SCIN4	0.797	3.983	0.785	-0.801	30.110	0.000	2.525
	SCIN5	0.801	3.973	0.832	-0.612	31.964	0.000	2.574
	SCIN6	0.795	3.97	0.797	-0.58	27.871	0.000	2.554
	SCIN7	0.743	4.03	0.802	-0.64	24.085	0.000	1.719

Source: Field Data, 2023

4.3.1 Discriminant Validity

The study also examined the differences between constructs (Hair et al., 2010; Henseler et al., 2016b). When assessing discriminant validity, each latent variable's square root of the AVE (diagonal value) must be bigger than the construct's maximum correlation. Table 4.8 shows discriminant validity. Again, multicollinearity is not present (Byrne, 2013). Discriminant validity has been proven as all of the HTMT values are below 0.90 or 0.85, as shown in Table 4.8. Discriminant Validity Using HTMT Table 4.8. HTMT and Fornell and Larcker criteria showed discriminant validity. Table 4.8 reveals that data-driven decision making is 0.874 with itself, 0.461 with industry 4.0, and 0.668 with SC innovation. Industry 4.0 was 0.833 with itself and 0.516 with SC innovation. SC innovation correlated 0.791.

Table 4.8: Fornell-Larcker criterion

Construct	**1**	**2**	**3**
Data-Driven Decision-Making	0.874		
Industry 4.0	0.461	0.833	
Supply Chain Innovation	0.668	0.516	0.791

Source: Field Data, 2023

Table 4.9: Heterotrait-Monotrait Ratio (HTMT)

Construct	**1**	**2**	**3**
Data-Driven Decision-Making			
Industry 4.0	0.509		
Supply Chain Innovation	0.729	0.576	

Source: Field Data, 2023

4.3.2 Model fitness indices

The values for the Extracted-Index Fitness, SRMR, Root Mean Square of Approximation, and Chi-Square are all appropriate (Table 4.10). Both the rare and extracted indices are much lower than 0.9, the threshold for acceptability. Considering that the square of the residual is not close to zero, the root demonstrates that the residual is unsatisfactory. The Root Mean

Square Approximation and the Total Residual Value are both unacceptable. These numbers are much larger than 0.1 and 3. This suggests that all relevant factors need to be taken into account in future research. A SRMR of 0.063 was found in Table 4.10, which is within the range of values considered acceptable in this research. Chi-square = 489.401, and the normed fit index was 0.852.

Table 4.10: Model fitness indices

Model fitness indices	Estimated model
SRMR	0.063
d_ULS	0.533
d_G	0.268
Chi-square	489.401
NFI	0.852

Source: Field Data, 2023

4.3.3 Predictive Relevance (R^2 and Q^2)

As shown by coefficient of determination analyses, the independent factors do account for part of the variance in the dependant variable (R2). Calculating R2 indicates how well the result was predicted by the independent variables. Predictive significance was defined as an R2 of 0.10 or above by Falk and Miller (1992). Table 4.10 shows that both data-driven decision-making and SC innovation have high levels of predictive accuracy (R2).

A second method for validating PLS models is using Q2 (Hair et al., 2020). This statistic is generated by randomly removing a data point, replacing it with an appropriate value, then computing the model's phase (Zhang, 2022). Model explanatory power and sample data predictions are used in Q2 (Hair et al., 2020). This approximate value aids the blind method in making sense of output data. When Q2 outcomes are better than expected and estimates are near to baseline, accuracy increases (Zhang, 2022). For endogenous estimations to be valid, Q2 must be greater than zero. Q2 greater than 0, 0.25, and 0.50 generates low, medium, and low predictions from the PLS path model, respectively. (Zhang, 2022). In the second quarter, the study received scores of 0.194 and 0.249, respectively, for data-driven decision-making and SC innovation (Table 4.10). All Q-square values over 0.5 indicate a highly predictive model fit.

Table 4.10: Predictive Relevance (R^2 and Q^2)

Construct	R-square	Q^2predict
Data-Driven Decision-Making	0.212	0.194
Supply Chain Innovation	0.502	0.249

Source: Field Data, 2023

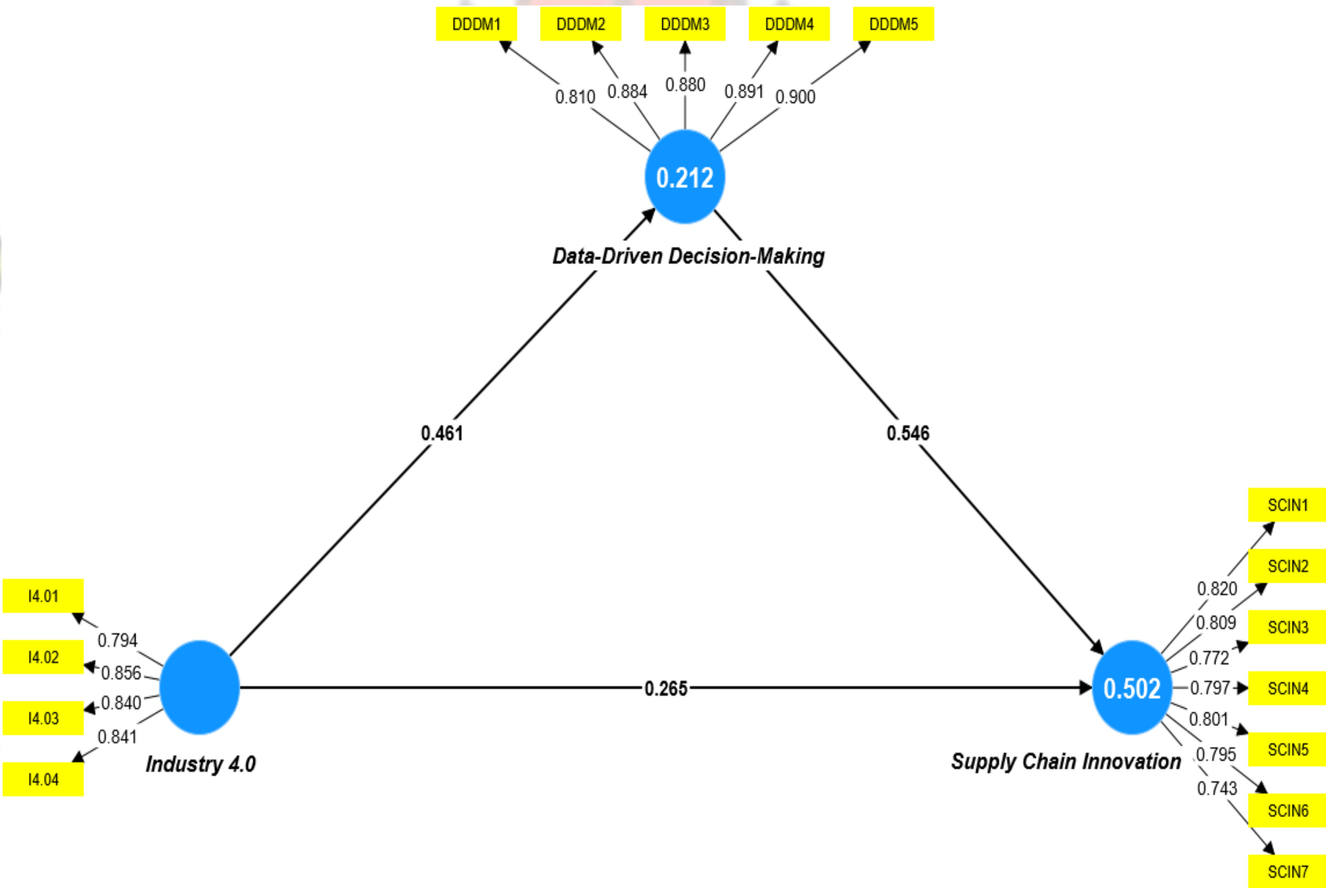

Figure 4.1: Measurement Model Assessment

4.5 Hypotheses for Direct and Indirect Relationship

The second phase of the analysis which deals with the structural model evaluation is depicted in Figure 4.2 below. The result of the structural model evaluation is presented in Table 4.11 and Figure 4.2. The PLS bootstrapping with 5, 000 samples were used in testing the significance of the four (4) paths in the model. This study analyses the impact of industry 4.0 on SC innovation through the mediation effect of data-driven decision making. This section discusses the analyses of the direct and indirect relationships as shown in Table 4.12 and Figure 4.2.

Table 4.12: Hypotheses for Direct and Indirect Relationship

Path	Path Coefficient	T statistics (|O/STDEV|)	P values	Hypothesis Validation
Data-Driven Decision-Making -> Supply Chain Innovation	0.546	10.022	0.000	Accepted
Industry 4.0 -> Data-Driven Decision-Making	0.461	6.723	0.000	Accepted
Industry 4.0 -> Supply Chain Innovation	0.265	4.600	0.000	Accepted
Industry 4.0 -> Data-Driven Decision-Making -> Supply Chain Innovation	0.252	5.762	0.000	Accepted

Source: Field Data, 2023

Table 4.12 shows that the relationship between data-driven decision making and SC innovation is significant (B = 0.546, t = 10.022, P = 0.000, and Sig < 0.05). Given that the p-value for H1 was less than 0.05 and the path coefficient was positive, it can be concluded that data-driven decision making have a direct effect on SC innovation. This suggests that when the data-driven decision-making increases, SC innovation also increases. Data-driven decision making enhance SC innovation by 54.6%.

Industry 4.0 directly affects data-driven decision making (B = 0.461; t = 6.723; P = 0.000; Sig < 0.05). The path coefficient was positive and the p-value for H2 was less than 0.05, indicating a significant positive direct influence on industry 4.0 to data-driven decision making. Industry 4.0 enhances data-driven decision making because the path coefficient is positive. Industry 4.0 accounts for 46.1% of data-driven decision making.

Industry 4.0 directly affected SC innovation (B = 0.265; t = 4.600; P = 0.000; Sig < 0.05). Since the p-value was less than 0.05 and the path coefficient was positive, industry 4.0 had a significant direct influence on SC innovation, validating the third hypothesis (H3). The positive path coefficient indicates that SC innovation will improve with industry 4.0. Industry 4.0 boosts SC innovation by 26.5%.

Data-driven decision making indirectly affected industry 4.0 and SC innovation (B = 0.252; t = 5.762; P = 0.000; Sig < 0.05). Data-driven decision-making mediates industry 4.0 and SC innovation positively since the p-value for H4 was less than 0.05 and the path coefficient was positive. The positive path coefficient indicates that data-driven decision making positively and fully mediates interactions between industry 4.0 and SC innovation. This also means that data-driven decision making mediates 25.2% of the I4.0-SCI connection.

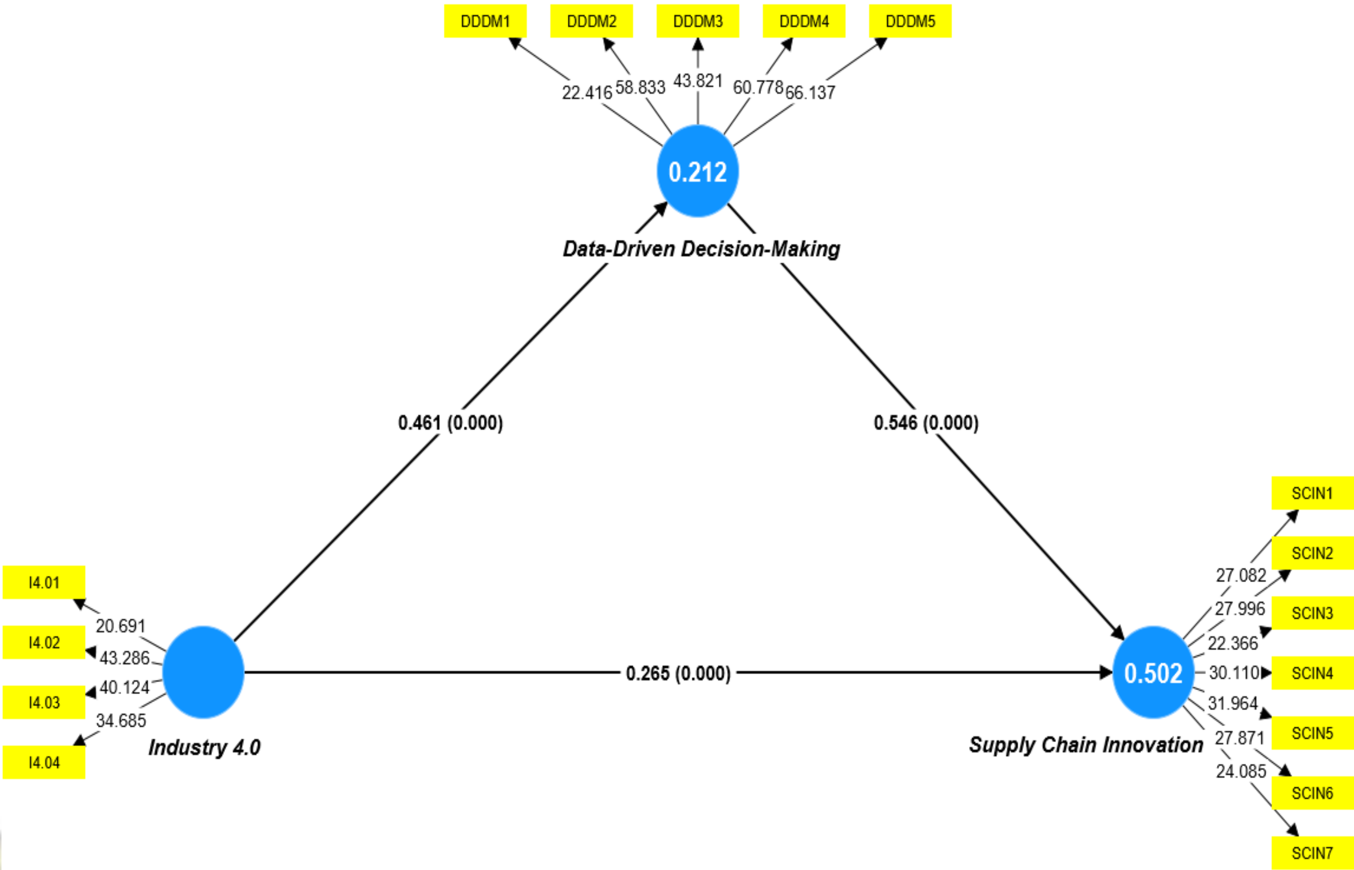

Figure 4.2: Structure Model Evaluation

4.6 Discussion of Key Findings

The purpose of this study was to investigate the relationship between industry 4.0 and SC innovation by highlighting the intervening role of data-driven decision making. This section has presented a discussion of the key findings in line with existing theories and studies.

4.6.1 Effect of Industry 4.0 Capabilities on SC Innovation

The initial objective of this study determined the effect of Industry 4.0 capabilities on supply chain innovation in Ghana. The result reveals that industry 4.0 had a significant direct influence on SC innovation. The positive path coefficient indicates that SC innovation will improve with industry 4.0. Industry 4.0 boosts SC innovation by 26.5%. This implies that managers should gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically. This study's results back with what other research has found: that Industry 4.0 may improve innovation by boosting energy consumption, facility capacity, and human capital (Lasi et al., 2014). As a result, the businesses' capacity to engage with the environment through technology has a significant impact on innovation performance. Firms that are able to take advantage of new technologies that improve environmental analysis will be in a good position to use existing resources to turn the information they gather into novel products and services (Jeandri et al., 2021). Previous research has demonstrated the importance of industry 4.0, digitization, automation, and technology in driving improved innovation performance among firms in developing economies and large-scale businesses (Ozkeser and Karaarslan, 2018; Kroll et al., 2018; Chu et al., 2019; Mubarak et al., 2021; De Giovanni and Cariola, 2021; Sarbu, 2022; Jankowska et al., 2022; Tirgil and Findik, 2022).

4.6.2 Effect of Industry 4.0 Capabilities on Data-Driven Decision Making

The next objective investigated the contribution of Industry 4.0 capabilities on data-driven decision-making in Ghana. The result indicates a significant positive direct influence on industry 4.0 to data-driven decision making. Industry 4.0 enhances data-driven decision making because the path coefficient is positive. Industry 4.0 accounts for 46.1% of data-driven decision making. This implies that managers should gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs. From the previous study, Bousdekis et al. (2021) argue that in conjunction with the rise of cyber-physical systems and cloud technologies for data processing and storage, next-generation maintenance decision-making would become increasingly responsive and capable of allowing correct and proactive judgments. Tripathi et al. (2022) also found that the efficacy of the created decision-making system may be increased by combining the lean principle with other process optimization strategies for shop floor management under various production settings, such as Industry 4.0. As a consequence of making decisions, many businesses collect real - time data, which they then utilize to drive innovation (Ardito, Messeni Petruzzelli, et al., 2019; Fortunato et al., 2017). As a result, businesses have a number of chances to save money, increase productivity, and attract and retain consumers by coming up with novel ways to solve problems (Del Vecchio et al., 2018; Chen et al., 2012).

4.6.3 Effect of Data-Driven Decision Making on SC Innovation

The following objective determined the effect of data-driven decision-making on supply chain innovation in Ghana. The result concludes that data-driven decision making have a direct effect on SC innovation. This suggests that when the data-driven decision-making increases, SC innovation also increases. Data-driven decision making enhance SC innovation by 54.6%. This implies that managements should constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically. According to the study of Yu et al. (2021), data-driven supply chain orientation has a considerable financial impact. Bhatti et al. (2022) investigated the influence of organizations' big data analytic capability on supply chain innovation and found that big data analytics has a substantial impact on supply chain innovation. Using data strategies may help providers effectively generate new goods or expand existing lines. Supply chain organizations may use huge volumes of data from various sources to predict events and trends (Ghasemaghaei et al., 2016). Businesses may use data-driven decision making to predict sales and performance, which might drive the innovation or improvements to modern products (Ghasemaghaei, and Calic, 2019). Online businesses may utilize customer online activity and purchase history (including page views and time spent on each page) to anticipate consumer behaviour when creating new items (Dawson, 2021). Prescriptive data and a defined strategy may also assist exploration and exploitation procedures (Ghasemaghaei, and Calic, 2019).

4.6.4 Mediating Effect of Data-Driven Decision Making

The final objective of this study identified the role of data-driven decision-making in mediating the relationship between Industry 4.0 capabilities and supply chain innovation in Ghana. Data-driven decision making mediates industry 4.0 and SC innovation positively. The positive path coefficient indicates that data-driven decision making positively and fully mediates interactions between industry 4.0 and SC innovation. This also means that data-driven decision making mediates 25.2% of the I4.0-SCI connection. This implies that managements should constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs in order to gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically. The study of El Hilali et al. (2021) examined how big data analytics increases firms' sustainability commitment. 41 Moroccan companies from diverse sectors were studied quantitatively. Partial Least Squares-Structural Equation Modeling (PLS-SEM). Technical skills like big data analysis did not improve big data's sustainability mediation function.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSIONS, AND RECOMMENDATIONS

5.0 Introduction

This section discusses and interprets the results of this research work and presents the conclusion of the study. It summarizes the findings in connection with the objectives for the study, as per the empirical findings in the previous chapter. The main thrust of this chapter is to present the summary of findings and conclusions with regards to the contribution of the study emanating from the research objective which is to determine how industry 4.0 capabilities influence SC innovation and further examine how data-driven decision making can influence the relationship. The chapter further talks about the limitations of the research and also provide suggestions for future research directions.

5.1 Summary of Findings

5.1.1 Effect of Industry 4.0 Capabilities on SC Innovation

The initial objective of this study determined the effect of Industry 4.0 capabilities on supply chain innovation in Ghana. The result reveals that industry 4.0 had a significant direct influence on SC innovation. This implies that managers should gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically.

5.1.2 Effect of Industry 4.0 Capabilities on Data-Driven Decision Making

The next objective investigated the contribution of Industry 4.0 capabilities on data-driven decision-making in Ghana. The result indicates a significant positive direct influence on industry 4.0 to data-driven decision making. This implies that managers should gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs.

5.1.3 Effect of Data-Driven Decision Making on SC Innovation

The following objective determine the effect of data-driven decision-making on supply chain innovation in Ghana. The result concludes that data-driven decision making have a direct effect on SC innovation. This suggests that when the data-driven decision-making increases, SC innovation also increases. This implies that managements should constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically.

5.1.4 Mediating Effect of Data-Driven Decision Making

The final objective of this study identified the role of data-driven decision-making in mediating the relationship between Industry 4.0 capabilities and supply chain innovation in Ghana. The results indicates that data-driven decision making positively and fully mediates interactions between industry 4.0 and SC innovation. This implies that managements should constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs in order to gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically.

5.2 Conclusion

The main objective is to examine the mediating role of data-driven decision-making of the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. The study employed cross-sectional research design. This survey was conducted using a quantitative approach. Stratified sampling was used to choose 381 participants. A prepared questionnaire was the main tool used for data collection. Both SPSS v26 and SmartPls v4 were used for the statistical analysis. Both descriptive and inferential approaches were used to analyse the data. The result reveals that industry 4.0 had a significant direct influence on SC innovation and data-driven decision making. The result also concludes that data-driven decision making have a direct effect on SC innovation. The results indicates that data-driven decision making positively and fully mediates interactions between industry 4.0 and SC innovation. The study therefore concluded that managements should constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs in order to gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically.

5.3 Recommendations for Management

This section provides recommendations based on the findings of the research for various stakeholders. These ideas should be taken into consideration by management and academics.

- The result revealed that industry 4.0 had a significant direct influence on SC innovation. The study recommended that managers should gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically.
- The result indicates a significant positive direct influence on industry 4.0 to data-driven decision making. The study suggested that managers should gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and

decentralised to constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs.

- The result concludes that data-driven decision making have a direct effect on SC innovation. The study therefore recommended that managements should constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically.
- The results indicated that data-driven decision making positively and fully mediates interactions between industry 4.0 and SC innovation. The study therefore concluded that managements should constantly review and change their approaches, remind their personnel to make decisions based on facts, not emotions, and choose reasoning over instinct when presented with actual data that contradicts their beliefs in order to gathers data and draws conclusions, have real-time capacity, and makes decisions virtually and decentralised to innovate supply chain operations, regularly innovate supply chain service, and innovate technologically.

5.4 Limitations and Recommendation for Future Research

Numerous possible avenues for further research are obstructed by the constraints of this study. First, both managers from the analysed firms were included in the study sample. Therefore, a similar study on employees may provide more generalizable results. Causation is difficult to prove using cross-sectional research design. Future research may use longitudinal and panel data to empirically determine causality. Quantitative analysis examined industry 4.0 capabilities, data-driven decision making, and SC innovation. Qualitative research methods may be needed for future comparable studies. This study suggests that future research may benefit from using other statistical analysis methods. Future research may replicate this study in other countries to verify similar results.

REFERENCE

Al Kuwaiti, A., Al Muhanna, F.A. and Al Amri, S., 2018. Implementation of digital health technology at academic medical centers in Saudi Arabia. *Oman medical journal*, *33*(5), p.367.

Ardito, L., Petruzzelli, A.M., Panniello, U. and Garavelli, A.C., 2019. Towards Industry 4.0: Mapping digital technologies for supply chain management-marketing integration. *Business Process Management Journal*, *25*(2), pp.323-346.

Bahrami, M., Shokouhyar, S. and Seifian, A., 2022. Big data analytics capability and supply chain performance: the mediating roles of supply chain resilience and innovation. *Modern Supply Chain Research and Applications*.

Bai, C., Dallasega, P., Orzes, G. and Sarkis, J., 2020. Industry 4.0 technologies assessment: A sustainability perspective. *International journal of production economics*, *229*, p.107776.

Belhadi, A., Mani, V., Kamble, S.S., Khan, S.A.R. and Verma, S., 2021. Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, pp.1-26.

Bhagawati, M.T., Manavalan, E., Jayakrishna, K. and Venkumar, P., 2019. Identifying key success factors of sustainability in supply chain management for industry 4.0 using DEMATEL method. In *Proceedings of International Conference on Intelligent Manufacturing and Automation* (pp. 583-591). Springer, Singapore.

Bhatti, S.H., Hussain, W.M.H.W., Khan, J., Sultan, S. and Ferraris, A., 2022. Exploring data-driven innovation: What's missing in the relationship between big data analytics capabilities and supply chain innovation? *Annals of Operations Research*, pp.1-26.

Blome, C., Paulraj, A. and Schuetz, K., 2014. Supply chain collaboration and sustainability: a profile deviation analysis. *International Journal of Operations and Production Management*.

Bousdekis, A., Lepenioti, K. and Mentzas, G., 2021. A Review of Data-Driven Decision-Making Methods for Industry 4.0 Maintenance Applications. *Electronics*, *10*(7), p.828.

Bousdekis, A., Lepenioti, K., Apostolou, D. and Mentzas, G., 2021. A review of data-driven decision-making methods for industry 4.0 maintenance applications. *Electronics*, *10*(7), p.828.

Byrne, B.M., 2013. Structural equation modelling with AMOS: Basic concepts, applications, and programming. Hoboken.

Cai, L. and Zhu, Y., 2015. The challenges of data quality and data quality assessment in the big data era. *Data science journal*, *14*.

Camilleri, M.A., 2019. The use of data-driven technologies for customer-centric marketing. *Camilleri, MA (2019). The Use of Data-Driven Technologies for Customer-Centric Marketing, International Journal of Big Data Management. Forthcoming*.

Castelo-Branco, I., Cruz-Jesus, F. and Oliveira, T., 2019. Assessing Industry 4.0 readiness in manufacturing: Evidence for the European Union. *Computers in Industry*, *107*, pp.22-32.

Cegielski, C.G., Jones-Farmer, L.A., Wu, Y. and Hazen, B.T., 2012. Adoption of cloud computing technologies in supply chains: An organizational information processing theory approach. *The international journal of logistics Management*.

Chae, B. and Olson, D., 2022. Technologies and applications of Industry 4.0: insights from network analytics. *International Journal of Production Research*, *60*(12), pp.3682-3704.

Chalmeta, R. and Santos-deLeón, N.J., 2020. Sustainable supply chain in the era of industry 4.0 and big data: A systematic analysis of literature and research. *Sustainability*, *12*(10), p.4108.

Chatterjee, S., Chaudhuri, R. and Vrontis, D., 2021. Does data-driven culture impact innovation and performance of a firm? An empirical examination. *Annals of Operations Research*, pp.1-26.

Chaudhuri, R., Chatterjee, S., Vrontis, D. and Thrassou, A., 2021. Adoption of robust business analytics for product innovation and organizational performance: the mediating role of organizational data-driven culture. *Annals of Operations Research*, pp.1-35.

Chauhan, C., Singh, A. and Luthra, S., 2021. Barriers to industry 4.0 adoption and its performance implications: An empirical investigation of emerging economy. *Journal of Cleaner Production*, *285*, p.124809.

Chigoba, N.E., 2021. *Teacher Perceptions of Practices that Enculturate Data-Driven Decision-Making* (Doctoral dissertation, University of South Carolina).

Chu, Y., Tian, X. and Wang, W., 2019. Corporate innovation along the supply chain. *Management Science*, *65*(6), pp.2445-2466.

Cochran, W.G., 1977. *Sampling techniques*. John Wiley and Sons.

Cohen, J., 2013. *Statistical power analysis for the behavioral sciences*. Routledge.

Cohen, J., McCabe, E.M., Michelli, N.M. and Pickeral, T., 2009. School climate: Research, policy, practice, and teacher education. *Teachers' college record*, *111*(1), pp.180-213.

Cohen, L., Manion, L. and Morrison, K., 2017. Action research. In *Research methods in education* (pp. 440-456). Routledge.

Comuzzi, M. and Patel, A., 2016. How organisations leverage big data: A maturity model. *Industrial management and Data systems*.

Confrey, J. and Shah, M., 2021. Examining instructional change at scale using data from diagnostic assessments built on learning trajectories. *ZDM–Mathematics Education*, *53*(6), pp.1265-1283.

Constantiou, I.D. and Kallinikos, J., 2015. New games, new rules: big data and the changing context of strategy. *Journal of Information Technology*, *30*(1), pp.44-57.

Corallo, A., Latino, M.E. and Menegoli, M., 2018. From industry 4.0 to agriculture 4.0: a framework to manage product data in agri-food supply chain for voluntary traceability. *International Journal of Nutrition and Food Engineering*, *12*(5), pp.146-150.

da Rocha Torres, A.B., de Oliveira Borges, K., Espuny, M., Salvador, J.D.M.R. and Oliveira, O.J., 2022. Business transformation through sustainability based on Industry 4.0. *Heliyon*, *8*(8), pp.e10015-e10015.

Da Silva, V.L., Kovaleski, J.L. and Pagani, R.N., 2019. Technology transfer in the supply chain oriented to industry 4.0: a literature review. *Technology Analysis and Strategic Management*, *31*(5), pp.546-562.

Dallasega, P., Rauch, E. and Linder, C., 2018. Industry 4.0 as an enabler of proximity for construction supply chains: A systematic literature review. *Computers in industry*, *99*, pp.205-225.

Dalmarco, G. and Barros, A.C., 2018. Adoption of Industry 4.0 technologies in supply chains. In *Innovation and Supply Chain Management* (pp. 303-319). Springer, Cham.

Davidson, R., 2020. Cyber-Physical Production Networks, Artificial Intelligence-based Decision-Making Algorithms, and Big Data-driven Innovation in Industry 4.0-based Manufacturing Systems. *Economics, Management and Financial Markets*, *15*(3).

Dawson, A., 2021. Robotic wireless sensor networks, big data-driven decision-making processes, and cyber-physical system-based real-time monitoring in sustainable product lifecycle management. *Economics, Management and Financial Markets*, *16*(2), pp.95-105.

De Giovanni, P. and Cariola, A., 2021. Process innovation through industry 4.0 technologies, lean practices and green supply chains. *Research in Transportation Economics*, *90*, p.100869.

de Sousa Jabbour, A.B.L., Jabbour, C.J.C., Foropon, C. and Godinho Filho, M., 2018. When titans meet–Can industry 4.0 revolutionise the environmentally-sustainable manufacturing wave? The role of critical success factors. *Technological Forecasting and Social Change*, *132*, pp.18-25.

Devi K, S., Paranitharan, K.P. and Agniveesh A, I., 2021. Interpretive framework by analysing the enablers for implementation of Industry 4.0: an ISM approach. *Total Quality Management and Business Excellence*, *32*(13-14), pp.1494-1514.

Díaz-Chao, Á., Ficapal-Cusí, P. and Torrent-Sellens, J., 2021. Environmental assets, industry 4.0 technologies and firm performance in Spain: A dynamic capabilities path to reward sustainability. *Journal of Cleaner Production*, *281*, p.125264.

Ding, B., 2018. Pharma Industry 4.0: Literature review and research opportunities in sustainable pharmaceutical supply chains. *Process Safety and Environmental Protection*, *119*, pp.115-130.

Donkor, F., Papadopoulos, T. and Spiegler, V., 2021. The supply chain integration–Supply chain sustainability relationship in the UK and Ghana pharmaceutical industry: A stakeholder and contingency perspective. *Transportation Research Part E: Logistics and Transportation Review*, *155*, p.102477.

Duft, G. and Durana, P., 2020. Artificial intelligence-based decision-making algorithms, automated production systems, and big data-driven innovation in sustainable industry 4.0. *Economics, Management and Financial Markets*, *15*(4), pp.9-18.

El Hilali, W., El Manouar, A. and Idrissi, M.A.J., 2021. The mediating role of big data analytics in enhancing firms' commitment to sustainability. *International Journal of Advanced Technology and Engineering Exploration*, *8*(80), p.932.

Erboz, G., 2017. How to define industry 4.0: main pillars of industry 4.0. *Managerial trends in the development of enterprises in globalization era*, *761*, p.767.

Etikan, I., Musa, S.A. and Alkassim, R.S., 2016. Comparison of convenience sampling and purposive sampling. *American journal of theoretical and applied statistics*, *5*(1), pp.1-4.

Falk, R.F. and Miller, N.B., 1992. *A primer for soft modeling*. University of Akron Press.

Fan, H., Li, G., Sun, H. and Cheng, T.C.E., 2017. An information processing perspective on supply chain risk management: Antecedents, mechanism, and consequences. *International Journal of Production Economics*, *185*, pp.63-75.

Fathi, M. and Ghobakhloo, M., 2020. Enabling mass customization and manufacturing sustainability in industry 4.0 context: a novel heuristic algorithm for in-plant material supply optimization. *Sustainability*, *12*(16), p.6669.

Fatorachian, H. and Kazemi, H., 2021. Impact of Industry 4.0 on supply chain performance. *Production Planning and Control*, *32*(1), pp.63-81.

Felsberger, A., Qaiser, F.H., Choudhary, A. and Reiner, G., 2022. The impact of Industry 4.0 on the reconciliation of dynamic capabilities: Evidence from the European manufacturing industries. *Production Planning and Control*, *33*(2-3), pp.277-300.

Felstead, M., 2019. Cyber-physical production systems in Industry 4.0: Smart factory performance, manufacturing process innovation, and sustainable supply chain networks. *Economics, Management and Financial Markets*, *14*(4), pp.37-43.

Fernández-Caramés, T.M., Blanco-Novoa, O., Froiz-Míguez, I. and Fraga-Lamas, P., 2019. Towards an autonomous industry 4.0 warehouse: A UAV and blockchain-based system for inventory and traceability applications in big data-driven supply chain management. *Sensors*, *19*(10), p.2394.

Fernando, Y., Wahyuni-TD, I.S., Gui, A., Ikhsan, R.B., Mergeresa, F. and Ganesan, Y., 2022. A mixed-method study on the barriers of industry 4.0 adoption in the Indonesian SMEs manufacturing supply chains. *Journal of Science and Technology Policy Management*.

Fornell, C. and Larcker, D.F., 1981. Structural equation models with unobservable variables and measurement error: Algebra and statistics.

Frank, A.G., Mendes, G.H., Ayala, N.F. and Ghezzi, A., 2019. Servitization and Industry 4.0 convergence in the digital transformation of product firms: A business model innovation perspective. *Technological Forecasting and Social Change*, *141*, pp.341-351.

Galati, F. and Bigliardi, B., 2019. Industry 4.0: Emerging themes and future research avenues using a text mining approach. *Computers in Industry*, *109*, pp.100-113.

Galbraith, J.R. 1973. Designing Complex Organizations, Reading, MA, Addison-Wesley.

Galbraith, J.R. 1974. Organization design: An information processing view. Interfaces, 4 (3), Gao, B. and Paton, R.A., 2018, March. Growing SMEs the role of Service Innovation: The Case of CCoI. In *ISPIM Innovation Symposium* (pp. 1-18). The International Society for Professional Innovation Management (ISPIM).

Ghadge, A., Er Kara, M., Moradlou, H. and Goswami, M., 2020. The impact of Industry 4.0 implementation on supply chains. *Journal of Manufacturing Technology Management*, *31*(4), pp.669-686.

Ghadge, A., Kara, M.E., Moradlou, H. and Goswami, M., 2020. The impact of Industry 4.0 implementation on supply chains. *Journal of Manufacturing Technology Management*.

Ghasemaghaei, M. and Calic, G., 2019. Does big data enhance firm innovation competency? The mediating role of data-driven insights. *Journal of Business Research*, *104*, pp.69-84.

Ghasemaghaei, M. and Hassanein, K., 2016. A macro model of online information quality perceptions: A review and synthesis of the literature. *Computers in Human Behavior*, *55*, pp.972-991.

Ghobakhloo, M. and Fathi, M., 2021. Industry 4.0 and opportunities for energy sustainability. *Journal of Cleaner Production*, *295*, p.126427.

Ghobakhloo, M., 2018. The future of manufacturing industry: a strategic roadmap toward Industry 4.0. *Journal of manufacturing technology management*.

Global, M., 2015. The Internet of Things: Mapping the Value Beyond the Hype. McKinsey and Company, New York, NY, USA.

Goertzen, M.J., 2017. *Applying quantitative methods to e-book collections*. ALA TechSource.

Gong, Q., Yang, Y. and Wang, S., 2014. Information and decision-making delays in MRP, KANBAN, and CONWIP. *International Journal of Production Economics*, *156*, pp.208-213.

Grant, E., 2021. Big Data-driven Innovation, Deep Learning-assisted Smart Process Planning, and Product Decision-Making Information Systems in Sustainable Industry 4.0. *Economics, Management, and Financial Markets*, *16*(1), pp.9-20.

Gupta, H., Kumar, A. and Wasan, P., 2021. Industry 4.0, cleaner production and circular economy: An integrative framework for evaluating ethical and sustainable business performance of manufacturing organizations. *Journal of Cleaner Production*, *295*, p.126253.

Gupta, S., Justy, T., Kamboj, S., Kumar, A. and Kristoffersen, E., 2021. Big data and firm marketing performance: Findings from knowledge-based view. *Technological Forecasting and Social Change*, *171*, p.120986.

Hahn, G.J., 2020. Industry 4.0: a supply chain innovation perspective. *International Journal of Production Research*, *58*(5), pp.1425-1441.

Hair Jr, J.F., Howard, M.C. and Nitzl, C., 2020. Assessing measurement model quality in PLS-SEM using confirmatory composite analysis. *Journal of Business Research*, *109*, pp.101-110.

Hair Jr, J.F., Sarstedt, M., Hopkins, L. and Kuppelwieser, V.G., 2014. Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European business review*.

Hair, J. F., Hult, G. T. M., Ringle, C., and Sarstedt, M., 2016. A primer on partial least squares structural equation modeling (PLS-SEM) (2nd ed.). Sage Publications.

Hair, J.F., Black, W.C., Babin, B.J. and Anderson, R.E., 2010. Canonical correlation: A supplement to multivariate data analysis. *Multivariate Data Analysis: A Global Perspective, 7th ed.; Pearson Prentice Hall Publishing: Upper Saddle River, NJ, USA*.

Hallioui, A., Herrou, B., Santos, R.S., Katina, P.F. and Egbue, O., 2022. Systems-based approach to contemporary business management: An enabler of business sustainability in a context of industry 4.0, circular economy, competitiveness and diverse stakeholders. *Journal of Cleaner Production*, p.133819.

Harmoko, H., 2020. Industry 4.0 readiness assessment: Comparison of tools and introduction of new tool for SME. *Tehnički glasnik*, *14*(2), pp.212-217.

Haseeb, M., Hussain, H.I., Ślusarczyk, B. and Jermsittiparsert, K., 2019. Industry 4.0: A solution towards technology challenges of sustainable business performance. *Social Sciences*, *8*(5), p.154.

Heaslip, G., Kovács, G. and Haavisto, I., 2018. Innovations in humanitarian supply chains: the case of cash transfer programmes. *Production Planning and Control*, *29*(14), pp.1175-1190.

Henke, N.,. Bughin, J., Chui, M., Manyika, J., Saleh, T., Wiseman, B., and Sethupathy, G. 2016. The age of analytics: Competing in a data-driven world, *McKinsey Global Institute*, December, 1–123.

Henseler, J., Ringle, C.M. and Sarstedt, M., 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the academy of marketing science*, *43*(1), pp.115-135.

Henseler, J., Ringle, C.M. and Sarstedt, M., 2016b. Testing measurement invariance of composites using partial least squares. *International marketing review*.

Hofmann, E., Sternberg, H., Chen, H., Pflaum, A. and Prockl, G., 2019. Supply Chain Management and Industry 4.0: Conducting Research in the Digital Age. *International Journal of Physical Distribution and Logistics Management*, *49*(10), pp.945-955.

Hopkins, J.L., 2021. An investigation into emerging industry 4.0 technologies as drivers of supply chain innovation in Australia. *Computers in Industry*, *125*, p.103323.

Hossain, M.K. and Thakur, V., 2020. Benchmarking health-care supply chain by implementing Industry 4.0: a fuzzy-AHP-DEMATEL approach. *Benchmarking: An International Journal*, *28*(2), pp.556-581.

Hyers, D., 2020. Big Data-driven Decision-Making Processes, Industry 4.0 Wireless Networks, and Digitized Mass Production in Cyber-Physical System-based Smart Factories. *Economics, Management, and Financial Markets*, *15*(4), pp.19-29.

Ilebode, T. and Mukherjee, A., 2019. FROM CHAOS TO ORDER: A study on how data-driven development can help improve decision-making.

Israel, G.D., 1992. Determining sample size.

Ivanov, D., Dolgui, A. and Sokolov, B., 2019. The impact of digital technology and Industry 4.0 on the ripple effect and supply chain risk analytics. *International Journal of Production Research*, *57*(3), pp.829-846.

Jankowska, B., Mińska-Struzik, E., Bartosik-Purgat, M., Götz, M. and Olejnik, I., 2022. Industry 4.0 technologies adoption: barriers and their impact on Polish companies' innovation performance. *European Planning Studies*, pp.1-21.

Javaid, M. and Haleem, A., 2019. Industry 4.0 applications in medical field: A brief review. *Current Medicine Research and Practice*, *9*(3), pp.102-109.

Jimenez-Jimenez, D., Martínez-Costa, M. and Rodriguez, C.S., 2018. The mediating role of supply chain collaboration on the relationship between information technology and innovation. *Journal of Knowledge Management*.

Kache, F. and Seuring, S., 2017. Challenges and opportunities of digital information at the intersection of Big Data Analytics and supply chain management. *International journal of operations and production management*.

KARABACAK, M.E., 2019. *Data driven decision making in public administration: an assessment based on business intelligence maturity model* (Doctoral dissertation, Ankara Yıldırım Beyazıt Üniversitesi Sosyal Bilimler Enstitüsü).

Karaman, Kabadurmus, Fatma Nur 2020. *Antecedents to supply chain innovation. The International Journal of Logistics Management, 31(1), 145–171.* doi:10.1108/ijlm-04-2019-0096

Kayikci, Y., Subramanian, N., Dora, M. and Bhatia, M.S., 2022. Food supply chain in the era of Industry 4.0: Blockchain technology implementation opportunities and impediments from the perspective of people, process, performance, and technology. *Production Planning and Control*, *33*(2-3), pp.301-321.

Kiel, D., Müller, J.M., Arnold, C. and Voigt, K.I., 2020. Sustainable industrial value creation: Benefits and challenges of industry 4.0. In *Digital disruptive innovation* (pp. 231-270).

Klingenberg, C. and Antunes, J., 2017. Industry 4.0: what makes it a revolution. *EurOMA 2017*, pp.1-11.

Klovienė, L. and Uosytė, I., 2019. Development of performance measurement system in the context of industry 4.0: a case study. *Inžinerinė ekonomika*, *30*(4), pp.472-482.

Kock, N., 2015. Common method bias in PLS-SEM: A full collinearity assessment approach. *International Journal of e-Collaboration (ijec)*, *11*(4), pp.1-10.

Koh, L., Orzes, G. and Jia, F., 2019. The fourth industrial revolution (Industry 4.0): technologies disruption on operations and supply chain management. *International Journal of Operations and Production Management*, *39*, pp.817-828.

Kohnová, L., Papula, J. and Salajová, N., 2019. Internal factors supporting business and technological transformation in the context of Industry 4.0. *Verslas: Teorija ir praktika/Business: Theory and Practice*, *20*, pp.137-145.

Kothari, D.P., 2012, March. Power system optimization. In *2012 2nd National conference on computational intelligence and signal processing (CISP)* (pp. 18-21). IEEE.

Krejcie, R.V. and Morgan, D.W., 1970. Determining sample size for research activities. *Educational and psychological measurement*, *30*(3), pp.607-610.

Kroll, H., Horvat, D. and Jäger, A., 2018. *Effects of automatisation and digitalisation on manufacturing companies' production efficiency and innovation performance* (No. 58). Fraunhofer ISI Discussion Papers-Innovation Systems and Policy Analysis.

Krykavskyy, Y., Pokhylchenko, O. and Hayvanovych, N., 2019. Supply chain development drivers in industry 4.0 in Ukrainian enterprises. *Oeconomia Copernicana*, *10*(2), pp.273-290.

Kumar, P., Singh, R.K. and Kumar, V., 2021. Managing supply chains for sustainable operations in the era of industry 4.0 and circular economy: Analysis of barriers. *Resources, Conservation and Recycling*, *164*, p.105215.

Kumar, R., Khatri, S.K. and Diván, M.J., 2022. Optimization of power consumption in data centers using machine learning based approaches: a review. *International Journal of Electrical and Computer Engineering*, *12*(3), p.3192.

Kusiak, A., 2018. Smart manufacturing. *International Journal of Production Research*, *56*(1-2), pp.508-517.

Kusi-Sarpong, S., Gupta, H., Khan, S.A., Chiappetta Jabbour, C.J., Rehman, S.T. and Kusi-Sarpong, H., 2021. Sustainable supplier selection based on industry 4.0 initiatives within the context of circular economy implementation in supply chain operations. *Production Planning and Control*, pp.1-21.

Lasi, H., Fettke, P., Kemper, H.G., Feld, T. and Hoffmann, M., 2014. Industry 4.0. *Business and information systems engineering*, *6*(4), pp.239-242.

Lassnig, M., Müller, J.M., Klieber, K., Zeisler, A. and Schirl, M., 2021. A digital readiness check for the evaluation of supply chain aspects and company size for Industry 4.0. *Journal of Manufacturing Technology Management*, *33*(9), pp.1-18.

Lavidas, K., Petropoulou, A., Papadakis, S., Apostolou, Z., Komis, V., Jimoyiannis, A. and Gialamas, V., 2022. Factors affecting response rates of the Web survey with teachers. *Computers*, *11*(9), p.127.

Li, Ying; Dai, Jing; Cui, Li 2020. The impact of digital technologies on economic and environmental performance in the context of industry 4.0: A moderated mediation model. International Journal of Production Economics, 229(), 107777–. doi: 10.1016/j.ijpe.2020.107777

Liao, Y., Deschamps, F., Loures, E.D.F.R. and Ramos, L.F.P., 2017. Past, present and future of Industry 4.0-a systematic literature review and research agenda proposal. *International journal of production research*, *55*(12), pp.3609-3629.

Lim, L.L., Lau, E.S., Ozaki, R., Chung, H., Fu, A.W., Chan, W., Kong, A.P., Ma, R.C., So, W.Y., Chow, E. and Cheung, K.K., 2020. Association of technologically assisted integrated care with clinical outcomes in type 2 diabetes in Hong Kong using the prospective JADE Program: A retrospective cohort analysis. *PLoS medicine*, *17*(10), p.e1003367.

Lin, B., Wu, W. and Song, M., 2019. Industry 4.0: Driving factors and impacts on firm's performance: An empirical study on China's manufacturing industry. *Annals of Operations Research*, pp.1-21.

Liu, B. and De Giovanni, P., 2019. Green process innovation through Industry 4.0 technologies and supply chain coordination. *Annals of Operations Research*, pp.1-36.

Liu, H.C., Liu, L., Bian, Q.H., Lin, Q.L., Dong, N. and Xu, P.C., 2011. Failure mode and effects analysis using fuzzy evidential reasoning approach and grey theory. *Expert Systems with Applications*, *38*(4), pp.4403-4415.

López, M., 2022. The effect of sampling mode on response rate and bias in elite surveys. *Quality and Quantity*, pp.1-17.

Ludbrook, F., Michalikova, K.F., Musova, Z. and Suler, P., 2019. Business models for sustainable innovation in industry 4.0: Smart manufacturing processes, digitalization of production systems, and data-driven decision making. *Journal of Self-Governance and Management Economics*, *7*(3), pp.21-26.

Luo, W., Shi, Y. and Venkatesh, V.G., 2018. Exploring the factors of achieving supply chain excellence: a New Zealand perspective. *Production Planning and Control*, *29*(8), pp.655-667.

Luthra, S. and Mangla, S.K., 2018. Evaluating challenges to Industry 4.0 initiatives for supply chain sustainability in emerging economies. *Process Safety and Environmental Protection*, *117*, pp.168-179.

Manavalan, E. and Jayakrishna, K., 2019. A review of Internet of Things (IoT) embedded sustainable supply chain for industry 4.0 requirements. *Computers and Industrial Engineering*, *127*, pp.925-953.

Marinakis, V., Doukas, H., Tsapelas, J., Mouzakitis, S., Sicilia, Á., Madrazo, L. and Sgouridis, S., 2020. From big data to smart energy services: An application for intelligent energy management. *Future Generation Computer Systems*, *110*, pp.572-586.

Mastos, T.D., Nizamis, A., Terzi, S., Gkortzis, D., Papadopoulos, A., Tsagkalidis, N., Ioannidis, D., Votis, K. and Tzovaras, D., 2021. Introducing an application of an industry 4.0 solution for circular supply chain management. *Journal of Cleaner Production*, *300*, p.126886.

Matthyssens, P., 2019. Reconceptualizing value innovation for Industry 4.0 and the Industrial Internet of Things. *Journal of business and industrial marketing. -Bingley*, *34*(6), pp.1203-1209.

Meherishi, L., Narayana, S.A. and Ranjani, K.S., 2019. Sustainable packaging for supply chain management in the circular economy: A review. *Journal of cleaner production*, *237*, p.117582.

Mele, C., Pels, J. and Polese, F., 2010. A brief review of systems theories and their managerial applications. *Service science*, *2*(1-2), pp.126-135.

Melville, N. and Ramirez, R., 2008. Information technology innovation diffusion: an information requirements paradigm. *Information Systems Journal*, *18*(3), pp.247-273.

Mikalef, P., Boura, M., Lekakos, G., and Krogstie, J. 2019. Big data analytics and firm performance: Findings from a mixed-method approach. Journal of Business Research, 98, 261–276. https://doi.org/10.1016/j. jbusres.2019.01.044

Miragliotta, G., Sianesi, A., Convertini, E. and Distante, R., 2018. Data driven management in Industry 4.0: a method to measure Data Productivity. *IFAC-PapersOnLine*, *51*(11), pp.19-24.

Momeni, K. and Martinsuo, M., 2018. Remote monitoring in industrial services: need-to-have instead of nice-to-have. *The Journal of Business and Industrial Marketing*, *33*(6), pp.792-803.

Mosser, J., Pellerin, R., Bourgault, M., Danjou, C. and Perrier, N., 2022. GRMI4. 0: a guide for representing and modeling Industry 4.0 business processes. *Business Process Management Journal*, *28*(4), pp.1047-1070.

Müller, J.M., 2019. Business model innovation in small-and medium-sized enterprises: Strategies for industry 4.0 providers and users. *Journal of Manufacturing Technology Management*, *30*(8), pp.1127-1142.

Nica, E., 2019. Cyber-physical production networks and advanced digitalization in industry 4.0 manufacturing systems: sustainable supply chain management, organizational resilience, and data-driven innovation. *Journal of Self-Governance and Management Economics*, *7*(3), pp.27-33.

Nick, G., Kovács, T., Kő, A. and Kádár, B., 2021. Industry 4.0 readiness in manufacturing: Company Compass 2.0, a renewed framework and solution for Industry 4.0 maturity assessment. *Procedia Manufacturing*, *54*, pp.39-44.

Oesterreich, T.D. and Teuteberg, F., 2016. Understanding the implications of digitisation and automation in the context of Industry 4.0: A triangulation approach and elements of a research agenda for the construction industry. *Computers in industry*, *83*, pp.121-139.

Olajide, O.A., Kwak, D.W., He, Q. and Lim, M., 2019. A conceptual framework of environmental sustainability in the oil and gas supply chains: natural resource-based view (NRBV) and institutional theory approaches. In *Proceedings of the 24th International Symposium on Logistics (ISL 2019)* (pp. 95-103). Centre for Concurrent Enterprise, Nottingham University.

Ozkeser, B. and Karaarslan, C., 2018, August. The Innovation Performance Under the Shadow of Industry 4.0. In *The International Symposium for Production Research* (pp. 494-502). Springer, Cham.

Papadonikolaki, E., 2020. The digital supply chain: mobilising supply chain management philosophy to reconceptualise digital technologies and building information modelling (BIM). *Successful construction supply chain management: Concepts and case studies*, pp.13-41.

Papakostas, N., Constantinescu, C. and Mourtzis, D., 2020. Novel industry 4.0 technologies and applications. *Applied Sciences*, *10*(18), p.6498.

Parra, X., Tort-Martorell, X., Ruiz-Viñals, C., and Álvarez-Gomez, F. 2019. A Maturity Model for the Information-Driven SME. Journal of Industrial Engineering and Management, Vol. 12(No. 1), pp. 154-175

Patrucco, A., Ciccullo, F. and Pero, M., 2020. Industry 4.0 and supply chain process re-engineering: A coproduction study of materials management in construction. *Business Process Management Journal*, *26*(5), pp.1093-1119.

Pfohl, H.C., Yahsi, B. and Kurnaz, T., 2017. Concept and diffusion-factors of industry 4.0 in the supply chain. In *Dynamics in logistics* (pp. 381-390). Springer, Cham.

Pires, F., Cachada, A., Barbosa, J., Moreira, A.P. and Leitão, P., 2019, July. Digital twin in industry 4.0: Technologies, applications and challenges. In *2019 IEEE 17th International Conference on Industrial Informatics (INDIN)* (Vol. 1, pp. 721-726). IEEE.

Podsakoff, P.M. and Organ, D.W., 1986. Self-reports in organizational research: Problems and prospects. *Journal of management*, *12*(4), pp.531-544.

Podsakoff, P.M., MacKenzie, S.B., Lee, J.Y. and Podsakoff, N.P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *Journal of applied psychology*, *88*(5), p.879.

Politecnico di Milano (2017). Industria 4.0: la grande occasione per l'Italia. Observatory Industry 4.0, Milano.

Preindl, R., Nikolopoulos, K. and Litsiou, K., 2020, January. Transformation strategies for the supply chain: The impact of industry 4.0 and digital transformation. In *Supply Chain Forum: An International Journal* (Vol. 21, No. 1, pp. 26-34). Taylor and Francis.

Premkumar, G., Ramamurthy, K. and Saunders, C.S., 2005. Information processing view of organizations: an exploratory examination of fit in the context of interorganizational relationships. *Journal of Management Information Systems*, *22*(1), pp.257-294.

Pusala, M.K., Amini Salehi, M., Katukuri, J.R., Xie, Y. and Raghavan, V., 2016. Massive data analysis: tasks, tools, applications, and challenges. *Big Data Analytics*, pp.11-40.

Rad, F.F., Oghazi, P., Palmié, M., Chirumalla, K., Pashkevich, N., Patel, P.C. and Sattari, S., 2022. Industry 4.0 and supply chain performance: A systematic literature review of the benefits, challenges, and critical success factors of 11 core technologies. *Industrial Marketing Management*, *105*, pp.268-293.

Ragab, M.A. and Arisha, A., 2018. Research methodology in business: A starter's guide. *Management and organizational studies*, *5*(1), pp.1-14.

Ramanathan, K. and Samaranayake, P., 2021. Assessing Industry 4.0 readiness in manufacturing: a self-diagnostic framework and an illustrative case study. *Journal of Manufacturing Technology Management*, *33*(3), pp.468-488.

Ramirez-Peña, M., Sotano, A.J.S., Pérez-Fernandez, V., Abad, F.J. and Batista, M., 2020. Achieving a sustainable shipbuilding supply chain under I4. 0 perspective. *Journal of Cleaner Production*, *244*, p.118789.

Rennung, F., Luminosu, C.T. and Draghici, A., 2016. Service provision in the framework of Industry 4.0. *Procedia-Social and Behavioral Sciences*, *221*, pp.372-377.

Riley, C., Vrbka, J. and Rowland, Z., 2021. Internet of things-enabled sustainability, big data-driven decision-making processes, and digitized mass production in industry 4.0-based manufacturing systems. *Journal of Self-Governance and Management Economics*, *9*(1).

Rodriguez, L. and Da Cunha, C., 2018. Impacts of big data analytics and absorptive capacity on sustainable supply chain innovation: A conceptual framework. *LogForum*, *14*(2), pp.151-161.

Salimova, T., Vukovic, N. and Guskova, N., 2020. Towards sustainability through Industry 4.0 and Society 5.0. *International Review*, (3-4), pp.48-54.

Sarbu, M., 2022. The impact of industry 4.0 on innovation performance: Insights from German manufacturing and service firms. *Technovation*, *113*, p.102415.

Sarı, T., Güleş, H.K. and Yiğitol, B., 2020. Awareness and readiness of Industry 4.0: The case of Turkish manufacturing industry. *Adv. Prod. Eng. Manag*, *15*, pp.57-68.

Sarstedt, M. and Cheah, J.H., 2019. Partial least squares structural equation modeling using SmartPLS: a software review. *Journal of Marketing Analytics*, *7*(3), pp.196-202.

Schrauf, S. and Berttram, P., 2016. Industry 4.0: How digitization makes the supply chain more efficient, agile, and customer-focused. *Strateg. andTechnology*, pp.1-32.

Selvan, C. and Balasundaram, S.R., 2021. Data Analysis in Context-Based Statistical Modeling in Predictive Analytics. In *Handbook of Research on Engineering, Business, and Healthcare Applications of Data Science and Analytics* (pp. 96-114). IGI Global.

Shamout, M.D., 2019. Does supply chain analytics enhance supply chain innovation and robustness capability? *Organizacija*, *52*(2), pp.95-106.

Shamsuddin, I.M., Jafar, J.A., Shawai, A.S.A., Yusuf, S., Lateefah, M. and Aminu, I., 2017. Bioplastics as better alternative to petroplastics and their role in national sustainability: a review. *Adv. Biosci. Bioeng*, *5*(4), p.63.

Shao, X.F., Liu, W., Li, Y., Chaudhry, H.R. and Yue, X.G., 2021. Multistage implementation framework for smart supply chain management under industry 4.0. *Technological Forecasting and Social Change*, *162*, p.120354.

Shayganmehr, M., Gupta, S., Laguir, I., Stekelorum, R. and Kumar, A., 2021. Assessing the role of industry 4.0 for enhancing swift trust and coordination in humanitarian supply chain. *Annals of Operations Research*, pp.1-33.

Shrivastava, P., Ivanaj, S. and Ivanaj, V., 2016. Strategic technological innovation for sustainable development. *International Journal of Technology Management*, *70*(1), pp.76-107.

Simic, M. and Nedelko, Z., 2019. Development of competence model for Industry 4.0: A theoretical approach. *Economic and Social Development: Book of Proceedings*, pp.1288-1298.

Singh, A.S. and Masuku, M.B., 2014. Sampling techniques and determination of sample size in applied statistics research: An overview. *International Journal of economics, commerce and management*, *2*(11), pp.1-22.

Singh, M., 2017. *Care of the new born revised 8ed (2017)*. CBS Publishers and Distributors Private Limited.

Söderlund, O., 2022. Towards data-driven decision making: A Small Enterprise study.

Sony, M. and Naik, S., 2019. Key ingredients for evaluating Industry 4.0 readiness for organizations: a literature review. *Benchmarking: An International Journal*, *27*(7), pp.2213-2232.

Stentoft, J. and Rajkumar, C., 2018. Does supply chain innovation pay off? In *Innovation and Supply Chain Management* (pp. 237-256). Springer, Cham.

Stock, G.N. and Tatikonda, M.V., 2008. The joint influence of technology uncertainty and interorganizational interaction on external technology integration success. *Journal of operations management*, *26*(1), pp.65-80.

Stojčić, N., Vojvodić, K. and Butigan, N., 2019. Logistics innovations development in the CEE region. *Business Logistics in Modern Management*.

Sun, Z., Wu, L.Z., Ye, Y. and Kwan, H.K., 2022. The impact of exploitative leadership on hospitality employees' proactive customer service performance: A self-determination perspective. *International Journal of Contemporary Hospitality Management*, (ahead-of-print).

Swanson, L., 2003. An information-processing model of maintenance management. *International Journal of Production Economics*, *83*(1), pp.45-64.

Taherdoost, H., 2016. Sampling methods in research methodology; how to choose a sampling technique for research. *How to choose a sampling technique for research (April 10, 2016)*.

Telukdarie, A., Buhulaiga, E., Bag, S., Gupta, S. and Luo, Z., 2018. Industry 4.0 implementation for multinationals. *Process Safety and Environmental Protection*, *118*, pp.316-329.

Tirgil, A. and Fındık, D., 2022. How Does Awareness Toward the Industry 4.0 Applications Affect Firms' Financial and Innovation Performance? *Journal of the Knowledge Economy*, pp.1-23.

Tiwari, S., 2020. Supply chain integration and Industry 4.0: a systematic literature review. *Benchmarking: An International Journal*, *28*(3), pp.990-1030.

Tiwari, S., 2022. Supply Chain Innovation in the Era of Industry 4.0. In *Handbook of Research on Supply Chain Resiliency, Efficiency, and Visibility in the Post-Pandemic Era* (pp. 40-60). IGI Global.

Topleva, S., 2018. Industry 4.0: Transforming economy through value added. *Asian Journal of Economic Modelling*, *6*(1), pp.37-46.

Tripathi, V., Chattopadhyaya, S., Mukhopadhyay, A.K., Saraswat, S., Sharma, S., Li, C. and Rajkumar, S., 2022. Development of a Data-Driven Decision-Making System Using Lean and Smart Manufacturing Concept in Industry 4.0: A Case Study. *Mathematical Problems in Engineering*, *2022*.

Tseng, M.L., Tan, R.R., Chiu, A.S., Chien, C.F. and Kuo, T.C., 2018. Circular economy meets industry 4.0: Can big data drive industrial symbiosis? *Resources, conservation and recycling*, *131*, pp.146-147.

Tseng, M.L., Tran, T.P.T., Ha, H.M., Bui, T.D. and Lim, M.K., 2021. Sustainable industrial and operation engineering trends and challenges Toward Industry 4.0: A data driven analysis. *Journal of Industrial and Production Engineering*, *38*(8), pp.581-598.

Tushman, M.L. and Nadler, D.A., 1978. Information processing as an integrating concept in organizational design. *Academy of management review*, *3*(3), pp.613-624.

Usama Awan, Saqib Shamim;Zaheer Khan;Najam Ul Zia;Syed Muhammad Shariq;Muhammad Naveed Khan; (2021). *Big data analytics capability and decision-making: The role of data-driven insight on circular economy performance.*

Technological Forecasting and Social Change, *()*, –. doi: 10.1016/j.techfore.2021.120766

Varvne, M., Cederholm, S. and Medbo, A., 2020. The Major Challenges in DDDM Implementation: A Single-Case Study: What are the Main Challenges for Business-to-Business MNCs to Implement a Data-Driven Decision-Making Strategy?

Waldman, J.D. and Schargel, F.P., 2006. Twins in trouble (II): Systems thinking in healthcare and education. *Total Quality Management and Business Excellence*, *17*(1), pp.117-130.

Wamba, S.F. and Queiroz, M.M., 2022. Industry 4.0 and the supply chain digitalisation: a blockchain diffusion perspective. *Production Planning and Control*, *33*(2-3), pp.193-210.

Wang, M., Asian, S., Wood, L.C. and Wang, B., 2020. Logistics innovation capability and its impacts on the supply chain risks in the industry 4.0 era. *Modern Supply Chain Research and Applications*, *2*(2), pp.83-98.

Wiengarten, F. and Longoni, A., 2015. A nuanced view on supply chain integration: a coordinative and collaborative approach to operational and sustainability performance improvement. *Supply Chain Management: An International Journal*.

Wilton, M., Vargas, P., Prevost, L., Lo, S.M., Cooke, J.E., Gin, L.E., Imad, M., Tatapudy, S. and Sato, B., 2022. Moving towards More Diverse and Welcoming Conference Spaces: Data-Driven Perspectives from Biology Education Research Scholars. *Journal of Microbiology and Biology Education*, *23*(2), pp. e00048-22.

Wong, C.W., Lai, K.H., Cheng, T.C.E. and Lun, Y.V., 2015. The role of IT-enabled collaborative decision making in inter-organizational information integration to improve customer service performance. *International Journal of Production Economics*, *159*, pp.56-65.

Wong, D.T. and Ngai, E.W., 2019. Critical review of supply chain innovation research (1999–2016). *Industrial Marketing Management*, *82*, pp.158-187.

Xing, K., Cropley, D.H., Oppert, M.L. and Singh, C., 2021. Readiness for digital innovation and industry 4.0 transformation: studies on manufacturing industries in the city of salisbury. In *Business Innovation with New ICT in the Asia-Pacific: Case Studies* (pp. 155-176). Springer, Singapore.

Yadav, G., Kumar, A., Luthra, S., Garza-Reyes, J.A., Kumar, V. and Batista, L., 2020. A framework to achieve sustainability in manufacturing organisations of developing economies using industry 4.0 technologies' enablers. *Computers in industry*, *122*, p.103280.

Yao, X., J. Zhou, Y. Lin, Y. Li, H. Yu, and Y. Liu. 2017. "Smart Manufacturing Based on Cyber-physical Systems and 16 F. R. P. M. VIANNA ET AL. Beyond." Journal of Intelligent Manufacturing, no. 2017: 1–13. doi:10.1007/s10845-017-1384-5.

Yasmin, R., 2022. Supply Chain Orientation, Social Capital and Firm's Performance: The Mediating Role of Supply Chain Innovation Comparative Study of China and Pakistan. *Journal of Business Management Studies-JBMS*, *1*(03), pp.10-34.

Yu, W., Jacobs, M.A., Chavez, R. and Feng, M., 2019. Data-driven supply chain orientation and financial performance: the moderating effect of innovation-focused complementary assets. *British Journal of Management*, *30*(2), pp.299-314.

Yu, Y., Zhang, J.Z., Cao, Y. and Kazancoglu, Y., 2021. Intelligent transformation of the manufacturing industry for Industry 4.0: Seizing financial benefits from supply chain relationship capital through enterprise green management. *Technological Forecasting and Social Change*, *172*, p.120999.

Yuan, C., Liu, W., Zhou, G., Shi, X., Long, S., Chen, Z. and Yan, X., 2022. Supply chain innovation announcements and shareholder value under industries 4.0 and 5.0: evidence from China. *Industrial Management and Data Systems*, *122*(8), pp.1909-1937.

Zhai, N., 2021, August. Intelligent Management of Network Resources Based on Net of Things Technology. In *Journal of Physics Conference Series* (Vol. 1992, No. 3, p. 032044).

Zheng, T., Ardolino, M., Bacchetti, A. and Perona, M., 2021. The applications of Industry 4.0 technologies in manufacturing context: a systematic literature review. *International Journal of Production Research*, *59*(6), pp.1922-1954.

Zhou, K., Liu, T. and Liang, L., 2016. From cyber-physical systems to Industry 4.0: make future manufacturing become possible. *International Journal of Manufacturing Research*, *11*(2), pp.167-188.

APPENDIX I

KNUST School of Business \-

Department of Supply Chain and Information System

COLLEGE OF HUMANITIES AND SOCIAL SCIENCES

KWAME NKRUMAH UNIVERSITY OF SCIENCE AND TECHNOLOGY, KUMASI

Examining the mediating role of data-driven decision-making of the impact of Industry 4.0 capabilities on supply chain innovation in Ghana

Dear Survey Participant,
Kindly allow me to introduce this important study to you.

Thank you very much for participating in this study that seeks to understand the mediating role of data-driven decision-making of the impact of Industry 4.0 capabilities on supply chain innovation in Ghana. This study aims to obtain empirical evidence to support managerial decision-making and public policymaking in Ghana. You and your organization have been selected as exemplary context to study this phenomenon; hence your active participation would be very much appreciated.

The study is an academic exercise undertaken by this researcher, a student at Kwame Nkrumah University of Science and Technology (KNUST) School of Business. I can assure you that your responses will be treated in the strictest confidence, with the results collected being anonymised and used for statistical and academic purposes only. Kindly note that you are responding to this survey in your capacity as a senior manager or supply chain manager of your firm**.** The questionnaire has specific instructions to follow and scales to use to indicate your responses. Please consider yourself and your personal experiences in your organisation to respond to the statements in the survey. Although some statements appear quite similar, they are also unique in many ways, so **kindly do well to respond to each statement**. The questionnaire will take about 20 to 25 minutes to complete, and we think it will be more appropriate if you respond to it at your convenient time..
Please, indicate your consent for participation here ☐ I

SECTION A: DEMOGRAPHIC CHARACTERISTICS:

This section requires you to tick which category fits your description which will be used for classification and comparison purposes of variables necessitated by this study only. Please indicate by ticking (√) appropriately in the box provided.

Please answer the following questions:

1. *Gender of respondent*: Male ☐ Female ☐
2. *Age of respondent*:

   18-30 years ☐ 31-40 year's ☐ 41-50 years ☐ Above 50 years ☐
3. *Level of Education of respondent*:

   Junior High School ☐ Senior High School ☐ Diploma ☐ Bachelor Degree ☐ Graduate Studies (Master / Ph.D.) ☐ Others ☐ For Others, Please specify:………………
4. *Your Position in the Firm*

   Business Owner ☐ Business Owner and Manager ☐ Manager ☐ Production Manager ☐ Others ☐ For Others, Please specify:…………………
5. *How many years have you been working in your firm?*

   1 - 5 years ☐ 6 - 10 years ☐ 11 – 15 years ☐ 16 years and above ☐
6. *How many employees are in the firm?*

   Less than 5 employees ☐ 5 – 29 employees ☐ 30 – 99 employees ☐ More than 100 ☐
7. *How many products does the firm produce?*

   1-2 Products ☐ 3-5 Products ☐ More than 5 Products ☐
8. *How many years has the firm been in operation?*

   1 to 5 years ☐ 6 to 10 years ☐ More than 10 years ☐

Cont. on the next page…

SECTION A: INDUSTRY 4.0:

Section A: Statements describing Industry 4.0

Please answer the following questions by considering your firm's use of supply chain analytics.

On a scale of 1 to 5 ***(1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree*)** indicate your opinion ***by ticking √ where appropriate*** in the following statements.

Industry 4.0						
I4.01	Our organization systematically collects and extracts insights from data	1	2	3	4	5
I4.02	Our organization uses real-time capability	1	2	3	4	5
I4.03	Our organization uses distributed systems to system interoperability	1	2	3	4	5
I4.04	Our organization uses virtualization and decentralization of decision-making	1	2	3	4	5

Section B: Supply Chain Innovation (Panayides and Lun, 2009)

Indicate the extent to which you agree or disagree with each statement by checking the appropriate number from 1 to 5 using the following scale:

Item	**Statement**	**1**	**2**	**3**	**4**	**5**
SCIN1	We frequently try out new ideas in the supply chain context.					
SCIN2	We seek out new ways to do things in our supply chain					
SCIN3	We are creative in the methods of operation in the supply chain.					
SCIN4	We often introduce new ways of servicing the supply chain					
SCIN5	We motivate supply chain members to suggest new ideas					
SCIN6	We pursue continuous innovation in core processes					
SCIN7	We pursue new technological innovation					

SECTION D: Data-Driven Decision-Making (Gupta and George, 2016)

Indicate the extent to which you agree or disagree with each statement by checking the appropriate number from 1 to 5 using the following scale:

Item	**Statement**	**1**	**2**	**3**	**4**	**5**
DDDM1	We consider data as an asset.					
DDDM2	We base most of the decisions on data rather than instinct.					

DDDM3	We are willing to override our intuition when data contradict our viewpoints.					
DDDM4	We continuously assess our strategies and take corrective action in response to the insights obtained from data.					
DDDM5	We continuously coach our people to make their decisions based on data.					