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Effect Of Industry 4.0 and Supply Chain Analytics on Innovation Performance Among Agribusinesses Firms: The Mediated-Moderated Role of Circular Economy and Green Mindfulness

By

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DECLARATION

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

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DEDICATION

I dedicate this work to the Lord God Almighty, my wife (Mrs. Joyce Kamewor Naa), our precious children (Emerald Narkie Kamewor and Kendrick Kofi Kamewor) and all duly acknowledged who contributed to this success especially Carisca for the grant and the support to complete this work.

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I say “God bless you all”.

ABSTRACT

The purpose of this study was to investigate the relationship between industry 4.0, supply chain analytics and innovation performance by highlighting the intervening role of circular economy, and the moderating role of green mindfulness between circular economy practice and innovation performance. To achieve this objective, a review of existing literature was conducted and gaps were identified. Based on the gaps identified, a conceptual framework with eight hypotheses was developed. To validate the model, a well-structured questionnaire was designed and piloted and data was gathered from 326 senior managers of agribusinesses firms in Ghana. The hypothesized model was validated with PLS-SEM. The study concludes that industry 4.0 and supply chain analytics are important in the quest to improve both circular economy practices and innovation performance. Circular economy does not just support innovation performance but serves as an avenue to reap superior innovation performance via industry 4.0 and supply chain analytics. The study also concludes that green mindfulness though may drive innovation performance, but it does not necessarily moderate the industry 4.0, supply chain analytics and innovation performance relationship. The GEA and GIZ should continue to undertake more extensive capacity-building programmes to help develop and enhance operators' knowledge resource innovation capabilities.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Agriculture plays essential support to many economies, whether developed or developing economies. The sector serves as the basic source of food supply and serves as are major employment avenue, particularly for emerging economies. The recent population growth has placed the sector under heavy pressure both in developed and developing economies. Owing to how essential the sector is to any economy, its failure adversely affects economic growth. Hence governments especially in developing economies have made significant strides in the quest for agricultural activities. Despite the effort of governments, the competitiveness of agriculture in many African countries continues to be low (Babu and Shishodia, 2018). In Africa, agriculture employs approximately half of the continent's workforce, hence higher competitiveness of the sector will not only boost economic growth but also support structural transformation. The majority of the crops grown in Africa are staples like maize, rice, sorghum, millet, cassava, yams, and sweet potatoes. A few traditional cash crops including coffee, cotton, cocoa, oil palm, sugar, tea, and tobacco are also grown there. However, there are significant differences in competitiveness between crops and nations. Furthermore, the agricultural industry in Africa is characterized by a high proportion of smallholder farmers (80%) who grow low-yielding basic foods on tiny plots with little assistance from modern inputs (Rapsomanikis, 2015). The limited use of modern inputs hampers the ability of businesses in the agriculture setting (Agribusiness) to innovate and become competitive.

In today's complex business world, many firms are investing in technology and data to find innovative ways to differentiate themselves from their competitors (Côrte-Real, Oliveira, and Ruivo, 2017). Indeed, 87% of firms believe investing in data will change the competitive landscape, and 89% believe they will lose considerable market share if they do not adopt big data within the next few years (Akter, Wamba, Gunasekaran, Dubey, and Childe, 2016). The extant literature has identified technology and data as “the next frontier for innovation, competition, and productivity” (Manyika and Roxburgh, 2011) and the “next big thing in innovation” (Gobble, 2013). Industry 4.0 is the umbrella term for "smart" and interconnected production systems that are created to sense, anticipate, and interact with the physical world to make decisions that support production in real-time (Fatorachian and Kazemi, 2021), and is capable of changing the innovation landscape by increasing the fit between consumers’ preferences and product features (Günther, Mehrizi, Huysman and Feldberg, 2017; Johnson, Friend and Lee, 2017). Additionally, the ability to digitize the production process and the system is not just enough to reap the full benefit of technology, however, the processes should be capable of gaining insight and extracting value from data generated through procurement, processing and distribution processes. The outbreak of the Covid-19 pandemic has increased investment in digitization across industries and businesses and agribusiness is no exception. Considering the growth in digitization in the agribusinesses setting in recent times, it is imperative to also understand how the ability of firms to generate insight and extract value from data generated through procurement, processing and distribution processes could aid innovation performance among firms, particularly agribusiness, this has therefore risen global discourse on the significance of supply chain analytics.

Extraction, diagnosis, integration, and transformation of supply chain data into useful information and discernible patterns for decision-makers are all aspects of supply chain analytics (Tiwari et al., 2018). According to Wang et al. (2016), supply chain analytics can improve a company's operational performance and provide insight into trends that could support supply chain innovation (Fosso et al., 2018; Jeble et al., 2018). Furthermore, data analytics and timely, accurate data can enhance supply chain innovation (Fernando et al., 2018).

Industry 4.0 and supply chain analytics could, in turn, enhance company performance through innovation. However, it is still unclear how supply chain analytics and industry 4.0 might improve innovation performance. Though recent research has urged for a deeper comprehension of the purportedly good relationship between industry 4.0, supply chain analytics, and innovation success (Gunasekaran et al., 2017; Johnson et al., 2017). Exploiting fresh information to develop, accept, and put into practice novel ideas is referred to as innovation (Calantone, Cavusgil and Zhao, 2002). Alegre, Lapiedra, and Chiva (2006) claim that the two components of innovation performance are efficacy and efficiency. Innovation efficiency represents the time and effort needed to reach that level of benefit, whereas innovation efficacy relates to the extent to which innovation is helpful to the firm (Alegre and Chiva, 2008). Supply chain analytics and industry 4.0 may enable businesses to exhibit successful and efficient firm innovation. Supply chain analytics, in particular, can assist businesses in gathering and processing market data to better comprehend consumer preferences, which can be crucial to the success of innovation. When compared to their rivals, businesses that integrate supply chain analytics into their operations may have a better chance of improving operating effectiveness and revenue growth (Marshall, Mueck, and Shockley, 2015). Despite these potential advantages, many businesses have struggled to use supply chain analytics to improve their innovation performance (Johnson et al., 2017), and some are still unaware of the links between industry 4.0 and supply chain analytics and their effects (Ghasemaghaei, Hassanein and Turel, 2017; Shamout et al., 2020). Hence, this study is conducted to examine the direct effect of industry 4.0 (I4.0) and supply chain analytics (SCA) on innovation performance as well as explore the indirect role of CE and OM in the I4.0, SCA and IP direct link within the agribusiness sector in Ghana.

1.2 Problem Statement

Despite the relevance of agribusiness to the economic growth of any country, agribusinesses in developing economies face numerous challenges which affect their innovative success (Abor, 2015; Afriyie et al., 2019). There is limited knowledge on how to improve the innovativeness of agribusiness firms through industry 4.0 and supply chain analytics (Liao and Barnes, 2015; Osei et al., 2016; Wadho and Chaudhry, 2018). Awan et al (2021) indicated both circular economy and supply chain analytics have limited empirical basics. In Africa, the governments of many nations have made a significant investment in developing agribusiness, especially regarding innovative ways of reducing post-harvest losses and improving their production methods, processes and systems to remain competitive. Despite the investment in technology and human resources development programs by successive governments, innovation in the agribusiness space is nothing to boost in developing economies, particularly in Sub Sahara Africa (SSA) which Ghana is no exception. Though prior studies (Albort-Morant et al., 2018; Revilla et al., 2018; Wiratmadja et al., 2020; Sousa-Ginel et al., 2021; Pascual et al., 2021; Dani et al., 2021; Lendowski et al., 2022; Sharif et al., 2022) have highlighted multiple external drives of innovation performance among large manufacturing firms, majority of this studies have focused in developed economies. This creates a contextual gap that needs to be filled.

Again, most of the existing studies have also focused on external factors which drive innovation performance, meanwhile, external factors do not always provide positive outcomes. In response, there have been recent calls on the need to identify internal factors that influence innovation performance, particularly in the agribusiness setting (Kumar et al., 2021; Kristoffersen et al., 2021). Atiase and Dzansi (2020) further indicated businesses in emerging countries including Sub Sahara Africa (SSA) lack the external support which is necessary to drive innovation. Prior studies have also described the African market as being slow to innovation due to poor infrastructure, human capital and dynamism in the environment which is needed to drive innovation remain shallow and unsupportive (Atiase et al., 2018; Atiase and Dzansi, 2020). This study, therefore, focuses on two important internal factors (supply chain analytics and industry 4.0) which may drive innovation performance among businesses.

Supply Chain Analytics and Industry 4.0 has received attention as a means of enhancing firms' supply chain performance ((Mubarik, 2019). It is therefore not surprising that various research has linked the competitiveness of firms to effective analytics capabilities. Supply Chain is very crucial among firms but lacks empirical justification on how it could accelerate innovation performance in the agribusiness context. Given that, the success of firms is heavily dependent on their capability to develop innovative products/services (Donkor et al., 2018; Osei et al., 2016). There is a need to explore innovative strategies that could help firms remain innovative, especially firms in the agribusiness space. Agribusinesses in Ghana are expected to continuously explore knowledge as a means to be innovative and competitive (Rajapathirana and Hui, 2018b), however, agribusinesses in Ghana are not innovative enough (GoG, 2016). Although various steps have been done over the years, it is still unclear whether government backing for innovations can improve enterprises' innovative performance (Osei et al., 2016). Emanating from the need to understand the above concepts in a developing country such as Ghana, this study is conducted to explore the effects of supply chain analytics and industry 4.0 on innovation performance.

To the best of the authors' knowledge, there have been no or limited studies which concurrently explore the effects of supply chain analytics and industry 4.0 on innovation performance. Though these variables have proven relevant in driving different organizational outcomes, their impact on innovation performance particular in the agribusiness space remains unknown. Apart from the fact, that the effects of supply chain analytics and industry 4.0 on innovation performance are silent in literature, these concepts are just at the infant stages in developing countries like Ghana, particularly in the agribusiness setting where technology is now receiving gradual acceptance (Bag et al., 2019; Bag et al., 2022). Though industry 4.0 and supply chain analytics have received global attention in innovation literature (Kumar et al., 2021; Awan et al., 2021; Chauhan et al., 2022). Whether or not I4.0 and SCA are able to drive innovation performance remains underexplored (Hao et al.,2019; Sarbu, 2022).

Also, assessing the bivariate relationship may not be sufficient (Donaldson, 2006). Usually, the relationship between dependent and independent variables may be influenced by another important variable. The relevant variable could be a mediator or moderator. Thus, it is advisable to propose and examine at least a trivariate causal relationship in other to have a valid generalization (Saeidi et al., 2019). Hence, this study proposes circular economy and green mindfulness as mediators and moderators respectively. Circular economy represents a waste reduction mechanism which allows resource usage and waste production to be reduced (Gupta et al., 2019). Though earlier studies demonstrated the relevance of CE in extant supply chain management literature, empirical studies on the concept are still scarce, particularly in developing countries with no empirical validation in the agribusiness space (Giudice et al., 2020).

In literature, the use of circular economy principles within the supply chain has received scant consideration (Aminoff and Kettunen, 2016; De Angelis et al., 2018; Lewandowski, 2016). As a result, research into the circular supply chain is still limited (Geissdoerfer et al., 2018). While Awan, Sroufe and Shahbaz (2021) call for the need to explore how data analytics capabilities and industry 4.0 may influence CE, Awan, Shamim, Khan, Zia, Shariq and Khan (2021) also recommended the need to examine the mediating role of CE within innovation performance relationship. Drawing from the gaps above, the author argues that the implementation of a circular economy requires the acquisition, elaboration and use of adequate information and knowledge from both internal and external environment to implement the desired changes in business operations effectively (Gupta et al., 2019; Sumbal et al., 2019; Giudice et a., 2020). Meanwhile, it would be difficult to achieve such operational efficiency without industry 4.0 and effective supply chain analytics. Thus, even in the absence of circular economy, supply chain analytics and industry 4.0 may drive innovation performance, but the maximum benefit could be achieved indirectly through circular economy practices. Hence this study examines the mediating role of Circular economy in the direct industry 4.0, supply chain analytics and innovation performance nexus which has not been explored in research.

Last but not least, prior research (Nguyen et al., 2020; Nguyen and Thanh, 2022) demonstrated that an organization's capacity for innovation is reliant on organizational mindfulness, which is the capacity of an organization to learn about emerging threats and develop the capacity to respond to them quickly (Vogus and Sutcliffe, 2012). The possibility that a company will successfully adapt to technology and use organizational resources to do so improves when organizational mindfulness is present (Li et al., 2021). By offering alternatives for innovative decision-making and emphasizing important components of change adaption, organizational mindfulness helps businesses to utilize technology (Singh et al., 2021; Nguyen and Thanh, 2022). The few studies on circular economy and innovation produces mixed outcome (Hysa et al., 2020; Bag et al.,2022; Rodríguez-Espíndola et al., 2022). To clear the confusion Zareen et al (2022) recommended further examination of green mindfulness as a moderator. It is therefore imperative to understand how green mindfulness (GM) plays a boundary condition between the I4.0, SCA and IP direct links. In addressing this gap, this study combines the RBV and Contingency theory as the theoretical lens to demonstrate how GM may also strengthen the between the I4.0, SCA and IP direct links. Finally, earlier studies (Kazançoğlu, et al., 2021; Jabbour et al., 2019; Demestichas and Daskalakis, 2020; Khan et al., 2022; Lahane et al., 2021; Edwin et al., 2021) have either used RBV or Institutional Theory, meanwhile, contingency approach is widely utilized in OM literature to investigate the relationship between contextual factors, the use of manufacturing practices (such as lean practices and environment management practices), and their effects on performance improvement (Sousa and Voss, 2008). Unfortunately combining the RBV and contingency theory remain unexplored. This creates a theoretical gap that requires attention. This study is hence conducted to examine the mediated-moderated roles of CE and green mindfulness in the I4.0, SCA and IP direct link within the agribusiness sector in Ghana. The outcome of this study makes multiple contributions to theory and practice. The combination of I4.0, SCA as drivers of innovation performance in the agribusiness space in the emerging economy makes a unique contribution as this relationship has not yet been tested. This study is therefore among the very first attempt to unravel how I4.0, SCA drives IP in developing economies, especially in SSA. Again, the introduction of CE and OM also makes an important contribution by demonstrating how superior innovation performance in agribusiness may be achieved. The moderated relationship explored in this study makes an important theoretical contribution.

1.3 Objectives of the study

Based on the gaps identified, this study is conducted to examine the direct effect of industry 4.0 (I4.0) and supply chain analytics (SCA) on innovation performance as well as explore the indirect role of CE and GM in the I4.0, SCA and IP direct link within the agribusiness sector in Ghana. In the quest to achieve the main objective of the study, the researcher intends to address the specific objectives below;

1. To examine the direct impact of industry 4.0 and supply chain analytics on the innovation performance of agribusinesses;
2. To explore the mediating role of circular economy in the direct effect of industry 4.0 (I4.0) and supply chain analytics (SCA) on innovation performance.
3. To evaluate the moderating effect of Green Mindfulness on the CEC and IP relationship.

1.4 Research Questions

1. Do I4.0 and SCA influence the innovation performance of agribusinesses?
2. Can circular economy mediate the direct effect of industry 4.0 (I4.0) and supply chain analytics (SCA) on innovation performance
3. Does Green Mindfulness moderate the CEC and IP relationship?

1.5 Significance of the Study

This study attempted to understudy the unvalidated relationship between I4.0, SCA and IP with the mediated-moderated roles of CE and organizational mindfulness in the I4.0, SCA and IP direct link within the agribusiness sector in Ghana. The study presents theoretical, practical, and policy significances to individual agribusiness and government agencies.

Of the many contributions of this study has been to extend the literature on I4.0, SCA and IP which is scarce, the study combined OIPT and Contingency theory to develop an integrated model which incorporated different variables. The findings of the study expand perspectives on the variables used in the study. Such as I4.0, SCA, CE and GM which are scarce in SSA. Thus, exhibiting the result of the set of intangible assets allows firms to use their intangible assets to achieve their current management activities and innovative objectives and aspirations. In as much as these variables have received much attention in research, it has been researched separately and in a different context. A combination of these factors in a single study, therefore, presents a unique contribution to the study. Therefore, this study may provide a better understanding to both practitioners and policymakers regarding the internal drivers of innovation performance in the agribusiness space.

In furtherance to that, the study will serve and act as a reference for future related research studies, especially within agribusiness. This research would be one of the kinds of work that would focus specifically on I4.0, SCA, CE and GM which are scarce in SSA, hence addressing the scarcity of research on stakeholders' perspectives within agribusiness space in the developing world such as Sub-Saharan Africa.

In terms of practical significance, the study will make specific managerial contributions to industrial and the management of agribusiness. The findings of the study may be useful in developing strategies that are geared toward developing and adopting the antecedent factors of I4.0, SCA, CE, GM and a firm's innovation performance in an agribusiness context. By establishing the influence of I4.0, SCA, CE, GM on innovation performance, managers will be able to identify the strongest predictor of CE on innovation amongst the constructs. This research will thus provide empirical evidence concerning the effect of I4.0, SCA, CE, GM activities on innovation performance.

1.6 Scope of the Study

This study focuses on the effect of industry 4.0 (I4.0) and supply chain analytics (SCA) on innovation performance as well as exploring the indirect role of CE and OM in the I4.0, SCA and IP direct link within the agribusiness sector in Ghana. This study was conducted in Ghana. It particularly focuses on the Agribusiness sector of Ghana. Agribusiness is noted of facing multiple constraints including innovation constraints (Clegg, 2018; Kou et al., 2021). Which directly or indirectly affects the business performance. The outbreak of the Covid-19 pandemic dampened worldwide sustainable development efforts, hurting all economic sectors, organizations, and industries, including Ghana's agribusiness sector. Agriculture is the backbone of the Ghanaian economy; hence the government has encouraged its transition from subsistence farming into a commercial industry that can ensure food security by 2030 (Ong'ayo, 2017). About 54% of Ghana's GDP and over 40% of export revenues come from agriculture. Meanwhile, 52% of the labor force is employed in agribusiness firms, ensuring that the country never goes hungry (FAO, 2022). The National Board for Small Scale Industries (NBSSI) was established by the government of Ghana to aid SMEs and improve their performance in the country. However, reports show that much work remains to be done to improve the performance of agribusinesses in Ghana (Amoah and Kwabena, 2018; Osei, 2017). And thus, the downfall of Ghana's agribusiness continues. Agribusiness in Ghana is made of marketing, manufacturing/ processing MSME. This study was conducted among, manufacturing/ processing MSMEs who through GIZ working with the Ghanaian Ministry of Trade and Industry supported 500 MSMEs in their business development, and technological solutions, with certification according to international standards and in using by-products in a circular economy. In addition, the project promotes companies that offer services and production inputs along the supply chains. The study was therefore conducted among 326 Agribusiness.

1.7 Research Methodology

This research used the cross-sectional descriptive research design which used quantitative research techniques. The survey method was used for the study. Usage of the survey method was considered to be efficient and economical, with its associated advantages to the researcher and appropriateness to the study. For instance, the cost implications compared to interviewing allow for anonymity, which may lead to more honest responses and have the possibility of eliminating there is bias due to varied ways of phrasing questions with various answers (Kothari, 2012; Durepos and Wiebe, 2019). The use of purposive and convenience sampling techniques was employed in the study. A sample of 326 MSMEs firms supported by the GIZ project was taken as the unit of analysis. Primary data was collected utilizing both online and face-to-face administrations of questionnaires. Using alternative software’s Smart PLS and MPUS, CFA was conducted to ascertain the reliability and validity of constructs in the model. Structural model evaluation was done using the Smart PLS to test the hypotheses proposed in the model (see Figure 2.1). The result was presented using appropriate tables and figures, interpreted and discussed with related literature.

1.8 Organization of the Study

This first chapter, also named as the introduction, has expanded the background to the study, statement of the problem, study objectives, and their corresponding research questions. The significance of the study, and the scope of the study. It has as well explained the terms used in this study. The chapter ends with the structure of the thesis proposal. Chapter two reviews the relevant literature on knowledge acquisition, product innovation, firm age, and government support from previous researches. The chapter discusses the theoretical review upon which the study is based in line with the concept of I4.0, SCA, CE, OM and innovation Performance (IP). The chapter also expounds on the key concepts and reviews empirical research related to them. Finally, the chapter ends with a summary highlighting identified gaps in the literature. In the nutshell, this chapter will explain the theoretical concept of the study as well as the development of the model based on previous studies. Chapter three describes the methodology to be used for this research, including research design, population, sampling design, and the development of survey instruments to measure the constructs in the research model. The chapter also presents tools to be used in analyzing the data and ends with ethical considerations germane to the study. Chapter four presents and discusses the results and analyses from the data gathered. It covers the response rate, preliminary data analysis, respondents' demographic characteristics, descriptive analysis of variables, inferential analysis, exploratory factor analysis (EFA). The chapter also presents the evaluation of SEM results, structural model analysis, and hypotheses testing. The final chapter five discusses of research outcome, the contribution of the study, limitations of the study, implications of the study, and conclusions.

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 which also highlights the gap explored in this study.

2.2 Conceptual Review

This section provides definitions, operationalizations and how the constructs have been used in this study. The model has five main constructs (Supply Chain Analytics, Industry 4.0, Circular Economy, Innovation Performance and Green Mindfulness). These constructs have been operationalized in subsequent sections below (see 2.2.1-2.2.5).

2.2.1 Supply Chain Analytics

According to the literature, data analytics has been used in a variety of sectors (Shayaa et al., 2018). Supply chain management is one sector that might really benefit from an analytics capacity (Saleem et al., 2020; Waller and Fawcett, 2013). Some studies have attempted to conceptualize supply chain analytics (SCA) while research on it is still evolving (Chae et al., 2014; Shafiq et al., 2019). Souza (2014) defines SCA as a supply chain management approach that employs prescriptive, descriptive and predictive approaches to guide supply chain operations such as supply chain planning, sourcing, production, and delivery. Analytics can be applied in a variety of ways, including data mining, optimization modeling and simulations, and risk analysis utilizing simulations (Bag et al., 2020; Sanders, 2016; Bag et al., 2020; Chen et al., 2015; Lassen et al., 2014; Sanders, 2016). In the opinion of many academics, a company's ability to collect, integrate, deploy, and analyze massive volumes of big data offers it a major competitive advantage in the marketplace (Shayaa et al., 2018). The company's data analytics capabilities allow it to better understand and respond to external events (Dubey et al., 2018). Effective and precise supply chain policies and plans can only be developed if a company has the ability to gather, analyze, synthesize, as well as synthesize data (Wamba et al., 2017). Supply chain analytics involve extricating, diagnosing, integrating and transforming supply chain data into valuable information and meaningful patterns for decision-makers (Tiwari et al., 2018). Supply chain analytics can boost the operational performance of firms (Wang et al., 2016) and provides foresight information and patterns that could aid innovative activities in the supply chain e.g., supply chain route or warehouse data (Fosso et al., 2018; Jeble et al., 2018). Moreover, timely and accurate data coupled with data analytics can improve innovation (Fernando et al., 2018). In this study, supply chain analytics is operationalized as the ability of agribusinesses to gather data, diagnose, integrate and transform their supply chain data into valuable information and meaningful patterns for decision-making. Table 2.1 provides a summary of a few studies that have used the construct in recent studies. The Table shows that supply chain analytics has varied outcomes on organizations, however, how it affects innovation performance, especially in the agribusiness setting is not yet been established. This justifies the inclusion of the construct in the model.

Table 2. 1 Summary of Evidence on Supply Chain Analytics.

Authors	Results
Khan, Piprani, and Yu (2022)	The data analytics in the supply chain was found to positively and significantly contribute to agility and adaptability.
Shafiq, Ahmed, and Mahmoodi (2020)	The finding reveals a significant positive association between SCAC and supply chain transparency.
Chae, Olson, and Sheu (2014).	Supply chain planning satisfaction (SAT) and SCM performance (SCP) are positively impacted by SCA.
Shamout (2019)	The study finds that supply chain analytics had a significant impact on supply chain innovation.
Shamout (2020)	Using supply chain analytics can help improve the robustness of the supply chain through supply chain innovation.

2.2.2 Industry 4.0

Integrated industry and smart manufacturing are two terms used to describe I4.0, which refers to the ability to impact the entire business from product creation through manufacture to delivery of the finished product (Hofmann & Rüsch, 2017). The introduction of smart technologies into the production environment has sparked the fourth industrial revolution, known as "Industry 4.0," following the first three, which were triggered by improvements in mechanization, electricity, and information technology (Wiengarten and Longoni 2015). The decentralization of business processes brought about by technological advancements is referred to as "Industry 4.0." M2M communications, the Internet of Things, Cyber Physical Systems, Artificial Intelligence, and Big Data Analytics (BDA) are all hallmarks of this new era (Brettel et al. 2014). Employees, machines, gadgets, and business systems are all linked by CPSs and the Internet as part of the "Industry 4.0" vision (Oberg and Graham 2016). Smart process management and new paradigms for industrial management have been enabled by this industrial revolution (Moeuf et al. 2017). Incorporating information and communication technologies (ICTs) into organizations has allowed for autonomous and dynamic manufacturing to be possible, and this, in turn, has improved the quality of the products and services that businesses provide (Tortorella and Fettermann 2017; Fatorachian and Kazemi 2018). Sustainable performance is a crucial element of smart factories because of these technical advancements that have made it possible to "efficiently utilise resources" (Strozzi et al., 2017; Fatorachian and Hadi, 2021).

In Germany, the concept of Industry 4.0 began in 2011 (Roblek et al., 2016). IoT, cloud computing, BCT, AI, and CPS are just a few of the technologies that make up Industry 4.0 (Awan et al., 2021; Fatorachian and Kazemi, 2021; Kumar, Jakhar and Bhattacharya, 2021; Umar et al., 2021). These industry 4.0 technologies have had a profound impact on the economic and organizational performance of the industry and have improved the accuracy, precision, and automation of the manufacturing process. In addition, industry 4.0 technologies have led to significant improvements in SC management, which have resulted in improved reaction time optimization and lower carbon emissions (Harris et al., 2020; Kumar, Jakhar and Bhattacharya, 2021; Mastos et al., 2020). Emerging trends in technical and organizational innovation have been identified by researchers such as (Rosa et al., 2020, Rajput and Singh, 2019). In this study, Industry 4.0 is the digital transformation of the field, providing agribusiness with real-time decision making. Table 2.2 provides a summary of a few studies that have used the construct in recent studies. Table 2.2 shows that industry 4.0 has varied outcomes on organizations, however, how it affects innovation performance, especially in the agribusiness setting remains unknown. This justifies the inclusion of the construct in the model.

Table 2. 2 Summary of Evidence on Industry 4.0.

Authors	Results
Sarbu (2022)	The findings show that the industry 4.0 initiative increases the likelihood of product innovation in the service sector and has a positive impact on product innovation intensity.
Mubarak, Tiwari, Petraite, Mubarik and Rasi (2021)	Open innovation is positively impacted by Industry 4.0, leading to green innovation behaviour.
Bag, Yadav, Wood, Dhamija and Joshi (2020)	The study reveals that intelligent logistics is greatly affected by Industry 4.0 resources, whereas interconnected and instrumented logistics are minimally affected.
Di Maria, De Marchi and Galeazzo (2022)	The result shows that CE was directly and positively correlated with both smart manufacturing and data processing technologies.
Lin, Wu and Song (2019)	Industry 4.0 can significantly improve firm performance, innovation activities, and stock returns, but it has no significant effect on supply chain efficiency.
Rahman, Kamal, Aydin and Haque (2022)	The study found that the services industry in both economies can be significantly improved and promoted by Industry 4.0.

2.2.3 Innovation Performance

Innovation is described as the introduction of a new or improved product or process, as well as a new marketing or organizational strategy in inter-company operations, workplace organization, and commercial connections, according to the Oslo Manual (OECD, 2005). Organizational innovations, according to the Oslo Manual, are improvements in corporate procedures aimed at increasing efficiency, productivity, competitiveness, adaptability, and ingenuity through the use of disembodied knowledge (Oslo Manual, 2018). Organizational innovation is about developing operations over time, such as new enterprise strategies and practices, understanding and adapting organizational practices to enhance performance, and modifying organizational strategies and processes to enhance public relations (Tseng et al., 2019; Karlsson and Tavassoli, 2016; Liao and Barnes, 2015). This is particularly true in business markets where the pressure to innovate leads the enhanced firm performance. Although, the ability to innovate no doubt remains critical and the approaches firms take in innovation are evolving from time to time. As espoused by Wadho and Chaudhry (2018), innovation is the process of developing and improving markets, procedures, and goods, along with the goal of the aggregate value. In the view of Ritala and Huizingh (2014), innovation is an indication of new product delivery to the market or to solve firm problems through innovative ideas for cost reduction, making processing faster or better, improving the organizational structure or networks, and as well as developing new or significantly improved systems. Innovation has also been described by Dereli, (2015) as the introduction of a new or improved product or process, as well as new promotional or operational strategies across workplace organization as well as promotional or operational strategy among inter-company activities. The Oslo handbook (2005) divides innovation into four types: product innovation, process innovation, marketing innovation, and organizational innovation, which could be further divided into technological and non-technology innovation. Literature of innovation indicates that any organization needs innovation to succeed and survive in an environment characterized by stiff competition (Jimenez and Sanz-Valle, 2011), and gather sustainable competitive advantage (Herman, Hady and Arafah, 2018). Production innovation has indeed been studied in relation to a wide range of management issues, notably emerging-market entrepreneurial ventures (Miocevic and Morgan, 2018; Oduro, 2019; Wang and Zhou, 2020). In matured businesses, ongoing innovation is essential (Cucculelli, 2018; Voeten, 2016), partnership networks and consequences from Rand D (Ferraris et al., 2019; Nieth et al., 2018), organizational values and leadership (Anning-Dorson, 2021; Gumusluŏlu and Ilsev, 2009; Hogan and Coote, 2014; Kahn, 2018; Zhou, Liu, Zhang and Chen, 2016). Innovation occurs when new things (products or services) are created and commercialized, or when performance attributes are enhanced (Rajapathirana and Hui, 2018). Innovations help businesses differentiate themselves from their competition by delivering solutions to critical national problems (Gamage et al., 2020; Metadata and Policies, 2018). Any good or service that is seen as novel by a person or a company is termed product innovation (Kotler and Keller, 2012). It also refers to the introduction of new products or services in order to attract new markets or to satisfy both existing and new customers (Aksoy, 2017; Kuncoro and Suriani, 2018; Najafi-Tavani et al., 2018). Product innovation necessitates a range of organizational approaches and also unique resources, which together lead to innovative outcomes (Simao and Franco, 2018). Firms' performance is still largely based on innovation (Cooper, 2014; Liu and Atuahene-gima, 2018; Osei et al., 2016; Wadho and Chaudhry, 2018). That is because enterprises that innovate enhance the quality of its product and products, which improves their performance and competitiveness. Product innovation, according to Federico et al. (2020), Liu and Atuahenegima, (2018), protects a firm against risks of competition, allowing the innovating firm to benefit from the 'early innovator' edge. The 4th edition of the Oslo manual (2018) describes product innovation as a new or improved good or service that differs significantly from the firm’s previous goods or services and that has been introduced on the market. Product innovation has been established to have a favourable and significant relationship with organizational success, according to (Liu and AtuaheneGima, 2018). According to Mahmutaj and Krasniqi, (2020) product innovation is highly significant to business growth. Furthermore, Osei et al., (2016) assert product innovation has a significant impact on business performance. Similarly, Li and Atuahene-gima, (2014) found innovation is linked to a successful business, which Wadho and Chaudhry, (2018) corroborated.

Prior studies (Chen et al., 2018; Ghasemaghaei and Calic, 2020; Ovuakporie et al., 2021) have classified innovation performance into two main headings, thus effectiveness and efficiency. Many companies have realized the need of launching new products and services in a timely way as time-based competition has grown more prevalent (Smith, 2011). In this study, innovation performance follows the earlier definition of Daft (2009) as cited in Slađana and Sven (2020) as the measure of how agribusinesses are able to effectively achieve innovation goals compared to their competitors and how they have dwelled on industry 4.0 enabled supply chain analytics to achieve their innovation agenda. In order to build a long-term competitive edge, an organization's innovation performance is essential (Anderson et al., 2014; Frederiksen and Knudsen, 2017; Santoro et al., 2020). It is also well known that while innovation performance results in personal satisfaction and rewards for the coworkers, it also has both costs and benefits for the organization as a whole (Janssen, 2003; Janssen et al., 2004). A number of issues influencing employees' innovative work behavior remain unresolved and immature, according to a new study (Anderson et al., 2014; Zhang et al., 2020). To attain innovation performance, a business must have people who come up with new ideas that can help them compete in the marketplace (Frederiksen and Knudsen, 2017), implying that creativity and innovation in any organization are vital for increased performance (Anderson et al., 2014). According to Singh et al. (2019), all previous research show that innovation performance plays a vital role in boosting organizational innovation. Indeed, there is considerable evidence supporting the linkage between innovation and organizational performance (Campanella et al., 2020; Wang and Dass, 2017). Table 2.3 provides a summary of a few studies that have used innovation performance in recent studies. Table 2.3 shows that innovation performance is driving by a number of factors and also has impact on organizational outcome, however, how SCA, I4.0 drives innovation performance, especially in the agribusiness setting remain unknown. This justifies the inclusion of the construct in the model.

Table 2. 3 Summary of Evidence on Innovation Performance.

Authors	Results
Lendowski, Oldeweme and Schewe, (2022)	An enterprise's innovation performance can be boosted by supporting a positive attitude towards risk-taking, risk management, and OI engagement.
Lopez Hernandez (2019)	The findings suggest that the development of TCCs in TBSs contributes to building new operational capabilities that result in higher innovation performance.
Molodchik and Nursubina (2012)	All types of intellectual capital except human capital are positively related to product innovations, according to the findings.

2.2.3 Circular Economy

CE describes the conversion of traditional industrial methods to circular ones that encourage the ideas of recycling and reusing (Khan et al., 2021). It is a regenerative strategy that seeks to regulate several energy and production loops in order to reduce a number of issues, including energy leakages, resource waste, and hazardous emissions (Geissdoerfer et al., 2017). A production system built on CE standards essentially guarantees maximal material and product functionality. In this approach, CE practices in particular improve efficient resource usage, which eventually improves business operational performance (Sehnem et al., 2019). By promoting good waste management, resource conservation, and effective financial use, the adoption of CE practices also benefits enterprises economically (Mangla et al., 2018). The primary factor for environmental degradation is the traditional production system (Bag and Pretorius, 2020). Therefore, using environmentally friendly and sustainable methods such as CE practices might greatly minimize waste and hazardous emissions, assisting enterprises in achieving sustainable performance (Konietzko et al., 2020). Similar to this, CE practices assist firms in using energy and resources more effectively, which leads to greater performance (Morais and Silvestre, 2018). Additionally, literature contends that a number of CE practices, including recycling, design, and procurement, could assist in establishing green sustainable management to achieve sustainable performance (Khan et al., 2021; Su et al., 2016). To optimize the ways in which resources and materials already on the market are used and to lower the consumption of raw materials and related waste, businesses that want to adopt a circular model must move toward technologies and business models that are long-lasting, renewable, reusable, and repairable (Gupta et al., 2019; Stahel, 2016). The adoption of cleaner production and distribution (supply chain) patterns is implied by the circular economy at the company level, particularly through the introduction of improved technology. This results in the adoption of new business models, which ask for a wider and far more thorough examination of the design of fundamentally alternative solutions, network ties, the involvement of individuals over the course of any activity, and drastic changes in behaviours (Ghisellini et al., 2016). Because it enables businesses to redesign and reorganize their operations (including manufacturing, supply chain management, and training) by minimizing resource inputs, waste, and emissions leakage, the circular economy is a crucial component of sustainable development that can give businesses a superior competitive advantage (Geissdoerferet al., 2018; Jabbouret al., 2019a). To do this, businesses must be set up so that the concepts of the circular economy, resource exchange, and interactions can benefit their processes (Ghisellini et al., 2016). The Ellen MacArthur Foundation and McKinsey Company (2012) and McKinsey Company (2014) both stressed the significance of moving from sustainable supply chain management to a circular supply chain, referring to it as the power of circling longer (i.e., a lengthening of the period of time during which materials are used).

Table 2.4 provides a summary of a few studies that have used the construct in recent studies. Table 2.4 shows that a circular economy has varied outcomes on organizations, however, how it affects innovation performance and how it indirectly plays a role as a mediator between the SCA, I4.0-IP link especially in the agribusiness setting remains unknown. This justifies the inclusion of the construct in the model.

Table 2. 4 Summary of Evidence on Circular Economy

Authors	Results
Moric, Jovanović, Đoković, Peković, and Perović (2020)	The study revealed that the implementation of circular economy activities improves company performance, as measured by productivity.
Pinheiro, Jugend, Lopes de Sousa Jabbour, Chiappetta Jabbour and Latan (2022)	Adoption of CE is found to positively impact market performance.
Kwarteng, Simpson and Agyenim-Boateng, (2021)	The CE policies, including the reducing, reusing, recycling, recovery and restoration of resources used in manufacturing, distribution, and consumption processes, are said to improve financial efficiency and financial performance through this study.
Omar (2020)	The study demonstrates that circular economy practices have a significant impact on the supply chain performance of chemical and allied manufacturing firms.
Yu, Khan and Umar (2022)	The study found that circular economy practices are positively connected to operational and economic performance.

Le, Behl and Pereira (2022)	The study showed that CEP and SSCM are positively correlated.

2.2.4 Green Mindfulness

A key part of practicing green mindfulness is paying attention to a variety of stimuli by making non-judgmental observations about one's immediate surroundings, acting mindfully, and writing down what one sees without judging it (Hwang and Lee, 2019). As a result, the term "green mindfulness" refers to the use of specific cognitive resources by employees in order to generate new ideas, products, processes, and services that help agribusinesses meet their objectives while also reducing their negative environmental impact (Dharmesti et al., 2020). It is well-known that many everyday behaviors are influenced by cognitive resources; therefore, green mindfulness encourages deeper self-world connection with the context, which in turn promotes sustainable environmental behavior. People who practice green mindfulness have a keen awareness of the most recent environmental information and knowledge available, and they are more likely to meet their own unique cognitive needs during the idea generation process, where new problems are likely to arise as solutions to old ones are sought (Langer and Moldoveanu, 2000). Common mindfulness has resulted in a favorable adjustment in behavior, particularly in terms of environmental activism (Bahl et al., 2016). In order to cultivate green mindfulness, one must learn to fix their attention, unlock their minds, and remain focused on the object of their attention (Bahl et al., 2016). To be mindful, from an ecological standpoint, necessitates a deeper connection to and understanding of one's immediate surroundings (Barbaro and Pickett, 2016). Extra attention spans include new kinds of provocations and shift expanded-scanning, context-specific translation of numerous viewpoints, examining several opinions, and appreciating multiple perspectives, among other things These aspects of mindfulness are essential if you want to improve your performance, find more purpose in your work, and develop your creative side (Choi et al., 2018). Table 2.5 provides a summary of a few studies that have used the construct in recent studies. Table 2.5 shows that green mindfulness has varied outcomes on organizations, however, how it affects innovation performance and how it indirectly plays a role as a moderator between the CE-IP link especially in the agribusiness setting remains unknown. This justifies the inclusion of the construct in the model.

Table 2. 5 Summary of Evidence on Green Mindfulness

Authors	**Results**
Chen, Chang and Lin (2014)	The mediation test reveals that green mindfulness partially mediates the link between green transformational leadership and green performance.
Zafar, Nisar, Shoukat and Ikram (2017)	The relationship between green transformational leadership and green performance is found to be partially mediated by green mindfulness.
Chen, Chang, Yeh and Cheng (2015)	The findings demonstrate that green mindfulness partially mediates the link between green shared vision and green creativity.
Aeknarajindawat and Jermsittiparsert, (2019)	The significant mediation effect created by green mindfulness is directly associated with green creativity.
Arslan, Kausar, Kannaiah, Shabbir, Khan and Zamir, (2022)	Only the relationship between green creativity and energy efficiency was moderated by green mindfulness.

2.3 Theoretical Review

An abundance of knowledge and information in the scope of innovation makes the research process to become challenging, difficult, and lengthy (Soetanto, 2017). Thus, to focus the research direction, 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 supply chain analytics, industry 4.0, circular economy, green mindfulness and innovation performance in the agribusiness setting. The driving theories of this study are the Resource-Based View Theory (RBV) and the Contingency 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. The study employed RBV and contingency theory as the theoretical lens of the study. Scholars have made the relationship between the firm and the environment in which it functions a major focus of their research (Makkonen et al., 2014; Chauhan et al., 2020). In the last two decades, theories from a variety of disciplines, including organizational behavior and strategic management, have gained widespread acceptance among OM experts (Buhman et al., 2009). A large body of organizational management (OM) literature that addresses the challenges of guiding an organization towards "best practices" is based on a contingency approach (Sousa and Voss, 2008). According to theories in the subject of contingency approach, an organization's performance is determined by how well it fits into the environment in which it functions. Organizations should modify their internal structure for improved performance (Donaldson, 2001; Chauhan et al., 2020). The contingency approach is widely utilized in OM literature to investigate the relationship between contextual factors, the use of manufacturing practices (such as lean practices and environment management practices), and their effects on performance improvement (Sousa and Voss, 2008).

2.3.1 Resource-Based View Theory (RBV)

RBV has been widely used in strategic management literature to explain why there are variances in inter-firm performance since the 1980s (Lado et al., 2006). RBV's basic tenet is that businesses obtain a competitive edge by utilizing their special resources and competencies (Barney, 1991). In the context of this study, I4.0 and SCA are seen as organizational resources that can be efficiently leveraged to enhance innovation performance among agribusiness firms. The authors believe that building strong system of automation and technology usage will help firms to gain new insight from existing data available, this will also be facilitating collaboration through effective strategic decisions that will help them to be innovative, based on the RBV enhanced innovation performance could be shaped through I4.0 and SCA.

2.3.2 Contingency Theory

From the contingency perspective, innovation performance may also be driven by situation or contextual factors, though circular economy appears to be new in the context of emerging economies, consumers of agriproducts are not just internal and hence face the global dynamic especially now that consumers are increasingly becoming loyal to environmentally friendly firm. This study therefore envisages that the rise of stakeholder's demand for sustainable production process and products may compel agribusiness to move from the traditional method to employ reuse practices. The ability of agribusiness to therefore combines the I4.0, SCA which are seen as a resources with the compelling contextual demand for environmentally friendly products will aid agribusiness to achieve high cost reduction, low waste generation and producing products that meets the needs of global consumers and ultimately achieving superior innovation performance. The study, therefore, argues that circular economy mediates the relationship between I4.0 and innovation performance among agribusiness firms. The study hence combined RBV and contingency theory as the theoretical lens of the study.

2.4 Conceptual framework and Hypotheses Development

RBV and Contingency Theories are the two pillars that support our theoretical model (see Figure 2.1). Owing to the dynamic nature of the business environment in recent times, the contingency theory has acquired a lot of traction among management researchers in their quest to combine firm resources and competencies to give a firm a competitive advantage in a highly uncertain environment. The ability to sense, seize and respond to emerging trends is considered a solution to uncertainty, which is consistent with earlier reasoning. Volatile and complicated work contexts, where high levels of uncertainty make efficient planning and decision-making difficult, exacerbate the requirement for supply chain analytics and industry 4.0. Drawing from the contingency theory, firm competencies of various forms is more beneficial in highly uncertain contexts. In this regard, we expect a direct link from supply chain analytics and industry 4.0 to both circular economy and innovation performance. The study further examined the indirect role of circular economy in the link between supply chain analytics and industry 4.0 and innovation performance. While the study also expects a direct impact of CEC on IP, it further expects green mindfulness to influence the CEC-IP direct link. The various hypotheses advanced in this study are further discussed below.

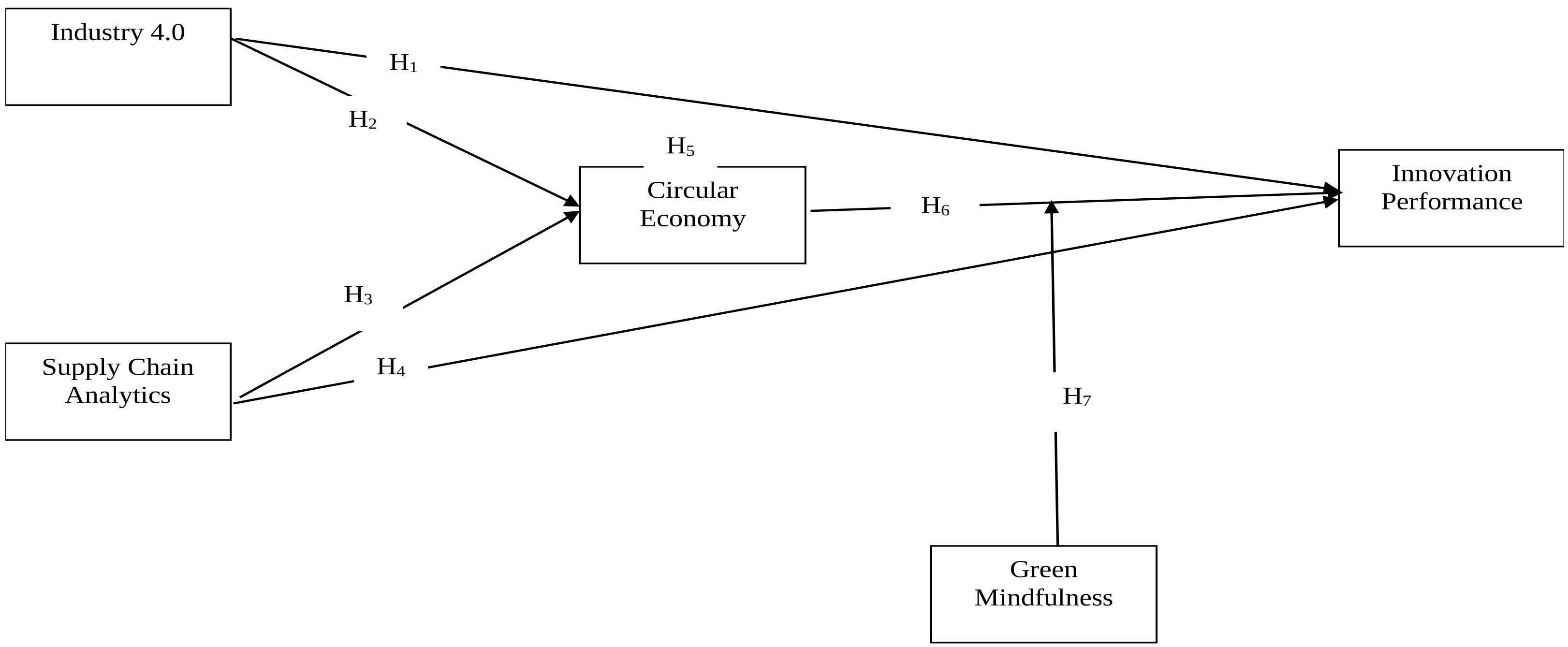

Figure 2. 1: Conceptual framework.

2.5 Hypotheses Development

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

2.5.1 Effect of Industry 4.0 on Innovation Performance

The relationship between industry 4.0 and innovation has attracted significant attention in recent times. The covid-19 pandemic pushed many firms and industries to invest in technology or digitization in their quest to innovate their business operations. Evidence to support the outcome of their investment, especially in the covid-19 era, remains a mirage, especially in the agribusiness setting. Prior studies have indicated that Industry 4.0 can boost energy, facilities and the use of human resources (Lasi et al., 2014). Industry 4.0 is a future-oriented framework, fostering the expansion of autonomous production processes using big data, IoT, CPS and blockchain (Mubarak et al., 2019; Jeandri et al., 2021). In the last decade, a new sensor based on technology has emerged that allows enterprises to track the operation of machinery, energy consumption and workforce preparation constantly. Data can be examined from many IoTs devices to increase the opportunities for industrial activities by fully analyzing the diverse Industry 4.0 breakthroughs (Song and Wang, 2016). In order to sustain innovation performance in manufacturing processes, innovations must be created in a way that preserves the environment, is socially viable, and economically sound. Industry 4.0 has coverage of socio-technical innovations in which ensure economic, social and organizational prospects (Beier et al., 2020). The performance of innovation can be enhanced by the adoption of Industry 4.0 technologies (Muhammad et al., 2021). Thus, innovation performance is highly dependent on the firms' ability to interact with the environment. Hence firms that are able to adopt emerging technologies which allow them to effectively analyze their environment stand a high chance of developing and utilizing available resources to transform the insight drawn from the environment into innovative outcomes (Jeandri et al., 2021). Prior studies (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 Fındık, 2022) have shown the essential role of industry 4.0, digitization, automation and technology in driving enhanced innovation performance among firms in developing economies and large-scale businesses. Drawing from the evidence from the above studies and the dynamic capability perspective, it is expected that innovation performance in the agribusiness setting could be driven via awareness, investment and utilization of industry 4.0 technologies. Hence, this brings the first hypothesis of the study that;

H1: Industry 4.0 has a positive significant effect on innovation performance

2.5.2 Effect of Industry 4.0 on Circular Economy Implementation

The latest trend in automotive production systems is toward automation and digitalization as part of the fourth industrial revolution (IR4.0). Since investment and government support have been readily available, the agribusiness sector has been rushing into this transformation (Zhang et al., 2021). Different practices such as circular purchasing, which is linked to co-operation with the supplier and purchasing of such type of material that is easy to remanufacture, and the circular design, which facilitates reverse logistics and green manufacturing, are all part of CE. (Dumée, 2021; Yu et al., 2022) Technology advancements have made it easier to move from linear to CE in the enterprises of corporations (Khan, Yu, et al., 2021). Ecological modernization theory emphasizes the use of technology in the evaluation of CE (Bergendahl et al., 2018; Gupta et al., 2020). The link between Industry 4.0 and the CE are vital to the contemporary digital era since these concepts have been garnering a lot of attention in recent years (Awan et al., 2021; Zhang et al., 2021). The use of industry 4.0 technology has become increasingly important as foreign and local manufacturers aim to satisfy the sustainability goal. Because of industry 4.0, the supply chain is more transparent and integrated, which improves manufacturing efficiency (Umar et al., 2021). Prior studies (Nascimento et al., 2018; Rajput and Singh, 2019; Abdul-Hamid et al., 2020; Razzaq et al., 2021; Dantas et al., 2021; Tavera

Romero et al., 2021; Massaro et al., 2021; Rosa et al., 2020; Zhou et al., 2020; Yu et al., 2022) have argued is a strong correlation between industry 4.0 and CE. Drawing from the discussion above, this study reexamines the effect of industry 4.0 in enhancing innovation performance in the agribusiness setting. This brings the second hypothesis of the study;

H2: Industry 4.0 has a positive significant effect on circular economy

2.5.3 Effect of Supply Chain Analytics on Innovation Performance

Outsourcing and offshore production are on the rise, which have advantages like lower costs and easier access to vast markets, but they also offer difficulties to the supply chain ecosystem, such as currency rate and transportation risks, political and ecological unpredictability. Traditionally, supply chain managers use SC risk management strategies to address these issues (Christopher and Lee, 2004). The contemporary way is the use of data-driven approaches. Meanwhile, it is impossible to perform an analysis of the supply chain without timely data and information. The IT-enabled resources, data management, and supply chain planning that go into supply chain analytics can be considered as a whole (Chae, Olson and Sheu, 2014). With the help of data science and information technology, supply chain decisions may be made more analytically and data-driven under the guidance of RBV. At its best, supply chain analytics aims to improve operational efficiency and reduce risk, but it may also serve as a catalyst for new product development and innovation. Maintaining a competitive advantage in today's business environment necessitates constant (Gao, Xu, Ruan and Lu, 2017). The identification of new approaches and methods and the creation of new ideas is a complex process in innovation performance (Lee, Lee and Schniederjans, 2011). Quantitative methods and techniques are used to analyze historical and current data in the supply chain. Converting raw data into useful information that can be used to enhance decision-making based on facts is a key goal of data transformation. Managers can use this technique to learn things they did not know before, such as how to better plan, monitor, and forecast their operations, as well as how to compare different time series. This kind of data can be used to pinpoint problem areas and devise solutions that can speed up delivery times, lower error rates, and lower costs. Spontaneous production can better support innovation with data analytic capabilities. Prior studies (Wu et al., 2019; Hooi et al., 2018; Hao et al., 2019; Zareravasan and Ashrafi, 2019; Sun et al., 2020; Ghasemaghaei and Calic, 2020; Muhammad et al., 2022) have shown that data analytics plays a complementary role of driving innovation performance. Though limited is known regarding the link between SCA and IP, drawing from earlier evidence that BDA drives innovation and the fact that SCA enhances supply chain innovation, this study expects that effective supply chain analytics will translate into enhanced innovation performance. Hence the third hypothesis of the study:

H3: Supply chain analytics has a positive significant effect on innovation performance

2.5.4 Effect of Supply Chain Analytics on Circular Economy

As a policy and commercial philosophy, CE is always changing. A CE paradigm could be beneficial for businesses (Bai et al. 2020; Jabbour et al. 2019). During the manufacturing and consuming processes, CE focuses on the 3R concept ('reduce, reuse, and recycle' materials) (Bai et al. 2020). Researchers and practitioners have focused on it because of its potential for material savings, time reduction and reduction of negative externalities, impacts and pressures, and creation of new businesses and employment prospects while reaping economic benefits of this area (Jabbour et al., 2019). When CE-based production systems are used in conjunction with long-term operations, they improve material circularity, natural resource efficiency, and product lifespan (Bai et al., 2020; Gupta et al., 2019). Research suggests that BDA capability can shed light on new concepts including the circular economy (CE) (Jiao et al., 2018; Gupta et al., 2019). Several CE-based activities to integrate processes and exchange resources rely on it (Jabbour et al., 2019). According to Gupta et al. (2019), the capability to analyze data provides great support for extracting critical insights from the data relating to CE members from the CE database. Managers can then use these findings as a basis for making decisions about 3R and material circularity issues at all organizational levels. Predictive maintenance, real-time route optimization, product use patterns, and customer requirements are some of the benefits of applying data analytics to enterprises (Kamble et al., 2021). Reuse and recycling of products and resources may be made easier using this knowledge. To make better use of the resources available, supply chain analytics insights can be applied across multiple processes and departments which will enhance innovation performance in the firm. Though empirical evidence to support the connection between supply chain analytics and circular economy is scanty, this study draws on the contingency perspective, that the ability of firms to analyze data generated along their supply chain activities will produce insights which can support circular economy practices. Hence the third hypothesis of the study:

H4: Supply chain analytics has a positive significant effect on the circular economy

2.5.5 Effect of Circular Economy on Innovation Performance

The circular economy has an important role in the innovation performance of firms, firms in the quest to remain competitive must innovate, however, in the process of innovation stakeholders have become vigilant against the negative implications on the environment. Circular economy practice has therefore become a central block for innovation. It is the goal of the CE to regenerate resources by dematerializing and reintroducing outmoded materials into production chains (Ellen MacArthur Foundation (EMF)), 2014, and by redefining trash (EEA Report, 2019) and repurposing it as resources (Wilts, 2017). It has a positive impact on reducing pollution and improving the use of natural resources (Yuan et al., 2006). The CE encourages more efficient use of resources, with a focus on decreasing waste and extending the useful life of products and materials. It also serves to resignify trash and aid in the natural system's regeneration (Padilla-Rivera et al., 2021). Other studies refer to the CE's assumptions of slowing down (to extend the time products can be used) and closing the loop (to close the loop between post-use and manufacturing [i.e., recycling]) as essential ones (Batista et al., 2019; Bocken et al., 2016). This rationale contributes to larger benefits received from the expenditures connected with the extraction of virgin raw materials (Urbinati et al., 2017). Available literature has cited circular economy as important driver of innovation among firms (Potting et al., 2017; Blomsma et al., 2019; Suchek et al., 2021; Sehnem et al., 2022; Herrero-Luna et al., 2022). Both I4.0 (Rajput and Singh, 2019; Abdul-Hamid et al., 2020; Razzaq et al., 2021; Dantas et al., 2021; Tavera Romero et al., 2021; Massaro et al., 2021; Rosa et al., 2020; Zhou et al., 2020; Yu et al., 2022). It is, therefore, possible to argue that CE has the potency of influencing or driving innovation performance. Hence the fifth hypothesis of the study.

H5: Circular Economy has a positive significant effect on Innovation Performance

2.5.6 Mediating Role of Circular Economy

Innovation has over the years been cited as the anchor of business survival or competitiveness; meanwhile, prior studies have shown that most businesses especially in developing countries are not innovative. Several studies reported the abysmal innovation performance of SMEs (Frimpong, 2013; ITC, 2016; Dansoh et al., 2017), a recent report by the Government of Ghana (2018) indicates that the performance challenges are attributed to the inability of SMEs to devise suitable new products on time to serve needs and wants in the market (GoG, 2018). To overcome similar challenges encountered in Vision 2020 (Danso, 2014), Ghanaian firms are encouraged to utilize government support in realizing more innovation activities that have the propensity to enhance their performance thereby contributing effectively to National Gross Domestic Product (GDP). This support such as innovation grants, R and D support grants, financial support, and non-financial support channeled through government agencies such as the NBSSI. Again, the Deutsche Gesellschaft für Internationale Zusammenarbeit (GIZ) has supported many businesses especially SMEs with modern technologies which allows them to digitize their operations. Prior studies have evidenced that Industry 4.0 and Supply chain analytics are all driven by the use of information technology. For example, artificial intelligence (AI) and machine learning are now being integrated into manufacturing processes across a wide range of organizations. Automation and embedded software in these "smart factories" collect and analyze data for enhanced decision-making. To get even more value from the information that was previously compartmentalized, data from production operations can be coupled with data from ERP, supply chain, customer service and other corporate systems. Using these digital technologies, companies can achieve unprecedented levels of efficiency and responsiveness to their consumers, as well as improved automation, predictive maintenance, self-optimization of process improvements, and other benefits not before achievable. Available literature has cited circular economy as important driver of innovation among firms (Potting et al., 2017; Blomsma et al., 2019; Suchek et al., 2021; Sehnem et al., 2022; Herrero-Luna et al., 2022). Both I4.0 (Rajput, S. and Singh, 2019; Abdul-Hamid et al., 2020; Razzaq et al., 2021; Dantas et al., 2021; Tavera Romero et al., 2021; Massaro et al., 2021; Rosa et al., 2020; Zhou et al., 2020; Yu et al., 2022) and data analytics capability (Wu et al., 2019; Hooi et al., 2018; Hao et al., 2019; Zareravasan and Ashrafi, 2019; Sun et al., 2020; Ghasemaghaei and Calic, 2020; Muhammad et al., 2022) has also been found as important strategies to enhance innovation performance. Evidence also suggests a positive association between I4.0, SCA and Circular economy (Abdul-Hamid et al., 2020; Razzaq et al., 2021; Rosa et al., 2020; Zhou et al., 2020; Yu et al., 2022; Kamble et al., 2021). However, despite recommendations on the need to examine the driver and implications of circular economy in emerging economies, there exists scanty literature on the indirect role played by the circular economy as a mediator in the I4.0, SCA and IP link. The author expects that though Innovation performance may be achieved via the direct impact of I4.0, SCA, a circular economy practice may serve as a channel to strengthen the I4.0, SCA and IP link. Hence the study envisages that an effective circular economy enabled I4.0, SCA may drive superior innovation performance. This study, therefore, expects that CE will mediate the I4.0, SCA and IP link. Hence the fifth and sixth hypotheses:

H6a: Circular economy mediates I4.0 and Innovation performance

H6b: Circular economy mediates SCA and Innovation performance

2.5.7 The moderating role of Green Mindfulness

Non-judgmental observations of the environment from present-moment experience, behaving with full awareness, and describing these observations in a non-evaluative manner are all components of green mindfulness (Hwang and Lee, 2019; Masood et al.,2021). As a result, the term "green mindfulness" refers to a set of cognitive resources that may be used by employees to generate new concepts, products, processes, and services while also reducing the environmental impact of the company's operations (Dharmesti et al., 2020; Masood et al.,2021). In Amel et al. (2009), they remark that many everyday behaviors are influenced by cognitive resources, and therefore green mindfulness encourages a deeper self-world connection with the context, which in turn promotes sustainable environmental behavior Because new problems are likely to arise while solving existing problems, people with green mindfulness possess an up-to-date awareness and understanding of the fresh information and knowledge regarding the environment in their current environment and have a propensity to meet individual cognitive needs that emerge during the idea generation process (Langer and Moldoveanu, 2000). To cultivate green mindfulness, one must learn to fix their attention, unlock their minds, and remain focused on the object of their attention (Bahl et al., 2016). To be mindful, there is the need to pay more attention to the natural world and the environment around you (Barbaro and Pickett, 2016). New types of provocations and shifts in enlarged scanning, situation-specific translation, taking into account numerous perspectives and understanding of multiple points of view are all part of this increased attention span. These aspects of mindfulness are essential in the attempt to improve innovation performance and develop the creative side of employees (Choi et al., 2018). Similar to mindfully green firms, green employees pay more attention to the external stimuli, which improves their job-specific talent and hence encourages innovations (Vogus and Sutcliffe, 2012). In addition, mindfulness helps cultivate problem-solving and decision-making abilities, enhances interpersonal and communication skills, and enhances concentration and attention toward one's professional responsibilities, all of which contribute to one's creativity and invention (Shalley et al., 2004). There are several benefits to cultivating a sense of environmental awareness, including the ability to make non-judgmental observations of the world around you, the ability to describe these observations without judgment, and the ability to act with full awareness of the environment. By way of extension from the DC perspective, the author believes that people with a high level of green mindfulness are more likely to adopt CE practices, and since green mindfulness is linked to innovation, agribusinesses with a high level of green mindfulness are more likely to reap superior innovation performance through CE practices than their competitors with a lower level of green mindfulness. A recent study by Zareen et al. (2021) found that green mindfulness moderates the association between energy efficiency and green creativity. This brings the seventh hypothesis of this study:

H7: Green Mindfulness moderate the relationship between CE and Innovation Performance.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

This chapter presents an outline of the various methods and strategies employed by the researcher to collect data, clean the data and analyze the data using the appropriate analytical tools. It looks at the research design, the population of the study, sampling technique and sampling size, data collection, data analysis, validity and reliability, and chapter summary.

3.2 Research Paradigm

Research is a scientific process for discovering new information. Consequently, all theories and research involve philosophical underpinnings. Indeed. There are underlying philosophical foundations of all theories and research which it is important to understand the research paradigm to use the appropriate research methods and philosophies (Hunt and Hunt, 2018; Zinkhan and Hirschheim, 1992). The philosophy of research is related to knowledge creation and the purpose of that knowledge (Saunders et al., 2009). According to Saunders et al. (2018), the research philosophy a researcher decides to adopt has integral assumptions of how he/she perceives the world. Even though many researchers research without considering the underlying philosophical foundations, some understanding of research philosophies is vital because it is useful in clarifying the research design chosen and also facilitates the choice of the suitable one given the study in question (Blumberg et al., 2005). In the nature of knowledge and the development of knowledge, various philosophical dimensions are available, among which epistemology is one of them. In the view of Sunders et al. (2009), knowledge generated, interpreted, and applied is at the core of the epistemology assumptions. The epistemological view acknowledges the use of a scientific approach to generating acceptable knowledge through the formation of hypotheses using a statistical test in the process (Cecez-Kecmanovic and Kennan, 2013; Chigbu, 2019; Singh, 2019; Wahyuni, 2012). The epistemological viewpoint, therefore, presents a viewpoint where knowledge keeps improving through constant new information generated.

Generally speaking, there are two extremely notable mutually exclusive research paradigms in the expansive field of social research: positivism and interpretivism. The former position is likened to a quantitative paradigm while the latter to a qualitative paradigm (Cohen et al., 2009; Singh, 2019). The quantitative paradigm makes observations that are objective, and often quantitative facts whereas the qualitative paradigm observes subjective interpretations of meanings. These assumptions compel researchers to conduct research in a particular way.

A cardinal principle in positivism research philosophy is that research examines whether theoretically formulated hypotheses hold true in the situations under consideration (Saunders, Lewis and Thornhill, 2016). When gathered empirical findings are obtained backs the hypotheses, then the result is considered germane and valid. That is to say that positivist researchers adopt quantitative approaches to testing hypotheses in answering research objectives (Chigbu, 2019; Straub et al., 2004). Based on the epistemological viewpoint, researchers will remain independent from the study sample to control for bias and be objective in assessing the research situation (Cohen et al., 2013, 2009; Pham, 2018; Creswell 2009; 2014).

Distinct from positivism is interpretivism philosophy, which involves the detection of occurrences in a situation of interest based on the subject meanings and interpretations of phenomena. Packard, (2017) argues that this philosophy offers a rich description of the phenomena of interest to a researcher, whose interpretation provides comprehension of what is happening. These assumptions compel researchers to research a particular way. Based on the epistemological viewpoint, researchers using qualitative approach deem it necessary to understand the actors and their social roles (Saunders et al., 2016) in their quest to acknowledge the different backgrounds and experiences by having a dialogue with participants which could give rise to multiple perspectives (Wahyuni, 2012). In between these two extreme approaches are mixed approaches which are also called triangulation.

The positivism research philosophy which is the underpinning philosophy for quantitative research can be considered to fit well with the objectives of the research study based on the above approaches. Subsequently, the study employed quantitative methods of data collection in a single study according to the nature of the study. This study uses the existing Resource Base View (RBV) theory and Dynamic Capability Theory as underpinning theories in the hypotheses development. Its purpose is to assess theoretically formulated hypotheses regarding the impacts of a collection of study variable constructs, as well as to use reliability and validity to appraise the results and generalize them. Proceeding to this, the investigator will optimize the principles of positivism philosophy after the epistemological standpoint.

3.3 Research design

In terms of data collection, measurement, and analysis, the research design refers to how a study will be carried out. It establishes the conditions for data collection and analysis in such a way as to strike a balance between relevance to the study purpose e and organizational efficiency (Kothari, 2004). The creation of that kind of planning and evaluation is for the most efficient research possible, resulting in the greatest amount of information. The goal of research design, to put it differently, is to collect as many available facts as feasible with minimum effort, time, and money (Cohen, Manion and Morrison, 2009).

The study employed the cross-sectional descriptive survey design where deductive reasoning is applied for the quantitative data (Cohen, Manion and Morrison, 2013). Deductive reasoning is used to make logical conclusions after the analysis. The deductive approach is a method where the researcher uses theories as bases to conduct an investigation which would be used to determine the result of a theory (Pham, 2018). The deductive method is usually made of quantitative techniques. The quantitative technique uses a survey questionnaire where data are normally collected from respondents Researchers that utilize quantitative approaches collect and analyze numerical data in order to understand, forecast, and/or control occurrences. It provides an in-depth insight into the specific testable study and focuses on examining the relationship between variables (Eyisi, 2016).

The survey method is employed for the quantitative study because it examines a sample of the population to produce a quantitative or numeric depiction of attitudes, practices, and opinions. Through face-to-face questionnaire administration, primary data was acquired in the quantitative research design. Usage of the survey method was considered to be efficient and economical; it brings many advantages to the researcher; For instance, it is economical compared to interviewing, authorizes secrecy, and could produce additional truthful answers, besides it has the possibility of eliminating prejudice owing to wording questions differently with diverse respondents (Kothari, 2012; Durepos and Wiebe, 2019).

Subsequently, the use of the quantitative technique was employed to help in understanding the underlying reasons of respondents to issues industry 4.0, supply chain analytics, circular economy and green mindfulness and how they affect innovation performance in the agribusiness space.

3.4 Population of the study

The population of interest refers to the target population constituting individuals or entities that the study seeks to treat (Majid et al., 2018). Lavrakas (2008) described population of interest as the specific groups of individuals, businesses, or entities that the researcher seeks to treat and make generalizations based on the characteristics of those groups. For this study, the population of interest consists of agribusiness establishments in Ghana. Since the variables in the study are organizational-level constructs, the single respondent’s approach was employed. As a result, the study targeted only senior managers including, owners, supply chain managers, operations managers, warehouse managers, production managers, and quality control managers. Identifying a list of agribusinesses was a challenge, hence the study relied on agribusiness establishments under GIZ agribusiness support initiative. The project provided capacity building, funding, and technological equipment to support agribusinesses. The project supported 500 businesses across the nation. The target population was, therefore, made up of managers of 500 agribusinesses establishments under the GIZ agribusiness project. The choice of the agribusiness establishments under GIZ agribusiness support initiative is justified by the fact that these businesses have been trained on data keeping and how to use data for decision making, they also have technology support which aid automation of their production processes and IT support to enable supply chain analytics.

3.5 Sampling techniques and sample size

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 in 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. In addition to that a rule of thumb that one can use to estimate the sample size for a study. For instance, Bosman (1998) recommend that a sample size of 400 can be used to collect data for a study. Likewise, Kolloway (1998) also suggested that a sample size of 200 can be used as a sample size for a study. However, to properly situate the study, an appropriate sample size must be employed. In this study, the sample size determination was established from Yamane’s simplified formula (1967) to decide the sample size for the study. It is defined as:

$$n = \frac{N}{1+N(e)^2}$$

Where:

n = Expected Sample Size N =

Study Population

E = Margin of error and the confidence interval is 95%

Using the formula, the sample size is calculated below

$$n = 500/1+500(0.05)^2$$

$$= 500/\ 1.2525$$

$$= 399.\ 202$$

$$= 400$$

Based on the formula, four hundred (400) was arrived as the sample size. After the determination of the sample size, the researcher must now determine the sampling technique for the study after determining sample size. Every researcher's dream would have been to collect data from every single person in a population. This scenario is only achievable when the researcher is working with small groups of people. When the population of interest is big, however, this census approach is not always viable. Accessing potential participants is also costly, time-consuming, and complicated. As a result of these issues, studies that use huge populations, such as this one, have depended on sampling procedures to pick a representative sample from the population of interest (Malhotra, 2010).

There are two types of sampling techniques available for use by researchers. Depending on the objective of the study, a researcher may use the probabilistic sampling technique or the non-probabilistic sampling technique. A probabilistic sampling technique is a technique that ensures that every item in the given population has a chance of being selected for the sample (Ahmed, 2016). It is choosing samples randomly from a larger population based on probability. Some of the probabilistic samples include simple random, stratified sampling, cluster, systematic and multi-stage sampling. The non-probabilistic sampling techniques do not guarantee an equal chance of items being drawn into the sample (Ahmed, 2016). It is not based on probabilistic selection but on the researcher's judgment. Some non-probabilistic sampling techniques include convenience sampling, quota, snowball, and purposive or judgmental sampling.

This study used the purposive sampling technique to draw senior managers including, owners, supply chain managers, operations managers, warehouse managers, production managers, quality control managers into the sample. The study employed convenience sampling to collect relevant information from employees who are well knowledgeable about the phenomena under enquiry. The type of data collected from respondents is discussed in the next section.

3.6 Data Collection

Two main sources of data exist to any research, this includes primary data and secondary data. While primary data refers to first-hand information gathered by the research for the purpose of the research, secondary data deals with already existing data gathered for a different purpose. The choice of data source in any research is dependent on the nature or the objective of the study. Considering the nature of this study, primary data is more suitable to be able to test the hypotheses proposed in Chapter two (2). The choice of primary data is justified by the quest to gather first-hand information on the views of managers in the agribusiness space on how industry 4.0, supply chain analytics, circular economy and green mindfulness may be combined to drive innovation performance. Data used in this study was therefore gathered using a well-structured questionnaire. The subsequent section provides the description of the research instrument and the method of data collection used in this study.

3.6.1 Instrument and Method of Data Collection

3.6.1.1 Questionnaire Development

The study employed the five-point Likert scale, which is better since the point scale's position between positive, negative, and neutral options is properly balanced, reducing misunderstandings in participant's responses (Croasmun and Lee Ostrom, 2011; Sarstedt and Mooi, 2019). On a scale of 1 to 5, 1 means strongly disagree, 2 means disagree, 3 means neutral, 4 means agree, and 5 means strongly agree. The survey had two parts. Part one is for gathering background information from participants, while part two is divided into four sections for bringing together information focusing on the independent variables. Section A, B, C, and D of the second part was designed in gathering information on industry 4.0, supply chain analytics, circular economy, green mindfulness and innovation performance correspondingly. Items used in the design of the questionnaire were sourced from previously validated instrument. Industry 4.0 in this study reflects the digital transformation of the field, providing agribusiness with real-time decision-making. This construct was measured using five (5) items adapted and modified from previous studies of (Guilherme et al., 2019; Mohammad et al., 2021). Green Mindfulness refers to the use of specific cognitive resources by employees in order to generate new ideas, products, processes, and services that help agribusinesses meet their objectives while also reducing their negative environmental impact (Dharmesti et al., 2020). Green Mindfulness was measured using six (6) items adapted and modified from previous studies of (Williams and Seaman, 2010; Masood et al., 2021). Innovation performance in this study reflects the ability of agribusiness to meet their innovation objective/targets. This construct was measured using nine (9) items adapted and modified from previous studies of (Cherrafi et al., 2018; Abdallah et al., 2019; Hongyun et al., 2020). Supply Chain Analytics in this study was operationalized as the ability of agribusinesses to gather data, diagnose, integrate and transform their supply chain data into valuable information and meaningful patterns for decision-making. This construct was measured using six (6) items adapted and modified from previous studies of (Wang and Byrd, 2017; Shamout, (2019). Circular Economy describes the conversion of traditional industrial methods to circular ones that encourage the ideas of recycling and reusing (Khan et al., 2021). Circular Economy was measured using nine (9) items adapted and modified from previous studies of (Zeng et al., 2017; Manlio., 2020). This is further summarized in Table 3.1 below.

Table 3. 1 Construct Measurement

Construct	Notation	Indicators	Source
Industry 4.0	I4.0	5	Guilherme et al., 2019; Mohammad et al., 2021
Supply Chain Analytics	SCA	6	Wang and Byrd, 2017; Shamout, (2019
Circular Economy	CEC	9	Zeng et al., 2017; Manlio., 2020
Green Mindfulness	GM	6	Williams and Seaman, 2010; Masood et al., 2021
Innovation Performance	IP	9	Cherrafi et al.,2018; Abdallah et al., 2019; Hongyun et al., 2020

Source: Authors Construct (2022)

3.6.2. Piloting of Questionnaire

According to Saunders et al. (2016), a pilot test of a study refers to using a smaller number in the target population to assess a questionnaire to reduce the probability of the respondents having challenges in replying to the questions and to also evaluate how valid and reliable the data will be. The researcher randomly selected 30 firms from the sampling frame after conducting the reliability and validity test. The essence was to identify any shortcomings in the questionnaire and to rectify them before the actual fieldwork was undertaken. Some authors have different views about the samples to select. According to Hill (1998), a range of 10 to 30 respondents will be ideal for the task while Connelly (2008) suggested a sample size of 10% of the sample respondents will be enough to carry out the pilot testing. In the view of Cooper and Schinder (2011), a sample of between 25 and 100 respondents is considered ideal for a pilot study. The current study used a sample of 30 respondents which is deemed appropriate as proposed by Hill (1998) (Treece and Treece, 1982) to undertake the pilot test. The result of the pilot data showed that the majority of the items except for two items of circular economy were reliable. Few issues including grammar errors and ambiguity were used to refine the questionnaire for the main data collection.

3.6.3 Data collection

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

3.7 Method of Data Analysis

The method of data analysis forms an essential component of any research such that the choice of the method of analyzing 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 analyzing 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, few questionnaires that were found incomplete were discorded. The analysis employed both Statistical Package for Social Sciences (SPSS) version 26.0 and Smart PLS 3. The Statistical Package for Social Sciences (SPSS) was used for the analysis such as frequencies, means, standard deviations, independent sample t test, correlation and exploratory factor analysis. Smart PLS-SEM was used for Confirmatory Factor analysis, Structural Model evaluation and other model fit indices that were explored in this study. The next section provides a detail discussion on the justification of the use of Partial Least Square-Structured Equation Modelling (PLS-SEM) and the various tests that were conducted.

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

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

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

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

3.8.1 Model Evaluation in using PLS-SEM

Thus, upon choosing the right analysis tool, in this case, the PLS-SEM, the next step is to consider the development of the model. As per Hair et.al (2011), there must be two separate model measurement processes in PLS-SEM which are the measuring model and the structural model. Those two forms of tests are suggested to indicate that the model established in the study is validated. Measurement model validation can be interpreted as assessing the construct of focus (latent construct) while the structural model describes the latent constructs related to each other.

3.8.2 Measurement Model Assessment

This section discusses the techniques that were used to ascertain the validity of the instruments and to verify the reliability of the constructs. In quantitative studies, assessing the measurement model is critical since it ensures the validity and outcome of the study. However, it is critical for researchers to focus on enhancing the quality of work (Hair et al., 2020). Likewise, there are two critical elements to consider when evaluating a measurement model: the study instrument's reliability and validity (Saunders et al.,2016).

3.8.2.1 Validity

A crucial aspect of research is ensuring that the instrument created to assess specific concepts actually and accurately measures the concept. The validity, according to Ringle and Ting, (2018), relates to the extent to which an instrument assesses its intended emphasis. The validity of the research instrument will be examined through face, content, convergent, and discriminant validity (Henseler, Ringle and Sarstedt, 2015). For content validity, the important issue according to Churchill (2001), is the methodology used to develop the questionnaire. Content validity was assessed through a thorough examination of the previous empirical and theoretical work of investigated constructs. The face validity of the questionnaire was assessed through the pretest exercise of the questionnaire with selected managers of agribusiness firms in Ghana as well as the supervisors' expert review of the applicability y and suitability of the questionnaire to achieve the study intended objectives. To ensure that the constructs were truly distinct from each other and will capture some phenomena, both convergent and discriminant validity was established (Khalid et al., 2012; Kothari 2012). When two or more items are highly associated and measure the same construct, they are said to have convergent validity. In the views of Hair et al., (2011, 2014), to demonstrate the convergent validity for the reflective measurement model in using PLS-SEM, a researcher needs to examine the average variance extracted (AVE) in which its value should be 0.50 or higher. Meanwhile, the discriminant validity which can be referred to as the degree to which the measures of one construct are distinct from another construct measurement, the study will examine two measures of Fornell-Larcker Criterion and cross-loading (Henseler et al., 2015). The Fornell-Lacker Criterion postulates that "the latent construct shares more variance with its assigned indicators than other latent variables in structural model". In statistical terms, it can also be said that each latent construct should have greater average variance extracted (AVE) than the shared variance (squared correlation) of any other latent construct for the discriminant validity is to have the cross-loading value in which the indicators loading of the associated latent construct should be higher than its loading with other constructs remaining (Hair et al.,2011).

Table 3. 2: Summary of Validity Test

Assessment	Attribute	Evaluation Criteria	Description	Reference
Content Validity	Face validity	Expert's opinion Empirical and theoretical work	The changes for the instrument developed must be endorsed by experts and literature.	Churchill (2001)
Construct Validity	Convergent validity	Average Variance Extracted (AVE)	To verify that the indicators are correlated. The average variance extracted (AVE) value should be 0.50 or higher	Hair et.al, (2011)
	Discriminant validity	Fornell-Lacker Criterion	The AVE of each latent construct should be greater than the squared correlation with any other latent construct.	Hair et.al, (2011)
		Cross Loadings	An indicator's loading with its associated latent construct should be higher than its loadings with all the remaining constructs	Hair et.al, (2011)

3.8.2.2 Reliability

Reliability refers to the consistency repeatedly reached and the consistency that is consistently achieved which is evidence of the instrument's stability and predictability y in measuring the concept (Mohajan, 2017). This could also be considered as being the capacity to replicate a study or study results. In the view of Khalid et al. (2012), they termed reliability measurement as the extent to which a measurement is devoid of random error by producing a consistent result. To measure the reliability of the instruments, the study of Hair et al. (2012) which have proposed two tests of reliability i.e., the internal consistency and indicator of reliability will be used. Composite Reliability test instead of Cronbach Alpha was used to prioritize the variables as per their reliability during model estimate (does not imply all variables are equally reliable), making it more appropriate for PLS-SEM. A Composite Reliability is from 0.7 to 0.9 will indicate sufficient reliability of the measures.

Table 3. 3: Summary of Reliability Test

Assessment	Attribute	Evaluation Criteria	Description	Reference
Reliability	Internal Consistency	Composite Reliability (CR)	To verify if the indicators of the constructs are closely related. The value should be higher than 0.7	Hair et.al, (2011)
Construct Validity	Indicator of Reliability	Indicator Loading	To measure the indicator variance underlying similar constructs. The value should be higher than 0.7	Hair et.al, (2011)

CHAPTER FOUR

DATA ANALYSIS, RESULTS AND DISCUSSION

4.1 Introduction

Chapter four provides the analysis of data gathered through the procedures and methods discussed in previous the chapter. The Chapter is organized in four (4) key sections. The first section of the chapter presents the result of the survey bias test, and descriptive analysis of the demographic characteristics at the individual level while those on the main constructs are analyzed on an aggregate level. This is because the theoretical and conceptual model was hypothesized at the organizational level. Section two also contained descriptive analysis and correlation among the study variable. The third section presents Confirmatory Factor Analysis, which evaluates model validity and reliability, model fit indices are also presented in the chapter. The next section presented the structural model evaluation which tests the various hypotheses proposed in the study. The last section presents a discussion on the key findings that were gathered from the results.

4.2. Response Rate and None Response Bias

Data were gathered from April 13th to July 10th, which is approximately three months. Overall, 430 questionnaires were administered to managers, supply chain professionals, procurement professionals, and operations managers using the approach described in the previous chapter. Of the 430 questionnaires administered, 336 valid questionnaires representing 76% were retrieved from respondents. According to Kamel and Lloyd (2015) the response rate of more than 50% in business management research is considered good for analysis. Therefore, the 76% response rate reported for this study served as an acceptable basis for drawing conclusions.

Considering the long duration of the data collection, it is imperative to evaluate the presence of survey bias in the dataset. In this regard, several precautionary procedures were taken in this study to avoid common methods and response bias (Podsakoff, MacKenzie and Podsakoff, 2012). First, as part of strategies to minimize bias in the dataset, questionnaires were translated into local language for few respondents who had issues with understanding the concepts as used in the study. Prior study of Brislin (1970) opined that translating into one's native language is beneficial for gathering reliable information about phenomena in a foreign environment. Secondly, respondents were informed that the information they submitted would be kept totally personal and private. This assurance kept them from succumbing to social desirability bias or giving appealing responses (Podsakoff et al., 2012). Thirdly, the researcher also provided definitions of the key constructs as used in the study, to guide respondents where the researcher was not available to provide such an explanation.

Apart from these strategies that were used, several statistical tests were conducted to validate the absence of bias in the data. Firstly, the data was subjected to Harman's one-factor test, as suggested by the study of (Scott and Bruce, 1994). Seven components with an eigenvalue greater than one accounted for 78% of the variance, and no single factor exceeded 50% of the total variance (See Appendix I). Again, the Partialling Out of General Factor in PLS Model procedure as recommended by Tehseen et al. (2017) was also employed. The result showed just a slight difference of 0.05 between the original R^2 and the R^2 after the general factor. Finally, the inter-correlation between the variables was investigated. The correlation result shows that the highest correlation among two constructs was found between circular economy and innovation performance (r=0. 695) since this correlation value is below the (r=0.90) see (Appendix II) threshold as indicated by earlier studies of (Pavlou and Xue, 2007; Spector and Brannick, 2010; Uddin et al., 2018).

When the number of people who take the survey is less than the total number of people in the population, this is called non-response bias. Low survey response rates are a common cause of non-response bias, which in turn can affect the quality of the sample used to draw conclusions and the validity of the study overall. Non-response bias was evaluated by contrasting the early and late respondents' responses in order to cut down on it in this study. Those that returned their questionnaires early did so inside the original one-month response frame, while those who returned theirs later are known as "late respondents." The result did not show any statistically significant differences between the two groups for any of the variables used in this study as suggested by Oppenheim (2001). The result confirms that non-response bias is not a problem in this study and samples represent targeted group. Specifically, the first 163 responses and the last 163 responses were considered as early responses and late responses respectively. Afterwards, a T-test analysis was employed to test for non-response bias. The results of the t-test analysis did not indicate any significant difference (see Table 4.1). Hence the study confirms that data gathered on the constructs in the first month is not different from the responses in the last month of the data collection.

Table 4. 1: Test for None Response Bias (Independent T Test)

Constructs	Groups	F	Sig.	T statistics
Industry 4.0	Early Response	0.780	0.378	1.684
	Late Response			
Supply Chain Analytics	Early Response	0.116	0.734	1.495
	Late Response			
Circular Economy	Early Response	1.496	0.020	1.871
	Late Response			
Green Mindfulness	Early Response	1.221	0.074	-0.171
	Late Response			
Innovation Performance	Early Response	1.867	0.173	1.453
	Late Response			

Source: (Field Data, 2022)

4.3 Demographic Characteristics of the Respondents

This section presents the demographic background of respondents as well as information on their relationship with the firms. Major information discussed in this section include Age of respondents, experience with the firm, education of the respondent, position or role played in the organization, years of operation of the firm, number of employees and number of products produced by the firm as summarized in Table 4.2.

Table 4. 2: Demographic Characteristics

Firm/Individual Profile	Category	Frequency	%
Age	Female	156	47.9
	Male	170	52.1
Experience	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	76	23.3
	HND	90	27.6
	Master / Ph.D.	33	10.1
	High School	127	39.0
Position	Business Owner	83	25.5
	Supply Chain &Logistics	151	46.3
	Operations Manager	52	16.0
	Production Manager	33	10.1
	Others	7	2.1
Years of Operation	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
Number of 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
Number of Products	1-2 Products	94	28.8
	3-5 Products	99	30.4
	More than 5 Products	133	40.8
	Total	**326**	**100.0**

Source; (Field Data, 2022)

It was determined that the research was required to identify the respondents' gender. Table 4.2 reveals that 156 (47.9%) were female and 170 (52.1%) were men. The data showed that most respondents were men. The study's conclusions show that the majority of agribusiness firms were owned and operated by men. Result in Table 4.4 showed 86 respondents (26.4%) who were between the ages of 18 and 30; 127 respondents (39.0%) who were between the ages of 31 and 40; 89 respondents (27.3%) who were between the ages of 41 and 50; and the last 24 respondents (7.4%) who were beyond the age of 50. The results showed that respondents were mostly between the ages of 31 and 40. The educational backgrounds of the interviewees were also taken into consideration in the survey. According to Table 4.4, 76 (23.3%) of the respondents had bachelor's degrees, 90 (27.6%) had HNDs, 33 (10.1%) had master's or doctoral degrees, and the remaining 33 (10.1%) held SHS certificates. The results show that the respondents are knowledgeable about the topic at hand at a suitable level. However, the report states that HND holders made up the bulk of the study's respondents. The findings showed that 168 (51.6%) of the 326 (100.0%) respondents were business owners or managers, 52 (16.0%) were operation managers, 33 (10.1%) were production managers, 83 (25.5%) were business owners, 151 (46.3%) were supply chain and logistics workers, and 7 (2.1%) were others. The majority of survey respondents were managers and business owners, the study's findings show. The findings also reveal that 95 respondents (29.1%) had worked for the company for one to five years, 86 respondents (26.4%) had worked there for eleven to fifteen years, 101 respondents (31.0%) had worked there for six to ten years, and 44 respondents (13.5%) had worked there for more than sixteen years. The majority of respondents, according to the study's findings, had between six and ten years of experience. The results in table 4.4 below also display how many people the firm employs. The findings showed that 124 (38.0%) of the respondents' enterprises had fewer than five employees, 160 (49.1%) had six to nine employees, and 9 (2.8%) had more than one hundred. The majority of respondents indicated in their comments, according to the study's findings, that their companies employed between 6 and 29 people. The number of items that the firm produces was also disclosed in the survey. The results show that 133 (40.8%) of the respondents' companies produced more than 5 goods, while 99 (30.4%) of the companies generated 3-5 products. 94 (28.8%) of the businesses make 1-2 products. The results of the survey show that most respondents' companies produce more than five different products. The survey also considered how long the company had been operating. According to the findings, 44 (13.5%) of the respondent's enterprises had been operating for more than 16 years, while 101 (31.0%) and 95 (29.1%) of the respondents' firms had been operating for between 1 and 10 years. The majority of firms have been in business for more than 16 years, the study's findings show. The report also includes details regarding the firm's line of business.

4.4 Descriptive Analysis of Constructs

This section provides descriptive statistics of the various constructs of the study which include Industry 4.0, Supply Chain Analytics, Circular Economy, Green Mindfulness and Innovation Performance. In all, five (5) constructs were used in this study. The results of the descriptive statistics performed are presented in Table 4.3.

Table 4. 3 Descriptive statistics for all constructs.

Constructs	Mean	Skewness	Kurtosis	StD	1	2	3	4	5
Innovation Performance	3.92	-0.649	-0.313	0.85	1				
Industry 4.0	3.88	-0.679	0.286	0.85	.634**	1			
Supply Chain Analytics	3.99	-0.260	-0.838	0.88	.588**	.684**	1		
Circular Economy	3.03	-0.576	4.860	1.27	.695**	.637**	.579**	1	
Green Mindfulness	3.97	-0.697	0.182	0.81	.301**	.185**	.173**	.185**	1

Source: (Field Data, 2022)

The mean values provide a summary of the raw data and the degree of which the mean values represent the data is also provided by the standard deviation (Field, 2009). The mean and standard deviation are used to measure how well the statistical mean fits the observed data (Kasimu et al., 2020). The result of the descriptive analysis is presented in Table 4.3. The result shows that innovation performance (IP) scored a mean and standard deviation of (M=3.92; StD= 0. 0.85). Industry 4.0 scored (M=3.88; StD= 0.85), Supply Chain Analytics scored (M=3.99; StD= 0. 88), Circular Economy scored (M=3.03; StD= 1.27) and Green Mindfulness scored (M=3.97; StD= 0. 81). The result shows that the deviations from the mean values of all the constructs were minimal, indicating the statistical or calculated mean does not vary from the observed mean. The Table 4.3 further presents kurtosis or skewness which are used to examine data normality. These two measures are recommended by Hair et al. (2010) as good measures to demonstrate the shape of the probability distribution of statistical data. The rule of thumb as indicated is for majority of the constructs should be within -2 and +2. However, the result in Table 4.3 shows Circular Economy is not within the acceptable limits and hence justifies the use of PLS-SEM in this study. The result in the Table 4.3 further shows the correlations between the variables used in the study. The result shows a strong positive correlation between Industry 4.0, Supply Chain Analytics scored, Circular Economy, Green

Mindfulness and innovation performance. The result suggests that improvement in any of the constructs: Industry 4.0, Supply Chain Analytics scored, Circular Economy, Green Mindfulness significantly enhances innovation performance among agribusinesses in Ghana. The correlation between the independent variables was found to be moderate, indicating no severe correlations within the predictor variables. This also suggests the absence of multicollinearity in the dataset and hence variables fit well for the model. To further confirm the fitness of the constructs within the model, confirmatory factor analysis is conducted and result presented in the next section.

4.5 Exploratory Factor Analysis (EFA)

If a study comprises between twenty and fifty items, exploratory factor analysis can be utilized as a strategy for measurement reduction (Chang and Chen, 2013). Exploratory factor analysis can be used to reduce variability in this study's indicators so that they are easier to interpret and analyze, as well as to evaluate each conceptual activity. Hypotheses also address the scale's correctness, and show the relationship between two or more variables in the formulation, validation, or rejection of other theories (Williams et al., 2012). When employing factor analysis to meet the goals of this section of the study, the process is as follows. In order to determine the items that could truly reflect or measure the latent variables, exploratory factor analysis was used in this study (Edkins and Pollock, 1996). The varimax method was used in conjunction with the principal components analysis (PCA) in the SPSS software. The varimax approach is used to guarantee that the study parameters are consistent, which allows for accurate interpretation. Pallant (2005) proposed that the loading of a matrix item should be more than or equal to 0.30 in order for it to be a relevant indicator. Significant factor loading, according to Norusis (1993), should be larger than or equal to 0.50. However, in this investigation, a threshold of 0.70 was chosen. Items that did not satisfy the criteria were thrown out.

Table 4. 4 KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.942
Bartlett's Test of Sphericity	Approx. Chi-Square	8954.301
	df	465
	Sig.	.000

4.6 Confirmatory Factor Analysis

The model for this research was established with the aid of the Partial Least Square (PLS). The Smart PLS version 3.2.7 can be used in taking the measurements and measuring the structural model for the study (Ringle et al., 2015). The results of accuracy were obtained from the measurement model since it evaluates the accuracy of measures developed on each construct. The reliability test measures the degree to which two or more sets of measures are used in measuring the same constructs and are freed from error (Hair et al., 1998). The most commonly used measure is the internal consistency reliability through the use of composite reliability. The validity however measures the extent to which the gathered data exactly represent the items studied (Newman, 1997). The mostly known validity test involves content validity, constructs validity, and external validity. This study however adopted internal consistency reliability and constructs validity (convergent and discriminant validity) as the model measurement tests. With the aid of the PLS-SEM approach in testing, the model measurement was attained by the evaluation of the discriminant and convergent validity. The convergent validity shows the extents to which a measure positively connects (Hair et al., 2014). This was evaluated by examining the constructs loadings and the average variance extracted (AVE). The constructs validity on the other hand was examined with both the composite reliability and internal reliability. The discriminant validity also measures the extent to which the measurement for one item or variable does not exhibit a relationship with measurements for other different variables.

These are assessed by investigating their interaction (Kline, 2005). In summary convergent validity is attained when an indicator only measures the constructs it is supposed to identify while the discriminant validity indicates that the items of the constructs do not measure other constructs (Neumann, 2003; Hair et al., 1998). As observed in the study, the results of the convergent validity and discriminant validity revealed that the indicators of the constructs are loaded on variables they expect to measure but do not load on other constructs. The section below indicates the outcome of the convergent validity and discriminant study of the model measurement.

For measurement model validity and reliability, Confirmatory Factor Analysis was conducted using Smart PLS version 3. The process employed the maximum likelihood estimation method for testing the validity and reliability of the constructs. The model measurement evaluation was conducted, as a prerequisite for the structural model analysis. The model measurement evaluation comprised reliability and validity using Composite Reliability (CR) and Average Variance Extracted (AVE). The result in Table 4.5 below shows that all the constructs had good scale reliability (ie. Composite reliability) that were higher than 0.7 (Fornell and Larcker, 1981; Henseler et al., 2015), hence all the constructs had acceptable internal consistency and reliability. Additionally, AVE which was also used to assess convergent validity of the constructs was found above the 0.5 threshold. Fornell-Larker criterion and HTMT ratio was used to assess discriminant validity of the model. The result provides evidence that the model used has no issue of discriminant validity, as the square root of the AVEs were higher than the within correlation among the variables in the model (see Table 4.5 below). The discriminant validity test was further explored using the HTMT ratio, the HTMT threshold (< 0.90) was met which also confirms discriminant validity of the research model (see Table 4.6; 4.7).

4.6.1.1 Composite Reliability

For this study, construct reliability was confirmed by the composite reliability. Composite Reliability (CR) was used to explore reliability of construct in the model. The Composite reliability (CR) provides a more retrospective approach of reliability, and estimates consistency of the individual construct including stability and equivalence of the construct (Hair, Black, Babin, Anderson & Tatham, 2010). A Composite Reliability (CR) value of 0.70 or higher is considered to have good scale reliability (Hair et al., 2010). The Table 4.7 displays the computed Composite Reliability (CR) of all the latent variables ranging between 0.910 and 0.966, and all were above the 0.70 threshold. Therefore, produces evidence that all the latent variables have good reliability.

4.6.1.2 Test for Validity

Validity in research is defined as how well a scientific test or piece of research actually measures what it sets out to, or how well it reflects the reality it claims to represent (Cohen et al., 2013). Three different ways that validity can be measured include convergent validity, discriminant validity and face validity (Bryman, 2015).

4.6.1.2.1 Convergent Validity

Convergent validity measures the extent to which construct correlates positively with alternative measure of the same construct. To determine the convergent validity in this study, the outer loading of indicators and the Average Variance Extracted (AVE). The outer loadings will be greater than 0.78 i.e., the latent variables can explain at least 50% of its indicator's variance. Loading of 0.4, 0.5, 0.6, and 0.7 can be accepted if it will lead to AVE, that is larger than 0.5. AVE compares the proportion of variance explained in the factor analysis. The value for AVE ranges from 0-1. It should exceed 0.5 to show adequate convergent validity (Bagozzi and Yi, 1988; Fornell and Larcker, 1981). The average variance extracted (AVE) for all items on each construct is the metric used to assess convergent validity. The AVE is computed by squaring the loading of each indicator on a construct and computing the mean value. A value of 0.50 or higher indicates that the construct explains at least 50% of the variance among its elements (Hair et al., 2019). The result of this study as presented in Table 4.7 below indicates that AVE which was also used to assess convergent validity of the constructs were found above the 0.5 threshold.

Table 4. 5 Validity and Reliability Test

Construct	Items	Loading	CA	CR	AVE	VIF	T Statistics	P Values
Circular Economy	CEC1	0.812	0.941	0.953	0.772	2.258	52.553	0.000
	CEC2	0.886				1.264	21.184	0.000
	CEC3	0.882				2.433	67.853	0.000
	CEC4	0.894				2.712	38.514	0.000
	CEC5	0.904				2.963	52.553	0.000
	CEC6	0.889				2.664	63.996	0.000
Green Mindfulness	GM1	0.926	0.952	0.963	0.840	1.496	39.645	0.000
	GM2	0.924				2.468	32.932	0.000
	GM3	0.932				2.57	35.467	0.000
	GM4	0.903				2.797	24.547	0.000
	GM5	0.897				2.795	39.491	0.000
Industry 4.0	I1	0.828	0.918	0.938	0.753	2.87	36.501	0.000
	I2	0.898				2.011	22.314	0.000
	I3	0.855				2.336	57.958	0.000
	I4	0.867				2.277	42.831	0.000
	I5	0.889				2.281	56.262	0.000
Innovation Performance	IP1	0.812	0.936	0.946	0.662	2.712	66.757	0.000
	IP2	0.805				2.963	49.288	0.000
	IP3	0.781				2.664	25.16	0.000
	IP4	0.819				1.496	26.656	0.000
	IP5	0.832				2.205	41.961	0.000
	IP6	0.822				2.146	48.91	0.000
	IP7	0.788				2.092	44.452	0.000
	IP8	0.850				2.614	32.751	0.000
	IP9	0.814				2.656	45.775	0.000
Supply Chain Analytics	SCA1	0.796	0.901	0.924	0.669	2.795	39.914	0.000
	SCA2	0.831				2.167	41.505	0.000
	SCA3	0.821				2.628	31.703	0.000
	SCA4	0.857				2.615	44.382	0.000
	SCA5	0.838				2.493	34.446	0.000
	SCA6	0.761				2.357	33.829	0.000

Source: Field Data (2021) *CA= Cronbach Alpha: VIF= Variance Inflation Factor; CR=Composite Reliability; AVE=Average Variance Extracted*

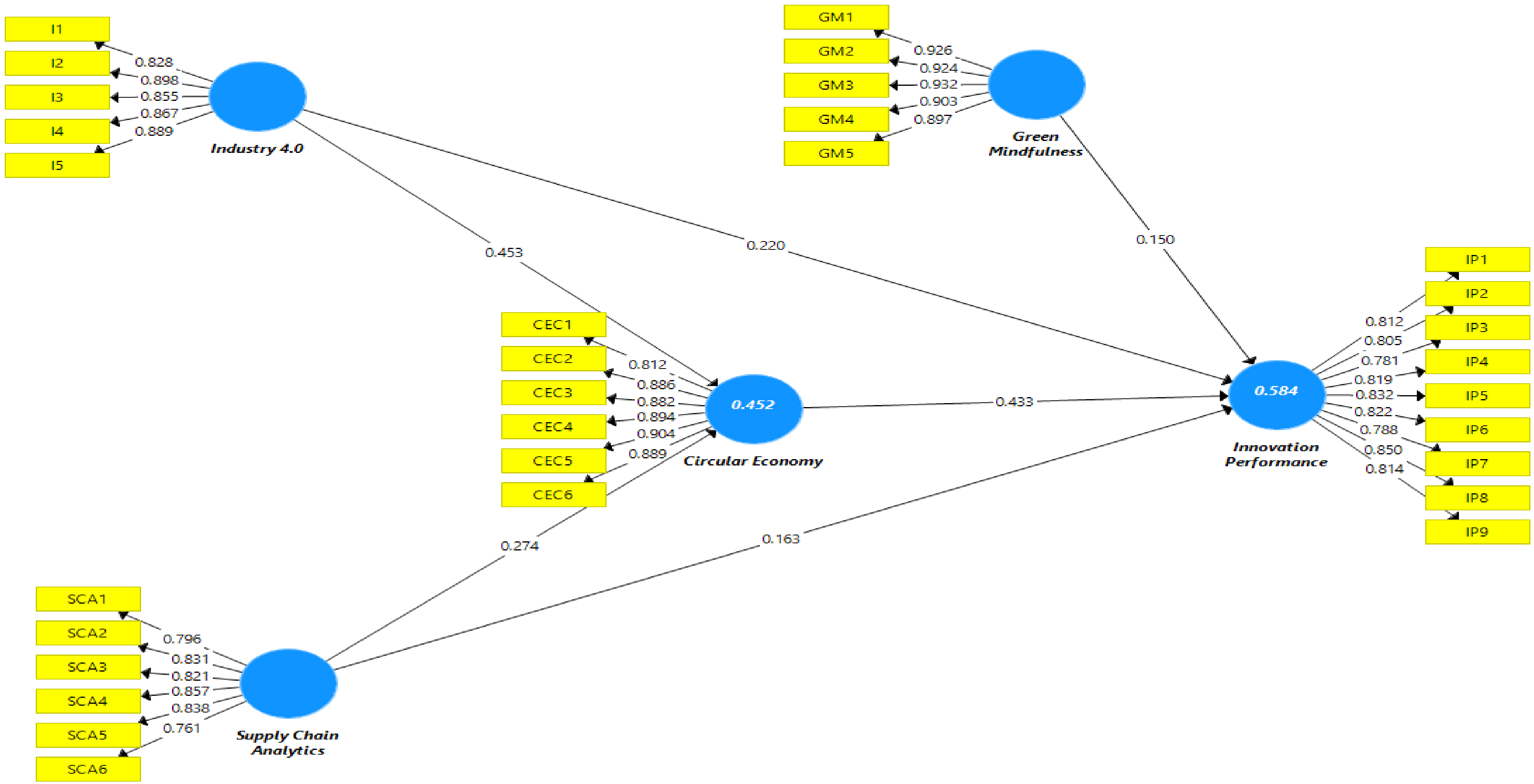

Figure 4. 1 Measurement Model Assessment

4.6.1.2.2 Discriminant Validity

Discriminant validity measures the extent to which a variable is truly different from other variables. It shows how a variable is unique. Cross loading and Fornell and Larcker criterion can be used to evaluate discriminant validity (Hair et al., 2014) and Hetero Trait-Mono trait (HTMT) which is developed to arrest the insensitivity of the Fornell and Larcker and cross loading criterion of ratio (Henseler, Ringle and Sarstedt, 2015). Henseler et al. (2015) show that the Fornell-Larcker criterion fails horribly when the indicator loadings on a construct differ only moderately (e.g., all the indicator loadings are between 0.756 and 0.892). The heterotrait-monotrait (HTMT) correlation ratio was proposed by Henseler et al. (2015) as a replacement (Voorhees et al., 2016). The HTMT is defined as the difference between the mean value of item correlations across constructs and the (geometric) mean of average correlations for items measuring the same construct. Discriminant validity difficulties develop when HTMT measurements are high. Henseler et al. (2015) offer a threshold value of 0.90 for structural models incorporating dimensions that are theoretically quite close, such as cognitive satisfaction, affective fulfillment, and loyalty. An HTMT score of more than 0.90 shows that discriminant validity is not present in this situation. A lower, more conservative threshold value, such as 0.85, is advised when constructs are more conceptually diverse (Henseler et al., 2015). Bootstrapping can be employed in addition to these criteria to examine if the HTMT value changes significantly from 1.00 (Henseler et al., 2015) or a lower threshold value of 0.85 or 0.90, which should be selected based on the study context (Franke & Sarstedt, 2019). As demonstrated in Table 4.7, all of the HTMT values are less than 0.90 or 0.85, indicating that discriminant validity has been proven. Table 4.7: Discriminant Validity using HTMT. In conclusion, the result from using both Fornell and Larcker criterion and HTMT test revealed the presence of discriminant validity.

Table 4. 6 Fornell and Larcker criterion

Constructs	1	2	3	4	5
Circular Economy	**0.878**				
Green Mindfulness	0.189	**0.917**			
Industry 4.0	0.642	0.186	**0.868**		
Innovation Performance	0.698	0.302	0.637	**0.814**	
Supply Chain Analytics	0.586	0.177	0.687	0.594	**0.818**

Source: Field Data (2022)

Table 4. 7 Heterotrait-Monotrait Ratio (HTMT)

Constructs	1	2	3	4	5
Circular Economy					
Green Mindfulness	0.197				
Industry 4.0	0.685	0.198			
Innovation Performance	0.741	0.318	0.684		
Supply Chain Analytics	0.626	0.187	0.751	0.639	

Source: Field Data (2021)

4.6.1.2.3 Cross Loading

Content validity is the communal approach amid others. According to Creswell (2009) and Heale and Twycross (2015) content validity tests the capabilities of items to measure the content which they are designed to measure. It is mainly executed via reviewing related literature. This research made use of instruments certified from past studies. However to be sure that the entire content of the research is covered, face validity was explored, and according to Netemeyer and Bearden, (2003) this approach uses experts to evaluate the instruments by ensuring that the instruments are appropriate in terms of their appearance, relevance and proper representation of the elements. The result of the cross loading in Table 4.8 shows the data has no issues of content validity.

Table 4. 8 Cross Loadings

Items	Circular Economy	Green Mindfulness	Industry 4.0	Innovation Performance	Supply Chain Analytics
CEC1	**0.812**	0.075	0.516	0.520	0.475
CEC2	**0.886**	0.165	0.514	0.589	0.492
CEC3	**0.882**	0.173	0.567	0.582	0.556
CEC4	**0.894**	0.199	0.565	0.650	0.512
CEC5	**0.904**	0.213	0.598	0.654	0.543
CEC6	**0.889**	0.160	0.613	0.667	0.508
GM1	0.145	**0.926**	0.170	0.265	0.167
GM2	0.163	**0.924**	0.132	0.251	0.099
GM3	0.163	**0.932**	0.178	0.287	0.179
GM4	0.207	**0.903**	0.195	0.297	0.180
GM5	0.185	**0.897**	0.171	0.276	0.178
I1	0.464	0.159	**0.828**	0.500	0.573
I2	0.590	0.165	**0.898**	0.583	0.602
I3	0.527	0.167	**0.855**	0.491	0.601
I4	0.577	0.135	**0.867**	0.603	0.620
I5	0.611	0.182	**0.889**	0.575	0.586
IP1	0.578	0.235	0.497	**0.812**	0.436
IP2	0.587	0.235	0.507	**0.805**	0.480
IP3	0.570	0.222	0.533	**0.781**	0.503
IP4	0.531	0.281	0.518	**0.819**	0.460
IP5	0.579	0.337	0.520	**0.832**	0.487
IP6	0.535	0.297	0.534	**0.822**	0.497
IP7	0.564	0.185	0.511	**0.788**	0.473
IP8	0.594	0.236	0.523	**0.850**	0.524
IP9	0.571	0.177	0.525	0.814	0.488
SCA1	0.380	0.097	0.498	0.383	**0.796**
SCA2	0.428	0.152	0.569	0.467	**0.831**
SCA3	0.493	0.193	0.622	0.537	**0.821**
SCA4	0.459	0.136	0.573	0.505	**0.857**
SCA5	0.480	0.165	0.538	0.487	**0.838**
SCA6	0.591	0.115	0.550	0.503	**0.761**

Source: Field Data (2022)

4.7 Structural Model Evaluation

The structural model also known as inner model enables researchers to determine the model's capability and to anticipate one or more target construct. Newton and Rudestan (1999) and Hair et al. (2017) were of the view that path coefficients is the degree of changes in the independent constructs while all the other independent constructs are held constants. As earlier stated in the structural model, the path coefficient indicates the hypothesized associations among the dependent and the independent variables (Henseler et al., 2016; Wang, 2016; Kock, 2015). The results for the structural path coefficient are showed in Table 4.10 and 4.11. There was a significant relationship between the constructs since at a significance level of 5%, if their t values were 1.96 or more**.** Also, it could be observed that p values of the constructs were either 0.10 or smaller. Once the measurement model evaluation meets all the reliability and validity thresholds, the next phase of the analysis is the structural model assessment and hypothesis testing via the variances of dependent variables in addition to the model's predictive relevance using stone-Geisser's Q^2, path coefficients and significance levels (t-values). The study used the blindfolding procedure to estimate the Q^2.

4.7.1 Bootstrap Resampling Method

The structural model is also termed as inner model which enhances researchers to determine the capability of the model and also to anticipate one or more target construct. With regards to the measurement model coefficients, the study further tests the mediating and moderating model using the bootstrapping 5000 with replacement and standard error (Hair, Sarstedt, Hopkins and Kuppelweiser, 2014). Below the structural model, the study considers measures including collinearity, f value, p value, path coefficient, the coefficient of determination, effect size (f^2) and effect size (g^2). Collinearity occurs when two indicators are highly correlated. The study made use of variance inflation factor in assessing the collinearity among the latent variables. The value of the threshold will include VIF>=5 in depicting potential collinearity issues (Hair et al., 2011). The path coefficient was assessed using +1 in showing a strong association in the structural model. In the circumstance where the path coefficients significantly depend on its standard error through bootstrapping, the study will make use of p values and t values for the structural path coefficients. The t value is estimated to be 1.96 at the 5% significance level.

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

According to Hair et al. (2018), the R^2 values of 0.75, 0.50 and 0.25 are considered substantial, moderate and weak. Chin et al. (2020) however, opine that it is necessary to interpret the R^2 by considering the context of the related discipline. The model shows moderate predictive accuracy (R^2) values of 0.452 and 0.584 towards circular economy and innovation performance respectively as displayed in Table 4.9 and Figure 4.1. The result implies that industry 4.0, supply chain analytics are able to explain 45% of variation in circular economy, 58% of variation in innovation performance. Thus, the model has a moderate predictive capability and hence good for prediction.

Additionally, another way to check the accuracy of a PLS model is to calculate the value of Q^2 (Geisser, 1974; Stone, 1974). This metric is based on the process of blindly removing a single point from the data matrix, setting the abstract point and estimating the model phase (Rigdon, 2014b; Sarstedt et al., 2014). Thus, Q^2 is not a prediction method, but combines the sample prediction element with the descriptive strength of the sample (Shmueli et al., 2016; Sarstedt et al., 2017a). Using this estimate as an introduction, the blindfold process predicts the data released. The slight difference between the predicted value and the baseline translates to a higher Q^2 value, thus, indicating greater accuracy. As a guide, the value of Q^2 should be greater than zero for a particular endogenous to indicate predictive accuracy of the structural model for that construct. As a rule, Q^2 higher than 0, 0.25 and 0.50 indicates small, medium and large predictive relevance of the PLS-path model. The results show Q^2 values of 0.343 and 0.379 for circular economy and innovation performance respectively (see Table 4.9). The results show medium predictive relevance of the model. Thus, the Q-square values are all above the threshold, indicating that the values are well reconstructed and that the model has predictive relevance.

Table 4. 9 Predictive Relevance (R^2) and Q2

Exogenous Constructs	R^2	Q^2
Circular Economy	0.452	0.343
Innovation Performance	0.584	0.379

Source: Field Data, 2022

4.8 Hypotheses Testing for Direct 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 4.10 and Figure 4.2. The PLS bootstrapping with 5, 000 samples were used in testing the significance of the six (6) paths in the model. Before the hypotheses testing, multicollinearity was evaluated using VIF, the result demonstrated that VIFs values recorded in this study were below the 3.3 thresholds recommended by (Kock, 2015) (see Table 4.10). This, therefore, provide evidence to justify that the predictors have no issues of multicollinearity. Model fit was also examined in line with the recommendation of Henseler and Ray (2016). The findings evidenced that the SRMR was approximately .73 which is way below the 0.8 threshold. This implies that a good fit exists between the hypothesized model and the observed data.

The analysis was done in line with the framework which hypothesized that when organizations deploy resources by improving and reconfiguring the current bundle of resources as well as capabilities in the changing environment such as industry 4.0, supply chain analytics, it will influence the ability of the organizations to improve their innovation performance. The present study is designed to investigate the relationship between industry 4.0, supply chain analytics and innovation performance by highlighting the intervening role of circular economy, and the moderating role of green mindfulness between circular economy practice and innovation performance. This section discusses the analyses of the direct relationships as shown in Table 4.9 and Figure 4.2.

4.8.1 Direct Hypotheses / Relationships

This section discusses the five direct hypotheses that were proposed in the study. The study hypothesized that industry 4.0 will have positive significant effect on innovation performance among agribusinesses in Ghana. The result of the structural model as presented in Table 4.10 shows that industry 4.0 has significant positive impact on innovation performance (B=0.231: t=3.655; p-value <0.005). This result also implies that, all other things being equal, a unit improvement in industry 4.0 among agribusinesses contributes approximately 23% of improvement in their innovation performance. This confirms that the first hypothesis of the study is supported and concludes that industry 4.0 significantly predict innovation performance in the Ghanian agribusiness setting.

The study also proposed a positive significant effect of industry 4.0 on circular economy practice among agribusiness firms in Ghana. The result of the structural model as presented in Table 4.10 shows that industry 4.0 has significant positive impact on circular economy practice among agribusiness firms in Ghana (B=0.453: t=7.071; p-value <0.005). This result also implies that, all other things being equal, a unit improvement in industry 4.0 among agribusinesses contributes approximately 45% of improvement in circular economy practice among agribusiness firms in

Ghana. This confirms that the second hypothesis of the study is supported and concludes that industry 4.0 significantly predict circular economy practice in the Ghanian agribusiness setting.

The study also hypothesized that supply chain analytics will have positive significant effect on innovation performance among agribusinesses in Ghana. The result of the structural model as presented in Table 4.10 shows that supply chain analytics has significant positive impact on innovation performance (B=0.173: t=2.515; p-value <0.005). This result also implies that, all other things being equal, a unit improvement in supply chain analytics among agribusinesses contributes approximately 17% of improvement in their innovation performance. This confirms that the third hypothesis of the study is supported and concludes that supply chain analytics significantly predicts innovation performance in the Ghanian agribusiness setting.

The study again proposed a positive significant effect of supply chain analytics on circular economy practice among agribusiness firms in Ghana. The result of the structural model as presented in Table 4.10 shows that supply chain analytics has significant positive impact on circular economy practice among agribusiness firms in Ghana (B=0.275: t=3.451; p-value <0.005). This result also implies that, all other things being equal, a unit improvement in supply chain analytics among agribusinesses contributes to approximately 28% of improvement in circular economy practice among agribusiness firms in Ghana. This confirms that the fourth hypothesis of the study is supported and concludes that supply chain analytics significantly predict circular economy practice in the Ghanian agribusiness setting.

Lastly, the study also expected a positive relationship between circular economy practices and innovation performance. The result of the structural model as presented in Table 4.10 shows that circular economy practices have significant positive impact on innovation performance among agribusiness firms in Ghana (B=0.449: t=6.923; p-value <0.005). This result also implies that, all other things being equal, a unit improvement in circular economy practices among agribusinesses contributes to approximately 45% of improvement in innovation performance among agribusiness firms in Ghana. This confirms that the fifth hypothesis of the study is supported and concludes that circular economy practices significantly predict innovation performance in the Ghanian agribusiness setting.

Table 4. 10 Hypotheses Testing for Direct Relationships

Hypotheses	Path Coefficient	StD	T Statistics	P Values	Result
H1: Industry 4.0 -> Innovation Performance	0.231	0.060	3.655	0.000	Supported
H2: Industry 4.0 -> Circular Economy	0.453	0.064	7.071	0.000	Supported
H3: Supply Chain Analytics -> Innovation Performance	0.173	0.065	2.515	0.012	Supported
H4: Supply Chain Analytics -> Circular Economy	0.275	0.080	3.451	0.001	Supported
H5: Circular Economy -> Innovation Performance	0.449	0.063	6.923	0.000	Supported

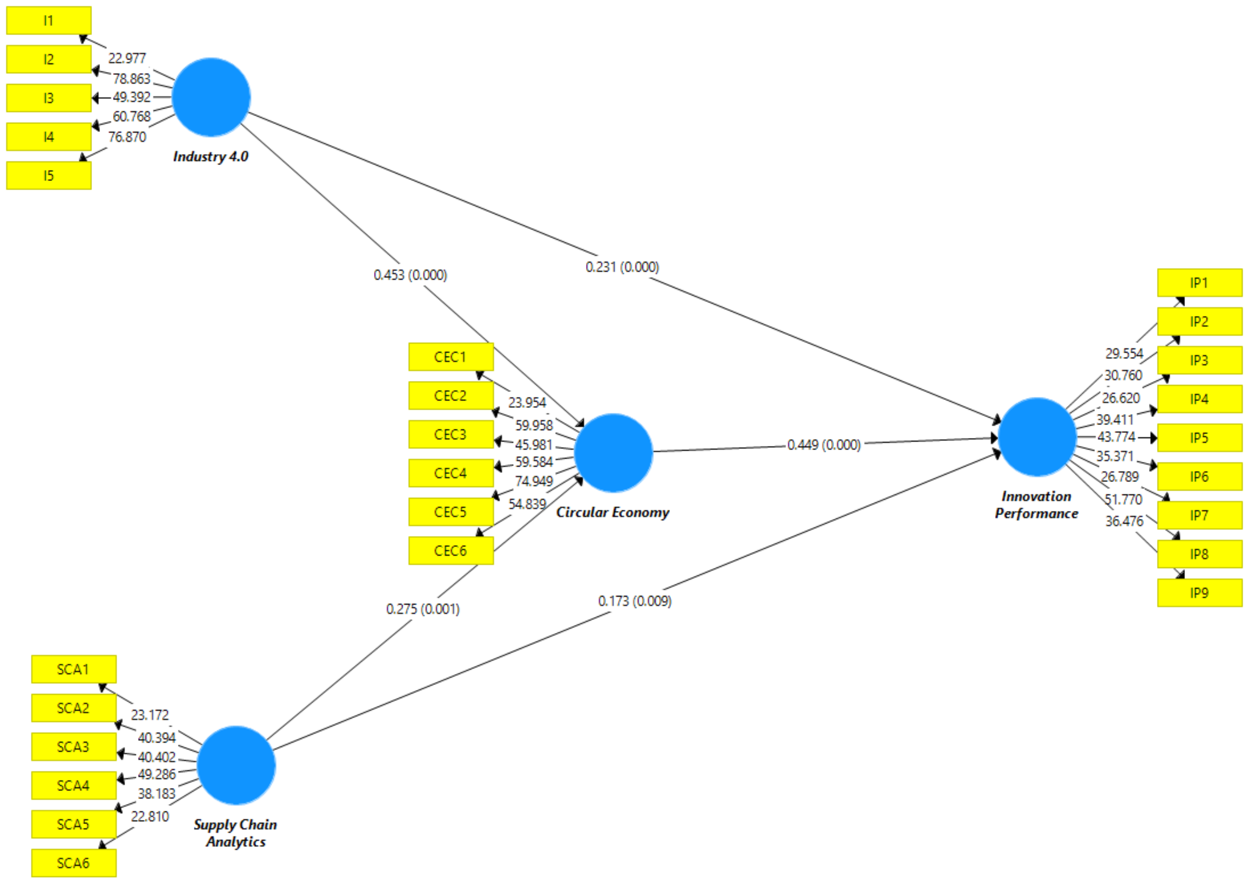

Figure 4. 2

4.8.2 Indirect Hypotheses / Relationships (Mediating and Moderating)

The study also explored the indirect role of CE and GM in the I4.0, SCA and IP direct link within the agribusiness sector in Ghana. This section therefore presents the result of the mediating role of circular economy in the direct effect of industry 4.0 (I4.0) and supply chain analytics (SCA) on innovation performance and the moderating effect of Green Mindfulness on the CEC and IP relationship. The results are discussed and summarized in Table 4.11 below.

The study also expected a positive mediation of circular economy in relationship between industry 4.0 and innovation performance. The result of the structural model as presented in Table 4.10 shows that circular economy practices significantly mediate between industry 4.0 and innovation performance among agribusiness firms in Ghana (B=0.202: t=4.734; p-value <0.005). This result shows that circular economy partially mediates between industry 4.0 and innovation performance among agribusiness. This confirms that the six hypothesis of the study is supported and concludes that circular economy practices mediate the relationship between industry 4.0 and innovation performance among agribusiness in the Ghanian agribusiness setting. The study also expected a positive mediation of circular economy in relationship between supply chain analytics and innovation performance. The result of the structural model as presented in Table 4.11 shows that circular economy practices significantly mediate between supply chain analytics and innovation performance among agribusiness firms in Ghana (B=0.123: t=4.734; p-value <0.005). This result shows that circular economy partially mediates between supply chain analytics and innovation performance among agribusiness. This confirms that the six hypothesis of the study is supported and concludes that circular economy practices mediate the relationship between supply chain analytics and innovation performance among agribusiness in the Ghanian agribusiness setting.

Finally, the eighth hypothesis which proposed a moderation between circular economy and innovation performance was not supported. The result demonstrated that the relationship between circular economy and innovation performance is not always dependent on the level of green mindfulness. Hence the eight hypothesis was rejected and concludes that moderation between circular economy and innovation performance was not significant.

Table 4. 11 Indirect Hypotheses / Relationships (Mediating and Moderating)

Hypotheses	Path Coefficient	StD	T Statistics	P Values	Result
H6: Industry 4.0 -> CEC -> Innovation Performance	0.203	0.043	4.734	0.000	Supported
H7: Supply Chain Analytics -> CEC -> Innovation Performance	0.123	0.042	2.909	0.004	Supported
H8: GM(CEC-IP)	-0.041	0.044	0.946	0.345	Not Supported

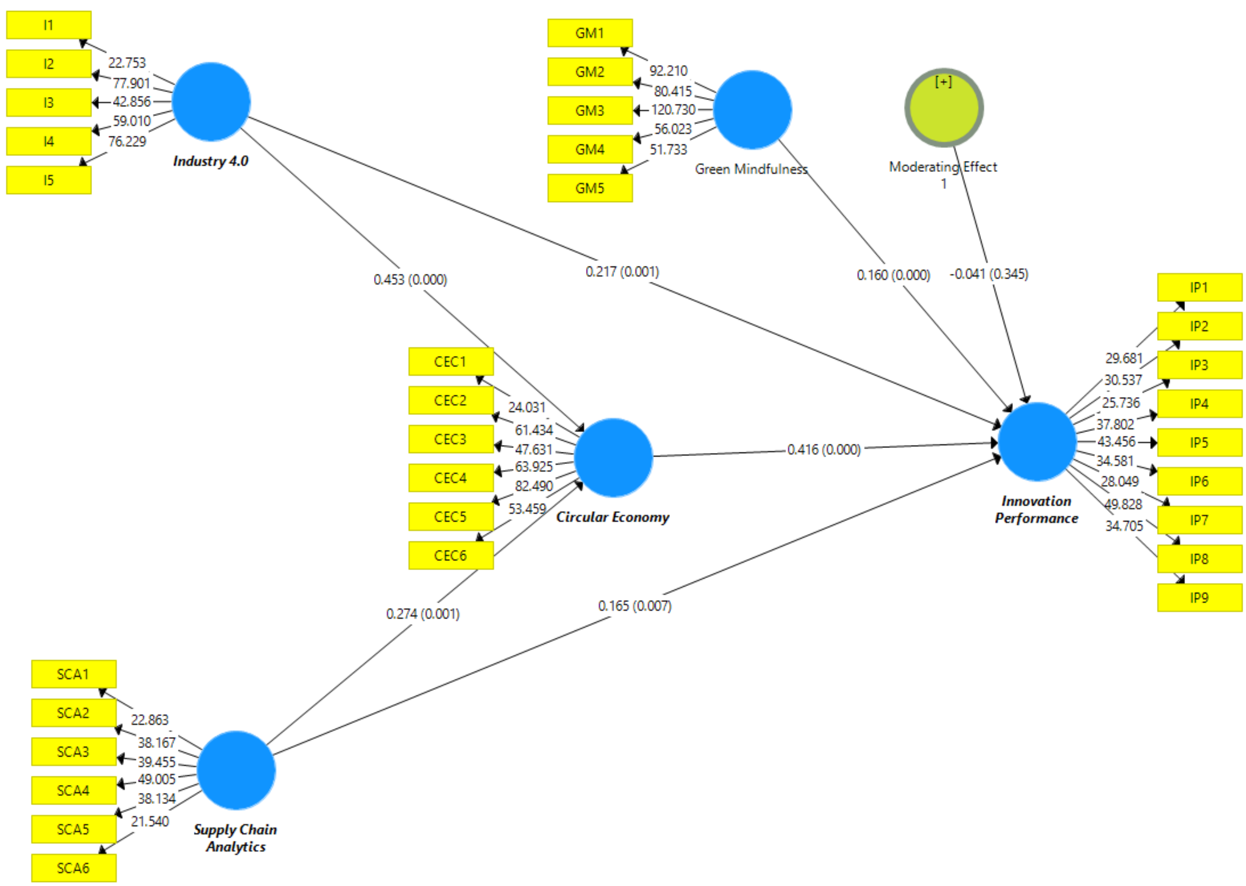

Figure 4. 3 Moderating Role of Green Mindfulness

4.9 Discussion of Key Findings

The purpose of this study was to investigate the relationship between industry 4.0, supply chain analytics and innovation performance by highlighting the intervening role of circular economy, and the moderating role of green mindfulness between circular economy practice and innovation performance. This section has presented a discussion of the key findings in line with existing theories and studies. Although the review conducted in this study shows that the concept of industry 4.0 and supply chain analytics are not new in research, their operationalization or use in the agribusiness space especially from the context of emerging economies like Ghana. Extant literature has also focused on external factors that drives innovation performance. This makes this study imperative and an urgent response to recent call on the need to critically identify ways to enhance the innovation drive in the agribusiness space in Sub Sahara Africa (SSA). The variables related to the proposed study has been categorized into independent variables industry 4.0, supply chain analytics; dependent variable innovation performance (IP), mediating variable circular economy, and moderating variable green mindfulness. The review showed the use of circular economy principles within the supply chain has received scant consideration (Aminoff and Kettunen, 2016; De Angelis et al., 2018; Lewandowski, 2016). As a result, research into the circular supply chain is still limited (Geissdoerfer et al., 2018). While Awan, Sroufe and Shahbaz (2021) call for the need to explore how data analytics capabilities and industry 4.0 may influence CE, Awan, Shamim, Khan, Zia, Shariq and Khan (2021) also recommended the need to examine the mediating role of CE within innovation performance relationship. This study is therefore among the first studies to operationalize these constructs in the agribusiness setting by investigating the relationship between industry 4.0, supply chain analytics and innovation performance by highlighting the intervening role of circular economy, and the moderating role of green mindfulness between circular economy practice and innovation performance. Using the methodology described in the previous chapter, SPSS and PLS-SEM was used to analyze 326 responses gathered from agribusiness organization in Ghana.

The study hypothesized that industry 4.0 will have positive significant effect on innovation performance among agribusinesses in Ghana. The result found that industry 4.0 has significant positive impact on innovation performance. This result also implies that, all other things being equal, a unit improvement in industry 4.0 among agribusinesses contributes approximately 23% of improvement in their innovation performance. This confirms that the first hypothesis of the study is supported and concludes that industry 4.0 significantly predict innovation performance in the Ghanian agribusiness setting. As mentioned in earlier discussion the relationship between industry 4.0 and innovation has attracted significant attention in recent times especially with the outbreak of the covid 19 pandemic. The covid-19 pandemic pushed many firms and industries to invest in technology or digitization in their quest to innovate their business operations. Evidence to support the outcome of their investment, especially in the covid-19 era, remains a mirage, especially in the agribusiness setting. The findings in this study confirms prior studies have indicated that Industry 4.0 can boost energy, facilities and the use of human resources to enhance innovation (Lasi et al., 2014). Thus, innovation performance is highly dependent on the firms' ability to interact with the environment via technology. Hence firms that are able to adopt emerging technologies which allow them to effectively analyze their environment stand a high chance of developing and utilizing available resources to transform the insight drawn from the environment into innovative outcomes (Jeandri et al., 2021). Prior studies (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 Fındık, 2022) have shown the essential role of industry 4.0, digitization, automation and technology in driving enhanced innovation performance among firms in developing economies and large-scale businesses. The findings in this study also provide empirical support to the RBV theory used in the study, it has been confirmed that innovation performance in the agribusiness setting could be driven via awareness, investment and utilization of industry 4.0 technologies.

The study also proposed a positive significant effect of industry 4.0 on circular economy practice among agribusiness firms in Ghana. The result revealed that industry 4.0 has significant positive impact on circular economy practice among agribusiness firms in Ghana. This result also implies that, all other things being equal, a unit improvement in industry 4.0 among agribusinesses contributes approximately 45% of improvement in circular economy practice among agribusiness firms in Ghana. This confirms that the second hypothesis of the study is supported and concludes that industry 4.0 significantly predict circular economy practice in the Ghanian agribusiness setting. The findings support the previous claims that technology advancements have made it easier to move from linear to circular economy in the enterprises of corporations (Khan, Yu et al., 2021; Dumée, 2021; Yu et al., 2022). Ecological modernization theory emphasizes the use of technology in the evaluation of CE (Bergendahl et al., 2018; Gupta et al., 2020). The findings on the link between Industry 4.0 and the CE provide empirical support to contemporary digital era since these concepts have been garnering a lot of attention in recent years (Awan et al., 2021; Zhang et al., 2021). The findings align with prior studies (Nascimento et al., 2018; Rajput and Singh, 2019; Abdul-Hamid et al., 2020; Razzaq et al., 2021; Dantas et al., 2021; Tavera Romero et al., 2021; Massaro et al., 2021; Rosa et al., 2020; Zhou et al., 2020; Yu et al., 2022) which argued is a strong correlation between industry 4.0 and CE. Drawing from the findings and the argument of the contingency theory, this study confirms a significant positive effect of industry 4.0 in enhancing circular economy practice in the agribusiness setting.

The study also hypothesized that supply chain analytics will have positive significant effect on innovation performance among agribusinesses in Ghana. The result revealed supply chain analytics has significant positive impact on innovation performance. This result also implies that, all other things being equal, a unit improvement in supply chain analytics among agribusinesses contributes approximately 17% of improvement in their innovation performance. This confirms that the third hypothesis of the study is supported and concludes that supply chain analytics significantly predicts innovation performance in the Ghanian agribusiness setting. The finding is not different from prior studies (Wu et al., 2019; Hooi et al., 2018; Hao et al., 2019; Zareravasan and Ashrafi, 2019; Sun et al., 2020; Ghasemaghaei and Calic, 2020; Muhammad et al., 2022) which have shown that data analytics plays a complementary role of driving innovation performance.

The study again proposed a positive significant effect of supply chain analytics on circular economy practice among agribusiness firms in Ghana. The result shows that supply chain analytics has significant positive impact on circular economy practice among agribusiness firms in Ghana. This result also implies that, all other things being equal, a unit improvement in supply chain analytics among agribusinesses contributes to approximately 28% of improvement in circular economy practice among agribusiness firms in Ghana. This confirms that the fourth hypothesis of the study is supported and concludes that supply chain analytics significantly predict circular economy practice in the Ghanian agribusiness setting. Prior research suggests that BDA capability can shed light on new concepts including the circular economy (CE) (Jiao et al., 2018; Gupta et al., 2019). Several CE-based activities to integrate processes and exchange resources rely on it

(Jabbour et al., 2019). According to Gupta et al. (2019), the capability to analyze data provides great support for extracting critical insights from the data relating to CE members from the CE database. Managers can then use these findings as a basis for making decisions about 3R and material circularity issues at all organizational levels. To make better use of the resources available, supply chain analytics insights can be applied across multiple processes and departments which will enhance innovation performance in the firm. Though empirical evidence to support the connection between supply chain analytics and circular economy is scanty, this study supports the RBV, that the ability of firms to analyze data generated along their supply chain activities will produce insights which can support circular economy practices.

Again, the study also expected a positive relationship between circular economy practices and innovation performance. The result showed that circular economy practices have significant positive impact on innovation performance among agribusiness firms in Ghana. This result also implies that, all other things being equal, a unit improvement in circular economy practices among agribusinesses contributes to approximately 45% of improvement in innovation performance among agribusiness firms in Ghana. This confirms that the fifth hypothesis of the study is supported and concludes that circular economy practices significantly predict innovation performance in the Ghanian agribusiness setting. The circular economy has an important role in the innovation performance of firms, firms in the quest to remain competitive must innovate, however, in the process of innovation stakeholders have become vigilant against the negative implications on the environment. Available literature has cited circular economy as important driver of innovation among firms (Potting et al., 2017; Blomsma et al., 2019; Suchek et al., 2021; Sehnem et al., 2022; Herrero-Luna et al., 2022). Both I4.0 (Rajput and Singh, 2019; Abdul-Hamid et al., 2020; Razzaq et al., 2021; Dantas et al., 2021; Tavera Romero et al., 2021; Massaro et al., 2021; Rosa et al., 2020; Zhou et al., 2020; Yu et al., 2022). The outcome of this study provide evidence to argue that CE has the potency of influencing or driving innovation performance.

The second objective of the study investigated the mediating role of circular economy in the relationship between industry 4.0, supply chain analytics and innovation performance. The study also expected a positive mediation of circular economy in relationship between industry 4.0 and innovation performance. The result of shows that circular economy practices significantly mediate between industry 4.0 and innovation performance among agribusiness firms in Ghana. This result shows that circular economy partially mediates between industry 4.0 and innovation performance among agribusiness. This confirms that the six hypothesis of the study is supported and concludes that circular economy practices mediate the relationship between industry 4.0 and innovation performance among agribusiness in the Ghanian agribusiness setting. The study also expected a positive mediation of circular economy in relationship between supply chain analytics and innovation performance. The result found that circular economy practices significantly mediate between supply chain analytics and innovation performance among agribusiness firms in Ghana. This result shows that circular economy partially mediates between supply chain analytics and innovation performance among agribusiness. This confirms that the six hypothesis of the study is supported and concludes that circular economy practices mediate the relationship between supply chain analytics and innovation performance among agribusiness in the Ghanian agribusiness setting. The findings form contemporary response to recommendations on the need to examine the driver and implications of circular economy in emerging economies, as there existed scanty literature on the indirect role played by the circular economy as a mediator in the I4.0, SCA and IP link. This study confirmed that though innovation performance may be achieved via the direct impact of I4.0, SCA, a circular economy practice may serve as a channel to strengthen the I4.0, SCA and IP link. Thus, an effective circular economy enabled I4.0, SCA could drive superior innovation performance. This study, therefore, confirms that CE partially mediate the I4.0, SCA and IP link.

Finally, the last hypothesis which proposed a moderation between circular economy and innovation performance was not supported. The result demonstrated that the relationship between circular economy and innovation performance is not always dependent on the level of green mindfulness. Hence the eight hypothesis was rejected and concludes that moderation between circular economy and innovation performance was not significant. Although green mindfulness was found to have positive impact on innovation performance, it could not serve as a condition to drive innovation performance but not always a pathway from circular economy practices.

4.10 Final Model

The final research model is presented in Figure 4.4. The model summarizes the conclusion of the current research and is based on significant relationships obtained from the study. The model indicates the mediating effects of circular economy in the relationship between Industry 4.0, SCA and innovation performance. Seven out of the eight paths were statistically significant ($t > 1.96$ indicating the partial mediation stance. According to Hair et al. (2017a), when the variable explains the predictive effects of an independent variable on a dependent variable, then it is a mediator. In the current model, circular economy mediates the relationship between I4.0 and IP while circular economy mediates the relationship between SCA and IP. Also, I4.0 and SCA all have a significant and positive effects on circular economy within the agribusiness supply chain context and was confirmed in this study. However, green mindfulness was found to insignificantly moderate the relationship between circular economy and IP within the Ghanaian agribusiness setting. In summary, the results of the study lend support to literature on I4.0, SCA and IP by counting circular economy as a mediator. The results indicate that, though I4.0, SCA affect IP, CE serves as an enabler promoting the effect of I4.0, SCA on IP. The study therefore reproduces final model showing direct and indirect significant relationship as shown in Figure 4.4. The results thus have suggestions for future research.

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION, AND RECOMMENDATIONS

5.1 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 and Supply chain analytics impacts innovation performance and circular economy and further examine how circular economy can influence the relationship between I4.0, SCA and innovation performance of Ghanaian agribusinesses. The chapter further talks about the limitations of the research and also provide suggestions for future research directions.

5.2 Summary of Findings

The purpose of this study was to investigate the relationship between industry 4.0, supply chain analytics and innovation performance by highlighting the intervening role of circular economy, and the moderating role of green mindfulness between circular economy practice and innovation performance. This section has presented a summary of the key findings in line with the objectives stated in chapter one. Although the review conducted in this study shows that the concept of industry 4.0 and supply chain analytics are not new in research, their operationalization or use in the agribusiness space, especially in the context of emerging economies like Ghana. Extant literature has also focused on external factors that drive innovation performance. This makes this study an imperative and urgent response to a recent call on the need to critically identify ways to enhance the innovation drive in the agribusiness space in Sub Sahara Africa (SSA). The variables related to the proposed study has been categorized into independent variables industry 4.0, supply chain analytics; dependent variable innovation performance (IP), mediating variable circular economy, and moderating variable green mindfulness. This study is therefore among the first studies to operationalize these constructs in the agribusiness setting by investigating the relationship between industry 4.0, supply chain analytics and innovation performance by highlighting the intervening role of circular economy, and the moderating role of green mindfulness between circular economy practice and innovation performance. Using the methodology described in the previous chapter, SPSS and PLS-SEM was used to analyze 326 responses gathered from agribusiness organization in Ghana.

5.2.1 Effect of Industry 4.0, Supply Chain Analytics on Innovation Performance

The first objective of the study was to examine the direct impact of I4.0 and SCA on the innovation performance of agribusinesses. The result found that industry 4.0 has significant positive impact on innovation performance. This result also implies that, all other things being equal, a unit improvement in industry 4.0 among agribusinesses contributes approximately 23% of improvement in their innovation performance. This confirms that the first hypothesis of the study is supported and concludes that industry 4.0 significantly predict innovation performance in the Ghanian agribusiness setting. The findings in this study also provide empirical support to the dynamic capability perspective, it has been confirmed that innovation performance in the agribusiness setting could be driven via awareness, investment and utilization of industry 4.0 technologies. The study also proposed a positive significant effect of industry 4.0 on circular economy practice among agribusiness firms in Ghana. The study also hypothesized that supply chain analytics will have positive significant effect on innovation performance among agribusinesses in Ghana. The result revealed supply chain analytics has significant positive impact on innovation performance. This result also implies that, all other things being equal, a unit improvement in supply chain analytics among agribusinesses contributes approximately 17% of improvement in their innovation performance. This confirms that the third hypothesis of the study is supported and concludes that supply chain analytics significantly predicts innovation performance in the Ghanian agribusiness setting.

5.2.2 Mediating Role Of Circular Economy In The Relationship Between 14.0, SCA And Innovation Performance

The second objective of the study investigated the mediating role of circular economy in the relationship between industry 4.0, supply chain analytics and innovation performance. The study also expected a positive mediation of circular economy in relationship between industry 4.0 and innovation performance. The result of shows that circular economy practices significantly mediate between industry 4.0 and innovation performance among agribusiness firms in Ghana. This result shows that circular economy partially mediates between industry 4.0 and innovation performance among agribusiness. This confirms that the six hypothesis of the study is supported and concludes that circular economy practices mediate the relationship between industry 4.0 and innovation performance among agribusiness in the Ghanian agribusiness setting. The study also expected a positive mediation of circular economy in relationship between supply chain analytics and innovation performance. The result found that circular economy practices significantly mediate between supply chain analytics and innovation performance among agribusiness firms in Ghana. This result shows that circular economy partially mediates between supply chain analytics and innovation performance among agribusiness. This confirms that the six hypothesis of the study is supported and concludes that circular economy practices mediate the relationship between supply chain analytics and innovation performance among agribusiness in the Ghanian agribusiness setting. The findings form contemporary response to recommendations on the need to examine the driver and implications of circular economy in emerging economies, as there existed scanty literature on the indirect role played by the circular economy as a mediator in the I4.0, SCA and IP link. This study confirmed that though innovation performance may be achieved via the direct impact of I4.0, SCA, a circular economy practice may serve as a channel to strengthen the I4.0, SCA and IP link. Thus, an effective circular economy enabled I4.0, SCA could drive superior innovation performance. This study, therefore, confirms that CE partially mediate the I4.0, SCA and IP link.

5.2.3 Moderating Role of Green Mindfulness in the Relationship between CE and Innovation Performance

Finally, the last objective which investigated the moderation between circular economy and innovation performance was not supported. The result demonstrated that the relationship between circular economy and innovation performance is not always dependent on the level of green mindfulness. Hence the eight hypothesis was rejected and concludes that moderation between circular economy and innovation performance was not significant. Although green mindfulness was found to have positive impact on innovation performance, it could not serve as a condition to drive innovation performance but not always a pathway from circular economy practices.

5.3 Contribution of the Study

The purpose of this study was to investigate the relationship between industry 4.0, supply chain analytics and innovation performance by highlighting the intervening role of circular economy, and the moderating role of green mindfulness between circular economy practice and innovation performance of agribusinesses in Ghana. Three main objectives were developed with eight sub hypotheses. All the three main objectives covering the study have been addressed. In as much as the implication of the study is important for discussion, it is also pertinent to deliberate on the practical and theoretical contributions of this research. Therefore, this study may provide a better understanding to both practitioners and policy makers regarding the internal drivers of innovation performance in the agribusiness space.

5.3.1 Theoretical Contribution

The main thrust of the study was to examine the role of Industry 4.0, supply chain analytics, circular economy, green mindfulness and innovation performance of agribusinesses based on the Resource Based-View Theory (RBV) and the Contingency theory. The findings of the study offer extant contribution to the growing body of literature on agribusiness digitization agenda on performance and advance the body of knowledge on the internal drivers of innovation performance. The current study set out to make contributions to the academic knowledge in the following ways:

The reviewed literature has confirmed that past studies over the period has seen the important relationship amongst the factors including b Industry 4.0, supply chain analytics, circular economy, green mindfulness and innovation performance. Studies gives an indication of the evaluation of these factors have been used individual in diverse settings, however, a combination of these variables to the best of the researcher's knowledge have not been seen studied especially in the Ghanaian agribusiness setting. This study addressed this identified gap in the present literatures, thus the researcher understudied by combining all the aforementioned variables to see how it can work in one model. The empirical testing of the above constructs in the study presents insightful empirical justification on the influence of industry 4.0 and supply chain analytics on innovation performance. Deducing form, the literature search, the presentation of these factors in a single study is unique to this study. Accordingly, this study offers a new approach in which agribusiness can be explored. The findings of the study expand perspectives on the variables used in the study. Such as I4.0, SCA, CE and GM which are scarce in SSA. Thus, exhibiting the result of the set of intangible assets allowing firms to use their intangible assets to achieve their current management activities and innovative objectives and aspirations. In as much as these variables has received much attention in research, it has been researched separately and in a different context. A combination of these factors in a single study, therefore, presents a unique contribution to the study.

Most of the studies have studied a section of it (Liao and Barnes, 2015; Liu and Atuahene-Gima, 2018; Osei et al., 2016; Roper et al., 2017; Wadho and Chaudhry, 2018) and even fewer in developing economies such as Ghana. Furthermore, there is still no evidence that a single study has presented all the above variables in a single study. This study makes a contribution by empirically testing the resource-based view theory of innovation performance in a developing economy in agribusiness context. Ghana, as a developing country is inundated with SME operations forming about 90% of businesses (Abor, 2015; Centre, 2016; Quartey et al., 2017). Therefore, this study contributes to the understanding of factors in their circular economy drive and subsequent innovation performance through circular economy as well as examines the robustness of the RBV to predict innovation performance among Ghanaian agribusinesses.

The study revealed that circular economy is an essential strategy for firms achieving better innovation performance. This means that the relationship between I4.0, SCA and innovation performance is strengthened through circular economy practice. With many researching into circular economy as independent variable, its presentation in this study as a mediating variable unveils its influence on the relationship. Hence, this piece of work adds up to existing knowledge by way of positively validating the effect of circular economy practice on Ghanaian agribusiness innovation performance drive.

5.3.2 Practical Contribution

From a general practice perspective, this study, hopefully, will assist agribusiness and SMEs in general in determining the knowledge factors that are important to influencing a firm's innovation drive geared towards performance. It will help them in formulating innovation strategies as well as assessing circular economy practices that could significantly affect their innovation performance. From a firm level, an awareness of I4.0, SCA, will assist firms in developing appropriate innovation mechanisms that contribute to enhanced innovation performance. A deeper understanding of these antecedents' factors can help firms and regulators to formulate policies and design and create appropriate innovations that have the propensity to higher performance and are environmentally friendly.

Though circular economy appears new in the agribusiness sector in Ghana, meanwhile the aggregation and exploitation of antecedental factors of technology in the sector is novel in Ghana. Owing to this fact, this study presents a new paradigm to Ghanaian firm's innovation performance. To the best of the researcher's knowledge, the study is new research done on the role of circular economy between agribusiness I4.0, SCA and innovation performance in Ghanaian agribusiness setting. Hence, this research provides very useful information to operators and regulators of the small and medium scale enterprises in the agribusiness sector to take into consideration the factors that would impact their circular economy drive and innovation performance.

Also, this study findings would offer support for the NBSSI now GEA management, GIZ other regulatory bodies, and agribusiness operators. GIZ will be able to focus on areas such as technology support, training and engagement to foster circular economy practices, data gathering and processing, continuous improvement through capacity building programmes, which will ensure appropriate utilization of knowledge assets and improved innovation of firm offerings to the market as a competitive advantage for superior firm performance. Firms will be able to acquire the right tools coupled with the required government support to achieve positive firm positioning results depicted in superior performance. Then the manifestation of the relevance of agriculture will be further enhanced. Finally, firms especially SMEs have to acknowledge the relevance of government support through financial and nonfinancial means. They need to maintain the effective adoption and utilization of available technologies and knowledge in accelerating their innovation drive. Government support can be fully utilized through the availability and accessibility of appropriate support mechanisms to further enhance the effectiveness and efficiency of the agribusiness operators.

5.4 Conclusion

The purpose of this study was to investigate the relationship between industry 4.0, supply chain analytics and innovation performance by highlighting the intervening role of circular economy, and the moderating role of green mindfulness between circular economy practice and innovation performance. To achieve this objective, a review of existing literature was conducted, gaps were identified. Based on the gaps identified, a framework of eighth hypotheses was developed. To validate the model, a well-structured questionnaire was designed, piloted and data gathered from

326 senior managers of agribusinesses in Ghana. The hypothesized model was validated by PLS-SEM. Results has been presented and discussed in previous chapter. The study concludes that industry 4.0 and supply chain analytics are important in the quest to improve both circular economy practices and innovation performance. Circular economy does not just support innovation performance but serves an avenue to reap superior innovation performance via industry 4.0 and supply chain analytics. The study also concludes that green mindfulness though may drive innovation performance, it does not necessarily moderate the industry 4.0, supply chain analytics and innovation performance relationship. The GEA and GIZ should continue to undertake more extensive capacity-building programmes to help develop and enhance operators' knowledge resource innovation capabilities. These capacity-building programmes should entail digitization, data acquisition, data integration, and innovation-building capacities. However, apart from the knowledge scope, GEA should endeavour to make the appropriate government support readily available to operators. Therefore, information gathering system or mechanism by operators should be properly put in place and it should also be effective to realize the full benefits. It is also important for GEA which is the supervisory body of the SMEs in the various districts to offer the right governmental support at the right time to support the firms. This will ensure a desirable firm performance in the Agric sector. The model of the study gives a clearer understanding of the core factors that influence innovation performance through firm knowledge-based resources. The outcome of the study also gave insight for practice by identifying individual antecedent factors that contribute to circular economy towards innovation

5.5 Limitation of the Study

As with any research, the present study is not without limitations. Firstly, this was conducted only in Ghana thus the results of this study do not necessarily reflect firm opinions in other countries. Again, it is not clear whether the outcome will have the same effect in another context since it may be possible that the needs and perception of firms in other countries may differ due to different levels of knowledge, and experience related to digitization and innovation context. More so, the factors that measured positive significant influence on innovation performance may prove otherwise in other countries.

Secondly, the outcome of the study dwells on cross-sectional data and it covered the views of the agribusiness operators at a specific period of time. Meanwhile using a cross-sectional strategy limits the study's capability to examine the phenomena over a period of time. However, a longitudinal approach that will transcend into studying operations over a time period in relation to the subject matter, could be used to offer much more insight. This research made use of quantitative techniques in data collection and analyses. The use of a questionnaire offered very valuable information on the subject matter, however, using qualitative data such as interviews could also offer more detailed information on the topic. The research collected data through quantitative means alone which gave very important information to the study, however collecting data from operators through purely qualitative means will also be proper to unravel much broader views on the topic.

5.6 Recommendation for Future Research

The outcome of the study shows that the model of the research truly predicts the role of circular economy and green mindfulness between I4.0, SCA and IP in agribusiness. This research was done among agribusiness firms in Ghana. Since the result cannot be generalized as it may be different for different industries, the researcher recommends that the scope of the study be extended to include other countries since different countries may have different concerns and needs that may influence the study outcomes**.** Again, a comparative study can be conducted across different countries to determine whether the outcome in Ghana can be similar for other countries.

Also, the research was conducted using quantitative methods. Qualitative approach can be used to conduct this same research and to examine the same relationship. In using qualitative method, detailed information could be obtained.

Moreover, future research should consider simulating the research framework in this study in other service and production areas like marketing, health, manufacturing, oil and gas, automobile, non-cold pharmaceutical services, amongst others. This will help confirm the findings of this study and also escalate the external generalizability of this research findings.

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APPENDIX 1: Total Variance Explained

Total Variance Explained

	Initial Eigenvalues			Extraction Sums of Squared Loadings		
Component	Total	% of Variance	Cumulative %	Total	% of Variance	Cumulative %
1	13.853	44.686	44.686	13.853	44.686	44.686
2	3.940	12.709	57.395	3.940	12.709	57.395
3	2.214	7.141	64.536	2.214	7.141	64.536
4	1.607	5.184	69.720	1.607	5.184	69.720
5	1.224	3.948	73.669	1.224	3.948	73.669
6	.800	2.582	76.251			
7	.633	2.041	78.292			
8	.585	1.886	80.179			
9	.520	1.678	81.857			
10	.476	1.535	83.392			
11	.439	1.417	84.808			
12	.409	1.321	86.129			
13	.396	1.278	87.407			
14	.354	1.142	88.549			
15	.331	1.069	89.618			
16	.322	1.039	90.658			
17	.309	.995	91.653			
18	.265	.856	92.509			
19	.262	.845	93.354			
20	.246	.792	94.146			
21	.224	.723	94.870			
22	.219	.708	95.577			
23	.197	.635	96.212			
24	.188	.606	96.818			
25	.186	.600	97.417			
26	.168	.541	97.958			
27	.155	.499	98.457			
28	.146	.471	98.928			
29	.133	.430	99.359			
30	.116	.373	99.731			
31	.083	.269	100.000			

Extraction Method: Principal Component Analysis.

APPENDIX 1I: Survey Instrument