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Effects of Data Analytics on Business Model Innovation: The Mediating Role of Knowledge Acquisition

By

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(B-Tech Procurement Management)

A thesis submitted to the Department of Supply Chain and Information Systems, Kwame Nkrumah University of Science and Technology, Kumasi, in partial fulfillment of the requirements for the award of the degree of

MASTER OF SCIENCE IN LOGISTICS AND SUPPLY CHAIN MANAGEMENT

AUGUST, 2023

DECLARATION

I hereby declare that this thesis is my own work towards a partial fulfillment of the requirements for the award of Master of Science in Procurement and Supply Chain Management. To the best of my knowledge, this is solely my genuine work and has not been submitted anywhere else by anyone for a degree or any academic purpose; and that all materials of other authors used in this study have been accordingly acknowledged and cited.

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DEDICATION

I dedicate this dissertation to my parents Apostle Frederick Owusu Afari and Ama Abrafi Amo. An expression of gratitude to them since they became the source of motivation and encouragement to even enroll me for this MSc program. God bless abundantly.

Moreover, a special expression of gratitude to a loving Wife, Janet Frimpong and children for their support in diverse ways through this journey to build my educational life. May your rewards from God be exceedingly great.

Finally, I dedicate this dissertation to my friends and siblings especially to Rev. Alfred Owusu, Rev. Emmanuel Adu Boateng, Ing. Emmanuel Osikani Agyapong, Samuella Enyan Afari, Janise Adom Enyan, Mr. Francis Kwamewor Tetteh and to the whole church family of New Generation International Christian Centre who have supported me throughout the process. All of you have been my best cheerers.

ACKNOWLEDGEMENTS

Glory be to God for the great things He has done. I express my earnest thankfulness to Him for His grace, mercies and inspiration that has brought me this far.

My earnest thanks go to Dr. Kofi Boateng Agyenim, my supervisor. I acknowledge his forbearance, calmness and endurance, his advice, directions, immense support, availability and constructive criticisms in the process of this study.

My appreciation also goes to all Management, lecturers, teaching and non-teaching staffs of KNUST and the Department of Supply Chain and Information System for their advice, suggestions and mentorship throughout the entire project, especially Dr. Kofi Boateng Agyenim, you are a true mentor and your leadership is outstanding. God bless you.

I am also very appreciative to the SMEs in Eastern Region. You made data collection easier for me, and you portrayed friendly environment that enhanced this research study. I sincerely acknowledge the support, generosity and love accorded me that made the study a success.

My heartfelt gratitude also goes to Mr. Francis Kwamewor Tetteh and Mr. Adu Boateng Emmanuel for their enormous care and expert guidance in the course of this study. You made it work! God bless you my brothers.

Finally, my profound gratitude to all who contributed in diverse ways for the success of this study, may God richly bless you.

ABSTRACT

The study's goal was to examine the mediating function of knowledge acquisition between data analytics and business model innovation in SMEs in developing economies. Quantitative data was gathered using cross-sectional surveys with a view toward inference and analyzed using inductive logic. The study focused on small and medium-sized enterprises (SMEs) in the Eastern Region of Ghana, whether they were engaged in manufacturing or providing services. By using a purposive sampling technique, data was collected from 384 knowledgeable employees on the study's major topics. The study proved the hypotheses by using SEM (SmartPLS 4). The data was summarized using descriptive statistics. The findings revealed that data analytics capability has a positive and significant effect on business model innovation among SMEs. Knowledge acquisition was shown to have a significant influence on business model innovation, and it was also found to mediate the relationship between data analytics capabilities and business model innovation. Therefore, this suggests that business model innovation in SMEs should benefit from managers' greater openness to acquiring data analytics knowledge and skills.

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CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Small and Medium Scale Enterprises (SMEs) play a pivotal role in bolstering the socio-economic development of numerous nations. The significance of these businesses in the progress of developing nations cannot be overstated (Azumah et al., 2021). Despite the invaluable contribution that SMEs make to national development, they grapple with a multitude of challenges. In the midst of these challenges that SMEs encounter, there is a progressive expansion of consumer needs beyond mere product quality to encompass factors such as sustainability, competitive pricing, and value for money (Tell et al., 2016). Consequently, there arises a compelling need to minimize wastage within the production system and to manufacture products that align with consumer demands. This imperative becomes integral in embracing substantial transformations along the path to enhancing operational efficacy (Dania et al., 2018).

The pivotal role of SMEs in fostering socio-economic advancement is widely acknowledged. As Azumah et al. (2021) underline, these enterprises constitute a fundamental pillar of national development in various countries. Their contribution goes beyond mere economic gains; they often serve as engines of innovation, employment generation, and poverty reduction, thus significantly impacting the overall fabric of society. Despite their pivotal role, SMEs face an array of challenges that hinder their growth and potential. These challenges span financial constraints, inadequate infrastructure, regulatory burdens, and limited access to markets. The existence of these hurdles underscores the complexity of the operating environment in which SMEs operate.

A remarkable shift is discernible in consumer expectations and preferences, as highlighted by Tell et al. (2016). Traditionally, consumers primarily focused on product quality. However, the contemporary consumer landscape is marked by a discerning clientele that demands more than just a quality product. Elements such as sustainable production practices, reasonable pricing, and demonstrable value for money have become paramount. This transition necessitates a paradigm shift within SMEs' operational paradigms. The imperative to realign production processes to not only meet stringent quality standards but also to integrate sustainability principles and cost efficiency becomes evident.

The drive towards minimizing waste along the production continuum gains heightened significance. As Dania et al. (2018) emphasize, this endeavor assumes critical importance in the journey towards augmenting operational proficiency. Efficient resource utilization and waste reduction are not only environmentally responsible but also make considerable economic sense. Embracing sustainable practices not only aligns SMEs with evolving consumer preferences but also fosters long-term viability and resilience. The indispensable role that SMEs play in shaping the socio-economic landscape of developing nations is undeniable. While their contributions are vast and varied, they grapple with a myriad of challenges that impede their progress. The changing consumer landscape further underscores the need for SMEs to adapt their operations to incorporate sustainability and value-centric paradigms. This entails the minimization of waste and the production of goods that resonate with the discerning consumer. As research by Azumah et al. (2021), Tell et al. (2016), and Dania et al. (2018) suggests, addressing these imperatives is pivotal for the holistic advancement of SMEs and, consequently, the development of nations.

Small and Medium Scale Enterprises (SMEs) encounter a multitude of challenges, including operational and financial constraints, as highlighted by Hessel and Parker (2013) and Clegg (2018).

These challenges have direct and indirect repercussions on the overall operational performance of these firms. The global outbreak of the Covid-19 pandemic dealt a severe blow to sustainable development endeavors worldwide, impacting economic sectors, organizations, and industries across the board. Among those significantly affected were Ghana's small and medium-scale enterprises. Even prior to the pandemic, SMEs in Ghana were grappling with challenges. In order to retain a competitive edge and preserve their competitiveness in the eyes of consumers, managers are compelled to acknowledge the pivotal role of business model innovation (BMI). It is noteworthy that the pandemic's aftermath has spurred managers' interest in innovating their existing business models. Consequently, BMI has gained remarkable prominence in management literature as a fundamental catalyst for securing competitive advantage and ensuring business continuity. This is substantiated by the works of Bocken and Geradts (2020), Vaska et al. (2021), Breier et al. (2021), Haaker et al. (2021), Mostaghel et al. (2022), and Clauss et al. (2022). At its core, BMI signifies a firm's ability to revolutionize its mechanisms for value creation, delivery, and capture, thereby enticing customers to invest in value and convert it into profitable outcomes, as articulated by Teece (2010).

The challenges faced by SMEs encompass a spectrum of issues, ranging from operational intricacies to financial limitations, as evidenced in the research of Hessel and Parker (2013) and Clegg (2018). These challenges inevitably reverberate across various dimensions of operational performance, casting a shadow on the growth trajectory of these enterprises. The advent of the Covid-19 pandemic cast a wide net of disruption across global sustainable development endeavors, cascading its impact across sectors, organizations, and industries, including the delicate fabric of Ghana's small and medium-scale business landscape. Even prior to the pandemic-induced turmoil, SMEs in Ghana were grappling with a host of obstacles, underscoring the complex landscape within which they operate. In the relentless pursuit of maintaining a competitive stance and meeting the evolving demands of consumers, managers are confronted with the undeniable significance of business model innovation (BMI). Remarkably, the aftermath of the pandemic has acted as a catalyst, galvanizing managerial interest in reimagining and rejuvenating their prevailing business models. As echoed by Bocken and Geradts (2020), Vaska et al. (2021), Breier et al. (2021), Haaker et al. (2021), Mostaghel et al. (2022), and Clauss et al. (2022), BMI has emerged as a linchpin in contemporary management discourse, wielding the potential to drive competitive advantages and fortify business resilience. BMI, as conceptualized by Teece (2010), encapsulates the crux of firms' adaptability and innovation prowess. It encapsulates the strategic capability of enterprises to revamp their strategies for value creation, delivery mechanisms, and value capture, thereby orchestrating an environment wherein customers recognize and invest in the delivered value, ultimately translating into sustainable profits. The growing acknowledgment of BMI's transformative power underscores its pivotal role in not only navigating challenges but also in steering SMEs toward a trajectory of renewed growth and prominence.

Previous research has contended that the notion of Business Model Innovation (BMI) has predominantly been associated with the initiatives of larger enterprises, focusing on the creation of novel customer offerings and revenue channels, as evidenced by the works of Wirtz et al. (2016) and Massa et al. (2017). However, it is noteworthy that Small and Medium Scale Enterprises (SMEs) often grapple with a lack of diversification and tend to rely heavily on a singular business model archetype, as highlighted by Pal et al. (2012) and Mostaghel et al. (2022). This is particularly relevant in the context of developing economies, where a proliferation of small-scale businesses is a prominent characteristic, as underscored by Avazov and Maxmudov (2020). It is crucial to acknowledge that the pursuit of innovative business models is inherently intricate and outcomes may not always align with initial expectations. Given this intricacy, managers exercise caution in navigating the terrain of business model innovation. While various strategies have been proposed to catalyze the process of business model innovation, the realm of data analytics capabilities as a catalyst for such innovation among SMEs, especially within the specific context of developing economies like Ghana, remains an underexplored domain. Historically, scholarly discourse has predominantly positioned Business Model Innovation (BMI) within the ambit of larger corporations, where its manifestation revolves around the generation of fresh customer propositions and novel revenue streams.

Again, Peter et al. (2020) have argued that technology remains an important tool for achieving the business objective, and the persuasive effects of technology have radically reshaped many industries. Technology or digitization has to do with how emerging digital technologies including analytics, cloud, mobile, and social media play an essential role in modifying existing business processes (Arias-Perez et al., 2021). In the presence of these many technologies, Deloitte (2021) have identified BDA as among the top three (3) most prioritized investment for enhancing customer value and revenue stream. Gurumurtty et al. (2020) opine that BDA alone contributes between 15-23% of customer and revenue value within the early stage of adoption and increases between 41-45% at the maturity stage of adoption. It is therefore expected that the greatest impact of BDA in firms lies in greater exploitation of new knowledge which can help to restructure existing business processes (Dahiya et al., 2021, Urbinati et al., 2019). While data analytics capability represents the ability of firms to capture and analyze data in the effort to generate novel knowledge or insight via efficient use of its data, technology, and talent, its usage in small businesses remains low (Henae-Garcia et al., 2021).

1.2 Problem statement

In the aftermath of the COVID-19 pandemic, small and medium-sized enterprises (SMEs) are increasingly recognizing the imperative of effectively managing both their internal and external data. This recognition stems from the remarkable surge in the significance of data, compelling

SMEs to leverage it in order to capitalize on emerging opportunities and sustain their competitive edge (Shan et al., 2019; Ciampi et al., 2021). As underscored by BD, this trend is anticipated to shape the forthcoming landscape of innovation, competition, and productivity, marking a pivotal shift in the business landscape (Manyika et al., 2011). Notably, the realm of innovation driven by data presents substantial potential for firms to leverage customer-generated big data (BD) as a means to instigate user-centered and user-driven innovation. This is notably exemplified through practices where customer-generated BD is harnessed, such as elucidated by Trabucchi et al. (2018). In this context, a pertinent application of customer analytics is witnessed, involving the meticulous exploration of users' behaviors, evaluations, and requirements, with the ultimate aim of refining the creation of novel offerings tailored to align with their demands (Hooi et al., 2018). It is worth acknowledging that the ongoing digitization wave has been proven to lay the groundwork for Business Model Innovation (BMI) (Ghosh and Stieber, 2021). However, the precise mechanisms through which SMEs can harness data analytics to catalyze Business Model Innovation remain inadequately understood, resulting in a substantial gap in existing knowledge that necessitates comprehensive exploration. Hence, this study undertakes the task of investigating the intricate nexus between Data Analytics and Business Model Innovation within the context of SMEs operating in Ghana.

In a bid to address this burgeoning knowledge gap, the study delves into the ramifications of Data Analytics on the catalysis of Business Model Innovation in the SME landscape of Ghana. By disentangling the intricate interplay between these two dimensions, the research endeavors to provide critical insights into how SMEs can harness data analytics as a catalyst for Business Model Innovation. Through empirical examination, the study aims to unearth the multifaceted ways in which SMEs can leverage data-driven approaches to transform and enhance their business models, ultimately contributing to their sustainable growth and competitiveness in the dynamic postCOVID era.

In summary, the post-COVID era has ushered in a heightened awareness among SMEs regarding the pivotal role of data management in fostering innovation and maintaining competitive advantage. This is substantiated by the surge in the significance of data as a driver of innovation and productivity, as underscored by BD. The utilization of customer-generated big data for usercentric innovation further accentuates the potential of data-driven transformation. Although prior research has acknowledged the correlation between digitization and Business Model Innovation, the specific mechanisms through which SMEs can leverage data analytics for BMI remain unexplored. Thus, this study emerges as a critical endeavor to bridge this knowledge gap by examining the impact of Data Analytics on Business Model Innovation within the SME landscape of Ghana.

Despite several benefits of SMEs in Ghana's economy, the performance of firms in the domestic supply chain among SMEs in sub-Saharan Africa, especially, Ghana has been facing a myriad of impediments mainly due to a lack of capacity to timely innovate their business model resulting in slow growth or performance in this industry (Memia, 2018). Data Analytics is an important phenomenon that firms and organizations cannot do away with. In Ghana, SMEs seem to implement few of the SCMPs such as outsourcing, information technology systems and lean practices (Almutairi & Riddle, 2018; Cooper, 2017; Shale, 2015) leaving out other contemporary SCMPs like Data Analytics (Marshal, 2015; Zhu et al., 2016; Das, 2018) which may add value and improve operational performance and enhance the productivity of SMEs, little attention have been paid to this practices by professionals and academicians.

Data Analytics (DA) embodies the capability of transforming raw data into actionable insights (Kwon et al., 2014). It pertains to a company's adeptness in employing technological tools and expertise to harness vast pools of big data, thereby furnishing the strategic insights essential for surpassing competitors (Mikalef et al., 2017). Nonetheless, the existing body of empirical research concerning the intricate interrelation between Data Analytics (DA) and Business Model Innovation (BMI) remains notably constrained (Ransbotham and Kiron, 2017). Within the contemporary landscape characterized by economic volatility, the notion of a static Business Model (BM) is rendered obsolete, as sustained competitiveness necessitates a perpetual cycle of BM reassessment, redesign, and evolution (Marolt et al., 2016; Pucihar et al., 2019; Nunes and Russo, 2019). Consequently, a compelling imperative exists to deepen our understanding of the driving forces that facilitate Business Model Innovation.

Amid the contemporary business landscape, the transformative potential of Data Analytics (DA) is palpable. This phenomenon involves the proficient utilization of data manipulation techniques to distill meaningful insights from vast and complex datasets. As underscored by Kwon et al. (2014), this process represents a pivotal bridge between raw data and informed decision-making, thereby furnishing organizations with a competitive edge in a data-driven environment. Mikalef et al. (2017) further illuminate the strategic dimension of DA, portraying it as a potent tool that empowers companies to tap into the reservoir of big data and extract actionable intelligence. This, in turn, equips organizations with the critical foresight needed to not only respond to market dynamics but to also strategically position themselves ahead of competitors.

Despite the undeniable potential of Data Analytics, the intersection of DA with Business Model Innovation (BMI) remains shrouded in limited empirical exploration (Ransbotham and Kiron, 2017). The symbiotic relationship between these two constructs is both complex and multifaceted. In the current era marked by economic turbulence and rapid technological advancements, the notion of a stagnant Business Model has become obsolete. As elucidated by Marolt et al. (2016), Pucihar et al. (2019), and Nunes and Russo (2019), the ability to consistently adapt and revamp the Business Model emerges as an indispensable requisite for survival and success. This imperative stems from the understanding that a dynamic, flexible BM has the potential to be a source of competitive advantage, facilitating the exploitation of emerging opportunities while navigating evolving challenges.

Existing research has primarily focused on defining the BM (Osterwalder et al., 2005; Teece, 2010; Zott and Amit, 2008) and BMI concepts (Carayannis et al., 2015; Foss and Saebi, 2017), antecedents and barriers to BMI (Hartmann et al., 2013; Amit and Zott, 2001), internal and external factors of BMI success (Hartmann et al., 2013; Teece, 2010), BMI activities in start-up businesses (De Reuver et al., 2009; Zhang et al., 2017), the impact of information technology on BMI (Lee et al., 2019; Pucihar et al., 2019; Nunes and Russo, 2019; Bouwman et al., 2019; Gil-Gomez et al., 2020; Szopinski et al., 2020; Hock-Doepgen et al., 2021).

In recent years, numerous studies have examined the multifaceted factors influencing Body Mass Index (BMI). While existing research has highlighted the need for more comprehensive investigations into these factors (Chesbrough and Rosenbloom, 2002; George and Bock, 2011; Zott and Amit, 2007), there has been a noticeable lack of attention directed towards understanding the impact of Data Analytics (DA) on BMI. This apparent gap in the literature underscores the motivation behind this study's endeavor to bridge the relationship between Data Analytics and BMI.

Moreover, the realm of innovation management has yet to explore the empirical implications of data analytics capacity and capabilities on BMI (Ciampi et al., 2021; Ransbotham & Kiron, 2017). This research aims to address this gap by drawing on existing evidence suggesting that the deployment of data analytics capabilities can yield significant enhancements in value creation (Elia, Polimeno, Solazzo, & Passiante, 2019). Leveraging the framework of Dynamic Capabilities

View (DCV), the study aims to investigate the potential positive influence of Data Analytics Capabilities (DAC) on business model innovation, given that DAC itself qualifies as a dynamic capability (Fosso Wamba et al., 2017).

Furthermore, Saiedi et al. (2017) argue against oversimplifying relationships between dependent and independent variables. They stress that other influential factors often shape these relationships, acting as either mediators or moderators. To address this complexity and pave the way for enduring solutions to BMI-related issues, the study proposes the development of a comprehensive model, including at least a trivariate relationship model. Specifically, the study delves into the mediating role of Knowledge Acquisition (KA) in the link between Data Analytics and BMI, aligning with the Dual-Capacity Theory (DCT). Drawing from this theory, the significance of knowledge acquisition in Small and Medium-sized Enterprises (SMEs) is emphasized, a realm that has been underexplored but holds immense importance in understanding performance within the context of manufacturing SMEs. Given that the success of firms is intrinsically tied to their ability to cultivate innovative business models (Donkor et al., 2018; Osei et al., 2016), this research seeks to shed light on the intricate interplay of factors that contribute to BMI and, by extension, organizational performance. By employing a comprehensive approach and drawing from established theoretical frameworks, the study endeavors to provide a nuanced understanding of how Data Analytics, Knowledge Acquisition, and Business Model Innovation interact within the context of SMEs in the manufacturing sector. In the context of Ghana's Small and Medium-sized Enterprises (SMEs), there is a recognized emphasis on the continuous pursuit of knowledge as a means to foster innovation and enhance competitiveness (Rajapathirana & Hui, 2018b). Despite this expectation, SMEs in Ghana have faced challenges in achieving the desired levels of innovation, as highlighted by the Government of Ghana's report in 2016 (GoG, 2016). While various efforts have been made to address this issue, it remains uncertain whether Knowledge Acquisition (KA) can effectively contribute to improve Business Model Innovation (BMI) through the utilization of Data Analytics (DA) (Osei et al., 2016).

Given the context of a developing nation like Ghana, there exists a significant need to comprehend the intricate interplay of these concepts. This study seeks to investigate the indirect effects of knowledge acquisition, specifically directed toward fostering Business Model (BM) innovation and enhancing overall organizational performance. The current gaps in the literature suggest a notable absence of a comprehensive and integrated model that adequately addresses the complex relationship between Data Analytics, Knowledge Acquisition, and Business Model Innovation. This gap in understanding presents a unique opportunity for this study to delve into the intricate dynamics of how Data Analytics influences Business Model Innovation, with Knowledge Acquisition acting as a mediating factor, within the specific context of SMEs in Ghana.

Through the lens of this research, it is evident that the relationship between Data Analytics and Business Model Innovation, mediated by Knowledge Acquisition, remains relatively unexplored and constrained. By focusing on this uncharted territory, the study aspires to make a significant contribution to the existing knowledge base. By shedding light on how these factors interact and impact SMEs in Ghana, this research could not only enhance our understanding of the dynamics involved but also provide valuable insights that could potentially aid policy-making and managerial strategies aimed at fostering innovation and competitiveness within the Ghanaian SME landscape.

1.3 Research Questions

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

1. What is the relationship between data analytics and business model innovation among SMEs?
2. Does data analytics Influence knowledge acquisition among SMEs?

3. What is the mediating role of knowledge acquisition in the relationship between data analytics and business model innovation among SMEs?

1.4 Objective of the Study

This study was conducted to examine the nexus between data analytics and business model innovation among SMEs in developing economies; the mediating role of knowledge acquisition. To achieve the purpose of the study, the research envisages;

1. To examine the relationship between data analytics and business model innovation among SMEs.
2. To assess the relationship between data analytics and knowledge acquisition among SMEs.
3. To examine the mediating role of knowledge acquisition in the relationship between data analytics and business model innovation among SMEs.

1.5 Scope of the Study

The study investigates the influence of DA on BMI among SMEs in Ghana, mediated by knowledge acquisition. Although there are several dimensions of SCMPs, this study focuses on DA, which has not been adequately explored. Also, reviewed literature identified that DA has not yet been tested within the SME setting. The study employed the Dynamic Capability Theory (DCT) and Relational View Theory from which the variables of the study are drawn.

1.6 Significance of the study

This study offers multiple contributions. Notwithstanding the numerous researches on SCMPs, the roles of DA and BMI are uncertain. Therefore, the researcher contends that, when the DA is well managed by infusing the above-mentioned SCMPs, they may need comparable development on KA to influence BMI. The study will also improve the knowledge on KA serving as a mediator in the relationship between DA and BMI. Thus, the study will test the mediation effect of KA in line with Pati et al. (2016), which ascertain that the role of examine the mediation effect has been ignored in the previous research. The study will also extend the knowledge of the model by introducing a mediating variable of KA to make another valuable contribution to the literature. This expunction and operationalizing of the model will add to the existing body of knowledge on SCM and subsequently benefit the academic community.

The study will also contribute to theory building in SCMPs by investigating the relevance of Dynamic Capability Theory (DCT) and Relational View Theory (RVT) in describing the effects of DA on BMI. Past studies investigated Resource Base View (RBV) (Veera et al., 2016; Bagheri et al., 2014), in explaining the relationship between DA and BMI. Incorporating DCT and RVT in this study is a considerable contribution to literature in the area of supply chain management field. These theories will be applied to explain the interrelationship between DA, KA and BMI.

1.7 Organization of Research Study

The study is structured into five primary chapters, with the first five chapters carrying the most significance. The initial chapter introduces the study, encompassing its background, identification of the problem, formulation of research questions, establishment of study objectives, delineation of the study's importance, clarification of its scope and limitations, and a preview of the forthcoming chapters. The second chapter, titled "Chapter Two," is dedicated to an exhaustive examination of the existing body of literature relevant to the subject under investigation. Furthermore, the third chapter delves deeply into the study's methodology, encompassing the research design, data origin and collection methods, the tool employed for data collection, and the analytical mechanisms employed. Subsequently, the analysis of the collected data and the ensuing discourse of the findings will be expounded upon in the fourth chapter. Lastly, the fifth chapter will encapsulate a summary of the key discoveries, concluding remarks, and recommendations that merit consideration.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

The second chapter of this thesis is structured into four primary subsections. Within this chapter, information is presented and categorized into distinct sections: conceptual review, theoretical review, empirical review, and the development of the research model and hypotheses. In the conceptual review section, there is a presentation of definitions, operationalizations, and an exploration of how the constructs have been employed in this particular study. Similarly, the theoretical review section elaborates on the theoretical foundations upon which this study is built. This chapter further encompasses the depiction of proposed hypotheses through a conceptual framework, outlining various relationships that have been extensively discussed. The chapter concludes with a summary that not only encapsulates the discussed content but also emphasizes the gaps that this study seeks to address.

2.2 Conceptual Review

2.2.1 Data Analytics Capability (DAC)

Data analytics capabilities involve integrating substantial data sets into the decision-making processes of an organization (Rialti et al., 2019). This encompassing approach not only encompasses the technical infrastructure for managing big data but also encompasses the human skills and knowledge required to adeptly embrace, adopt, and implement insights extracted from data-driven practices (Van De Wetering et al., 2019). Within the sphere of supply chain management, strategies employing data analytics are a pivotal realm of advancement, particularly in light of the contemporary complexity of supply chains, which grapple with copious volumes of diverse data types pertaining to a firm's operations (Trkman et al., 2010).

The extensive integration of supply chain analytics (SCA) remains relatively pioneering within the domain of procurement and supply chain practices (Chae et al., 2014a). This development aligns with the pressing demand to handle the immense influx of data facilitated by the proliferation of digital technologies within supply chains (Kwon et al., 2016). The generation of vast data volumes within supply chains emanates from multifarious sources and applications across transactions and operations, a trend that is consistently expanding (Holsapple et al., 2014; O'Dwyer and Renner, 2011). This surge is exemplified by the advent of sensor data and Internet of Things (IoT) solutions, ushering novel prospects within conventional supply chain operations (Opresnik and Taisch, 2015; Wang et al., 2016; Tortorella et al., 2019). Especially noteworthy is the enhancement in customer operations' visibility attributed to these technologies, facilitating the anticipation of customer needs (Holmström et al., 2010; Parry et al., 2016). Furthermore, the expanded availability of diverse data forms has engendered a necessity to explore the potential of big data analytics and IoT within the contours of supply chain dynamics (Aryal et al., 2018).

2.2.2 Business Model Innovation (BMI)

The precise definition of Business Model (BM) remains a subject of ongoing debate and divergence among both scholars and practitioners (George and Bock, 2011; Zott et al., 2011). Various researchers have presented distinct interpretations of BM, tailored to suit their specific research agendas (Table I). These divergent definitions reflect a multitude of perspectives, often with limited interconnection to other scholarly works (Amit and Zott, 2001; Baden-Fuller and Morgan, 2010; Casadesus-Masanell and Ricart, 2010; Chesbrough and Rosenbloom, 2002; Demil and Lecocq, 2010; Johnson et al., 2008; Morris et al., 2005; Seelos and Mair, 2007; Stewart and Zhao, 2000; Teece, 2010; Williamson, 2010).

In this specific study, the conceptualization of Business Model Innovation (BMI) is grounded in the foundational work of Hartmann et al. (2013a). Their perspective posits that BMI arises from the alteration or introduction of critical components that businesses employ to conceive, distribute, and capture value. This definition draws inspiration from an activity-based viewpoint, building upon prior explorations in the field of BMs (Zott and Amit, 2010). Additionally, it takes cues from endeavors aimed at dissecting and identifying the diverse constituents of BMs (Amit and Zott, 2001; Chesbrough and Rosenbloom, 2002; Margetta, 2002; Osterwalder et al., 2005). Further research also characterizes BM by its constituents concerning the generation, conveyance, and appropriation of value (Johnson et al., 2008; Massa and Tucci, 2013).

By integrating these perspectives and aligning with the literature on BM conceptualizations, this study establishes a foundation for understanding and investigating the intricacies of Business Model Innovation. The amalgamation of these conceptual threads facilitates a holistic comprehension of how changes in key components drive innovation in the way businesses generate, deliver, and capture value.

Amidst a landscape characterized by rapid technological shifts, evolving customer preferences, and emerging regulatory frameworks, scholarly investigations have underscored the escalating recognition of Business Model Innovation (BMI) as a pivotal wellspring of competitive advantage for businesses (Chesbrough, 2010; Sako, 2012; Teece, 2007, 2010; Zott et al., 2011; Bashir and Verma, 2016). However, antecedent research indicates that the pursuit of BMI necessitates substantial experimentation (McGrath, 2010; Smith et al., 2010) and, in certain instances, can entail intricacies and risks (Chesbrough, 2010; Im and Cho, 2013; Sosna et al., 2010). Furthermore, the heterogeneity of research outcomes underscores the demand for further investigation (Goyal et al., 2017).

A Business Model (BM) encapsulates the elucidation of a company's business rationale, detailing how it conceives, delivers, and accrues value (Osterwalder et al., 2005; Osterwalder and Pigneur, 2010). Within this purview, establishing a lucid understanding of the enterprise's BM emerges as an imperative managerial action. This endeavor necessitates a multifaceted approach, encompassing comprehension of consumer requisites and expectations, optimization of value delivery mechanisms, and synergistic collaboration with key partners to foster maximal mutual benefit (Rachinger et al., 2019).

The notion of Business Model (BM) signifies an orchestrated process wherein foundational constituents of an enterprise and its underlying business rationale undergo deliberate transformation, facilitating both operational and strategic advancements (Haaker et al., 2021). Similarly, Business Model Innovation (BMI) characterizes a purposeful course of action in which core elements of an enterprise and its inherent business logic are systematically reconfigured, with the overarching aim of attaining operational and strategic progress (Haaker et al., 2021; Foss and Saebi et al., 2018).

In previous research, it has been contended that there exist various catalysts driving businesses to overhaul their business models. Enterprises find themselves compelled to adapt due to evolving demands and shifts within their business ecosystem. Pressures stemming from escalating costs, the potential rise of economical alternatives, and the persistent pursuit of differentiation exemplify some of these triggers (Carayannis et al., 2015).

2.2.3 Knowledge Acquisition

Given that firms thrive on gathering information or knowledge, the role of knowledge acquisition has become the foundation on which organizations survive (Liao & Barnes, 2015). Many scholars have researched Knowledge acquisition and the role it plays (Bojica & Fuentes-fuentes, 2019; Johnson, 2017; Ramanathan et al., 2017). Hence, definitions of Knowledge acquisition as the mechanisms by which institutional players acquire knowledge fromtheir counterparts and are informed by it (Bojica & Fuentes- Fuentes, 2019). Out of the many articles from 2011 to 2020, just a few articles were related to knowledge acquisition antecedents. However, customer knowledge (6) and experience were often studied which results were more significant in the studies among others. This study will adopt customer knowledge and competitor knowledge and present it as market knowledge as part of the antecedent variables. In today's competitive marketplace, the utilization of customer and competitor awareness has advanced growth operations and progressively turn out to be a critical topic (Taghizadeh et al., 2018). Businesses might use such interaction mechanisms to implement innovative initiatives to ensure their long-term viability. Previous works in knowledge acquisition revealed customer knowledge as a frequently used variable which has proven significant results (Fidel, Schlesinger, & Cervera, 2015; Hoe, 2008; Johansson, Raddats, & Witell, 2019). For example, the result of the studies of Johansson et al., (2019), established a significant interaction between customer knowledge and firm performance. Hence the researcher, examining customer knowledge and competitor knowledge presented to be known as market knowledge, is seen as antecedents of knowledge acquisition. Having said that, Experience (4) and Prior knowledge available (2) has been known in the literature as very important factors in knowledge acquisition measures (Hailikari, et al., 2008; Shane, 2000). In recent studies of knowledge acquisition towards product innovation, experience, and prior knowledge have become a critical foundational factor for scholars (Pazzani et al., 1989; Rao & Monroe, 1988). Cowling, Liu, & Zhang, (2018) and Fatoki, (2014), found the inadequacies of experience in SME knowledge acquisitions. However, Evangelista & Mac, (2016) findings suggested that deliberate learning has a stronger effect on export learning than experience gathering these findings are surfacing inconsistent, calling for more investigations into experience and prior knowledge as a variable. Nevertheless, it's important to remember that corporations aren't operating alone in the market in this regard, but rather are attempting to leverage a range of sources of knowledge, including prior experience, knowledge from consumers and competitors, and technological and environmental knowledge. As a result of the preceding discussion, knowledge reasoning is comparable to knowing something and being able to think through it under different contexts.

2.3 Theoretical Review

2.3.1 Dynamic Capabilities Theory (DCT)

Teece and Pisano (1994) propose that the underpinning factors driving the development of Dynamic Capabilities (DCs) within organizations can be categorized into three core disciplines: operations, pathways, and locales. Operations denote the practical and regulatory methods employed for the execution of organizational functions. On the contrary, pathways encompass the pivotal choices available to organizations, as well as predictions of incentives and favorable circumstances. The concept of Dynamic Capabilities delves into the strategies organizations employ to connect, structure, and enhance their internal and external processes and proficiencies, ultimately effecting changes that confer a competitive advantage over rivals (Kim et al., 2012). In the realm of Dynamic Capabilities Theory (DCT), capability signifies an organization's intrinsic ability to effectively select, apply, and comprehend both internal and external resources or knowledge, thereby augmenting overall supply chain activities (Wu, 2006). The perspective of organizational Dynamic Capabilities asserts that distinctive resources possessed by organizations are pivotal in attributing meaning to variations in their performance (Barney, 1991), a category that encompasses competencies like the Big Data Analytics Capability (Wamba et al., 2020). An organization is considered to possess a capability when it undertakes a task with a fundamental proficiency, irrespective of the accuracy of the execution (Helfat et al., 2007). Notably, an organization need not be obligated to actively deploy a particular competence to be considered in possession of it.

Nevertheless, on an average basis, organizations are compelled to utilize their competencies in order to retain and harness their talents. Invariably, there exists an assumption akin to "use it or lose it" concerning an organization's proficiency (Helfat and Peteraf, 2009). Within this context, Helfat et al. (2007) assert that dynamic capability embodies "the capacity of a business to deliberately create, extend, and modify its reservoir of assets, comprising its inherent, personnel, and corporate resources" (Eisenhardt and Martin, 2000). Given the constantly shifting landscape, business capabilities must be consistently adapted. The efficacy of private enterprises in meeting consumer demands hinges on their ability to cultivate novel capabilities that optimize sustainable long-term performance. Drawing inspiration from the resource-based view (RBV), dynamic capabilities, as delineated by Teece et al. (1997), encapsulate the aptitude to amalgamate, fabricate, and reconfigure internal and external proficiencies to effectively navigate rapidly evolving contexts.

While the RBV primarily concentrates on the identification and selection of resources, the dynamic capability perspective underscores the deployment of resources and the construction of capabilities to effectively respond to transformations (Hitt et al., 2016). Private businesses are akin to intricate constructs, as exemplified by Beske (2012) who spearheaded the integration of dynamic capability within their operational framework, contending that dynamic capability signifies the coveted capacity of intricate systems to manage environmental shifts alongside intricate internal interactions. The Dynamic Capability View (DCV) emerges as an extensible theoretical facet of the Resource-Based View (RBV), elucidating how businesses manage to preserve competitiveness within an erratic business milieu across time (Ambrosini and Bowman, 2009; Maijanen, 2020; Ciampi et al., 2021).

Derived from the Resource-Based View (RBV) standpoint, the triumph of any enterprise hinges upon the accessibility and skillful orchestration of valuable, distinctive, non-reproducible, and irreplaceable assets. These assets enable the adoption of strategies that foster value creation, thereby yielding returns (Barney, 1991). Prolonged competitive advantages are attainable when businesses secure and regulate strategic resources, consequently fostering proprietary competencies intrinsically tied to the nature of resources amassed (Makadok, 2001). However, recent scholarship underscores the limitations of RBV's static approach in comprehending how firms wield their resources and capabilities within the dynamics of ever-changing markets. This limitation paves the way for the wider integration of the Dynamic Capability View (DCV) (Priem and Butler, 2001).

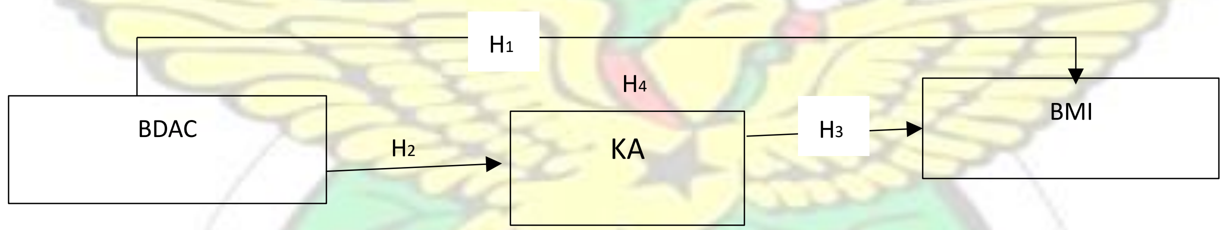
The essence of DC, as characterized by Teece et al. (1997, p. 516), resides in an organization's capacity to integrate, expand, and reconfigure both internal and external competencies to adeptly navigate swiftly evolving environments. DCs empower enterprises to cultivate distinctive organizational routines and strategic skills pivotal to their sustained prosperity and the forging of novel market landscapes (Fornell and Larcker, 1981). Prescott (2014) asserts that an organization's competitive edge is imperiled when it neglects to adapt its tangible and intangible resources to the ever-evolving external landscape, which can otherwise hasten their transformation into entrenched inflexibilities. With an incremental developmental trajectory, DCs can exert a significant influence on an enterprise's performance (Makkonen et al., 2014).

Within this context, the Dynamic Capability View emerges as a pertinent conceptual framework for exploring the potential of Data Analytics Capability (DAC) in facilitating Business Model Innovation (BMI), alongside examining the intermediary role of Knowledge Absorption (KA). The adoption of the Dynamic Capability View as the theoretical lens finds validation in existing management literature that has explored these constructs under the purview of Dynamic

Capabilities Theory (DCT) (Mikalef et al., 2017; Jiang et al., 2018; Khodaei and Ortt, 2019; Maijanen, 2020; Ciampi et al., 2021). Spearheaded by these preceding inquiries, this study posits that DAC embodies a pivotal competency that, when adroitly harnessed, could provide critical decision support for the overhaul of outdated business models, aligning them with the exigencies of the contemporary market. Anchored in the dynamic capability perspective, the research model (Figure 2.1) delineates the correlation between DAC and BMI, further elucidating the mediating function of KA within the context of enterprises situated in emerging economies.

2.5 Conceptual Framework and Hypotheses development

The framework shows the relationship between the independent, mediating variable and the dependent variable. The framework is shown in Figure 2.1. The relationships are discussed in the subsequent section of this chapter.



BDAC=Big Data Analytics Capability: KA= Knowledge Acquisition*: BMI=Business Model Innovation*

Figure 2. 1: Conceptual Framework

2.6 Hypothesis Development

This section discusses the hypothesis as depicted in figure 2.1 above. The Framework depicts four (4) hypotheses as discussed below.

2.6.1 Effect of DAC on Business Model Innovation

Firms operate in turbulent environments. In response to mitigating the disturbance in the environment, both manufacturing and service firms continue to embrace technology. The increasing acceptance of technology has enabled the diffusion of DAC, this enables firms to leverage on the available technologies to rethink/redesign their strategies to renovate existing BMs (Porter and Heppelmann, 2015). According to Paiola and Gebauer (2020), this is done via creating innovative product-service system, customer segregation optimization as well as pricing strategies, creating new delivery and communication modes, and rethinking the old revenue models and cost structures. Drawing from the DCT, firm without DCs will lack the capacity to reap the benefits of BDA as well as the opportunities to innovate their BMs to gain competitive advantage (Bouncken et al., 2019). When firms are able to stay relevant for its stakeholders over a period of time, it is considered as having successful BM. To be able to keep up with changing times and stay relevant to both internal and external stakeholders, it requires infrastructural, technical, managerial, and firm capabilities to control and manage the data resources that allows for dynamically innovate the business strategic logic (Gampi et al., 2021).

In today's rapidly evolving business landscape, firms are increasingly recognizing the importance of accurately anticipating market requirements to ensure their sustained success. As a response to this imperative, organizations are adopting professional Big Data Analytics (BDA) approaches to not only foresee emerging market demands but also to strategically reshape their structures and tactics. This paper delves into the realm of data-driven Business Model Innovation (BMI) and its transformative impact on aligning businesses with market needs. By harnessing analytical data and cutting-edge technologies, firms can enhance their innovativeness and gain real-time insights into business stakeholders, thereby enabling strategic decision-making and continuous optimization. The ability to accurately predict market requirements is pivotal for firms seeking to maintain a competitive edge. Gupta et al. (2019) suggest that adopting advanced BDA approaches empowers organizations to forecast market needs effectively. This proactive stance allows firms to modify their internal structures and strategies in alignment with the emerging market demands. Consequently, these adaptive measures enable businesses to stay ahead of the curve and provide tailored solutions to customers. Cheah and Wang (2017) emphasize a significant advantage of data-driven BMI, which is the potential to rationalize and complement management's intuitions and creative instincts. By leveraging data analytics, organizations gain swift and continuous access to new information about various business stakeholders, including customers, partners, and competitors. This real-time information infusion enhances decision-making accuracy, mitigates cognitive biases, and supports the development of innovative strategies that resonate with market needs.

In recent years, the landscape of business has undergone transformative changes due to rapid technological advancements and increased connectivity. As organizations strive to stay competitive, innovation has emerged as a crucial driver of growth and sustainability. This literature review aims to synthesize the findings from various studies that explore the impact of Big Data Analytics (BDAC) and Information Technology (IT) capabilities on both incremental and radical innovations, with a specific focus on Business Model Innovation (BMI) for private businesses.

The challenges faced by private businesses in developing countries, such as Ghana, are also highlighted in the context of their pursuit of adaptive strategies and resilience against external market threats.

Mikalef et al. (2019) shed light on the positive influence of corporate BDAC on innovation within firms. Their research demonstrates that BDAC facilitates both incremental and radical innovations, encompassing minor enhancements to existing products, services, and processes, as well as the creation of novel products and services. Building on this notion, Jimenez-Jimenez et al. (2019)

underscore the significant impact of IT capabilities, including data collection and analysis, on driving innovation. Their findings corroborate the idea that robust IT infrastructure contributes to knowledge exploration and exploitation, thereby fostering innovation, a notion also supported by Benitez et al. (2018).

Furthermore, Ransbotham and Kiron (2017) stress the critical importance of data governance skills in effective innovation. Their work emphasizes that successful innovation extends to processes, products, services, and even entire organizational configurations. This insight accentuates the holistic nature of innovation and the role of skillful management in leveraging data-driven insights. Complementing these perspectives, a recent study by Ciampi et al. (2021) underscores the substantial impact of BDAC on Business Model Innovation (BMI) among UK firms. Their findings underscore the relevance of BDAC in reimagining and reshaping the fundamental constructs of business models to adapt to changing market dynamics.

Private businesses in developing countries like Ghana face intricate financial challenges as they navigate the dynamic business landscape. These enterprises are particularly susceptible to external market threats, as evidenced by the Environmental Protection Agency of Ghana (EPA, 2020). This context highlights the vulnerability of such businesses and underscores the urgency for adaptive strategies. In this light, Business Model Innovation (BMI) emerges as a pivotal category of radical innovation that holds promise for private businesses (Ritala and Hurmelinna-Laukkanen, 2013). BMI empowers organizations to rethink their core value propositions, revenue streams, and cost structures, thereby enhancing their resilience and competitive advantage.

The reviewed literature underscores the pivotal role of Big Data Analytics (BDAC) and IT capabilities in fostering both incremental and radical innovations within organizations. These technological enablers provide avenues for enhanced data-driven decision-making and innovation across various dimensions of business. Moreover, the relevance of Business Model Innovation

(BMI) in the context of private businesses, especially in developing countries facing financial constraints and external threats, cannot be overstated. The insights gleaned from this literature review contribute to a deeper understanding of the multifaceted relationship between technology, innovation, and business strategy. The discussion above leads to the first hypothesis of this study:

H1: DAC has a positive relationship with Business Model Innovation.

2.6.2 Effect of BDAC on Knowledge Acquisition

Prior studies have conceptualized KA as an organizational capacity that can enable firms to withstand the shocks of disruption (Juttner and Maklan, 2011; Dubey et al., 2018) Wamba et al. (2019) operationalized SCA as a multidimensional construct comprising Supply Chain Agility and Supply Chain Adaptability. Prior studies have demonstrated the relevance of information sharing in enhancing agility and adaptability of supply chain (Kabra and Ramesh, 2016; Dubey et al., 2018; Yang et al., 2021; Baah et al., 2021). In the quest to improve the flow of quality information in the entire supply chain, there is the need to pay critical attention to creating linkage in the supply chain to improve visibility (Gunasekaran et al., 2017). Lee et al. (2010) opine that BDA play essential role in enhancing visibility in the supply chain, by minimizing the negative implications of distortions in the supply chain, enabling firms to be more agile, adaptable, creating strategic value, and enhancing operational efficiency and planning (Chen et al 2014; Qi et al., 2017; Dubey et al., 2018; Wei and Wang, 2010; Coridi et al., 2010). Additionally, Srinivasan and Swink (2018) argue that achieving visibility in supply chain is linked to developing BDAC capacity. Hence visibility and BDAC are complementary to each other (Gunasekaran et al., 2017). Following the argument of Srinivasan and Swink (2018), this study expects that firms that able to develop their BDAC are likely to have a visible supply chain. While Dubey et al. (2018) found direct impact of SCV on SCAG and SCAD, Wamba et al. (2019) also found positive effect of BDAC on SC ambidexterity

(SCAG and SCAD). Hence this study expects that managers or firms that make efficient and effective use of BDAC are likely to sense rapid variations in the market, enabling them to develop mitigation strategies that can help them respond to the changes promptly. The above discussions lead to the second hypothesize of the study:

H2: DAC has a positive relationship with knowledge acquisition.

2.6.3 Effect of Knowledge Acquisition on Business Model Innovation

The nexus between KA and BMI has received minimal or no attention in extent management literature. Knowledge of a company is typically rooted in organizational practices, technology, personnel, as well as other resources (Grant, 1996). It follows that knowledge stock can be the basis for applying existing knowledge and the point of departure for future studies (Antonelli & Colombelli, 2018). Xie et al., (2018) endorse this finding; they argue that an established knowledge base of a company will promote the acquisition of new knowledge. Furthermore, the existing stock of knowledge will affect the form of knowledge to be sought for innovation and how companies handle the conflict between the paths of discovery and development towards effective learning (Rupietta & Backes-Gellner, 2019). But on the other hand, the knowledge search for exploration doesn't have a well-defined resolution space; thus, it introduces the firm outside its current experience to a heterogeneous knowledge domain (Lee & Huang, 2012). In research by Liao & Barnes, 2015 on knowledge acquisition and product innovation flexibility in SMEs, a total of 118 respondents through a web-based survey data revealed the mediation of knowledge acquisition on product i n n o v a t i o n flexibility. Using a structural equation modeling to test the hypothetical framework on SMEs with fewer than 250 employees who participated in the survey revealed that knowledge acquisition partially mediates the relationship between information capability and product innovation flexibility. In their view, there should be further research on information capability on product innovation flexibility. Similarly, using 896 Spanish ICT SME sector through a structured telephone interview that obtained 215 responses, Bojica & FuentesFuentes, 2019 sought to establish the relationship between knowledge acquisition and corporate entrepreneurship in the SME ICT sector. It was observed in their study that knowledge acquisition moderates corporate entrepreneurship and performance negatively depending on the knowledge base assets of the company. The above discussion can be concluded that knowledge acquisition is a very vital factor for the realization of firm performance, therefore KA has a high positive effect on FP (Hagemeister & Rodríguez-Castellanos, 2019). Though to the best of the researcher's knowledge, no prior study has examined the nexus between KA and BMI,

drawing on the above discussion, the study posits that:

H3: KA has a positive relationship with Business Model Innovation

2.6.4 Mediating Role of Knowledge Acquisition

The fourth hypothesis of the research posits that Knowledge Absorption (KA) acts as a mediator in the association between Big Data Analytics Capability (BDAC) and Business Model Innovation (BMI). With the confirmation that Data Analytics Capabilities (DAC) have a positive influence on both KA and BMI, it is also evident that KA independently contributes to the enhancement of BMI. This suggests a complex interplay between DAC, KA, and BMI, where the relationship between DAC and BMI is influenced by the mediating role of KA. In this regard, the study anticipates that the direct connection between BDAC and BMI could be amplified in the presence of two key supply chain factors: Supply Chain Adaptability (SCA) and Supply Chain Alignment (SCAlignment).

As previously highlighted, the significance of Supply Chain Adaptability has been emphasized in facilitating both explorative and exploitative efforts aimed at innovative operational process redesign. Simultaneously, it enables the ongoing enhancement of productivity (Lee et al., 2015). This acknowledgment underscores the pivotal role of SCA in creating an environment conducive to both radical and incremental innovation endeavors.

In the context of this study, the findings suggest that BDAC not only directly influences BMI but also does so indirectly through its impact on KA. The interplay between these variables is expected to be further nuanced by the presence of supply chain-related attributes. The hypothesized mediation of KA in the BDAC-BMI relationship underscores the intricate nature of the innovation process, where knowledge absorption acts as a bridge connecting technological capabilities with tangible innovative outcomes.

The investigation into the mediating role of Knowledge Absorption and the moderating effect of supply chain attributes on the relationship between Big Data Analytics Capability and Business Model Innovation sheds light on the multifaceted dynamics at play within the innovation landscape. As organizations continue to harness the power of data analytics, these findings offer insights into how knowledge absorption and supply chain adaptability can amplify the impact of data-driven innovations on business models.

Previous research has established the significant influence of Big Data Analytics Capability (BDAC) on various strategic orientations of businesses, including market orientation, learning orientation (Gnizy, 2019), and entrepreneurial orientation (Ciampi et al., 2021). Among these potential mediators, Supply Chain Adaptability (SCA) emerges as a particularly fitting mediator between BDAC and Business Model Innovation (BMI), as it embodies the capacity to align and adapt across the entirety of a business unit (Gibson and Birkinshaw, 2004). Notably, firms equipped with robust BDAC are adept at gathering and analyzing external data, enabling them to perceive and shape emerging business opportunities (Garmaki et al., 2016). This dynamic translates into the cultivation of SCA, which, empowered by the insights derived from data analysis, empowers firms to surmount limitations in their business models, thereby fostering innovative and consistent development endeavors concerning new products and processes, albeit often entailing substantial risk (Garmaki et al., 2016) (Marzi et al., 2020; Usai et al., 2018).

The interplay between the discrete behavioral facets constituting SCA within the context of the BDAC-BMI nexus underscores the concept of Knowledge Absorption (KA) as a positive mediator in this relationship. Firstly, it is reasonable to posit that organizations proficient in implementing effective Big Data Analytics practices are inherently inclined toward fostering innovation, creativity, and forward-thinking strategies (Lumpkin and Dess, 1996). This inclination extends to pursuing data-driven strategies capable of disrupting conventional business models (Wang et al., 2020). Secondly, companies endowed with strong data analysis capabilities are better poised to perceive market signals and latent consumer needs (Hughes and Morgan, 2007), thereby facilitating the anticipation and instigation of shifts within the external environment through radical adjustments to their business rationale. Lastly, as Data Analytics Capability enhances corporate intelligence and data analysis systems, it stimulates managers to explore innovation prospects beyond conventional methodologies and thought patterns, thereby promoting a willingness to undertake higher risks and embrace profound alterations to business value mechanisms (Roberts et al., 2016).

In summary, the research landscape underscores Supply Chain Adaptability as a pivotal mediator between Big Data Analytics Capability and Business Model Innovation. The symbiotic relationship between BDAC and SCA engenders a fertile ground for innovative strides, ultimately facilitated by Knowledge Absorption as a conduit for amplifying the effects of BDAC on BMI.

This multifaceted interaction serves to elucidate the intricate dynamics that underlie the fusion of data-driven capabilities and innovation outcomes.

Based on the above, the study expects KA to strengthen the direct DAC-BMI link. Hence the fourth hypothesis

H_4: KA mediates the relationship between DAC and BMI.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Introduction

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

3.2 Research design

Before data collection and analysis can begin in the social sciences, there must be a plan of action or design, much like the structure itself. An appropriate research design, as defined by Griffee (2012), "is a model or blueprint of how the researcher intends to perform the research and answer the research question" (s). Saunders et al. (2019) provide further clarification and emphasise the importance of thinking about the research design in terms of its goals, methods, data collecting and analysis approaches, procedures, and techniques, timeline, and ethical issues. The research design is the overarching framework that guides the decisions made throughout the study, from the questions posed to the methods used to collect data to how that data will be analysed and interpreted.

According to Okesina (2020), there are several aspects to research design, including the research purpose (descriptive, explanatory, exploratory, or a mix of two or more purposes), research methodologies (quantitative, qualitative, and mix methods), and time horizon (cross-sectional or longitudinal). In light of what has been discussed, the pragmatist viewpoint informed the decision to use an explanatory research design rather than a descriptive or exploratory one for this investigation. This is because the quantitative portion of the study came first, followed by the qualitative phase, whose goal was to provide an explanation for or improvement upon the quantitative findings. Furthermore, the study was a cross-sectional design rather than a longitudinal one, using terminology from Okesina (2020), as data will be collected over the course of just a month. This research design supports this study taking into consideration that the research problem was best addressing by embracing quantitative approach.

As a pivotal aspect of the research design, the cross-sectional survey methodology is leveraged, employing deductive reasoning to dissect quantitative data (Cohen, Manion, and Morrison, 2017). The survey design is optimally suited for capturing data across diverse units within a delimited timeframe. Given the study's temporal constraints, the cross-sectional survey approach emerges as an apt choice to investigate the intricate dynamics surrounding the impact of data analytics capability on business model innovation, while concurrently illuminating the mediating role of knowledge acquisition. In sum, by embracing the positivist paradigm and strategically deploying quantitative methods through the cross-sectional survey design, this study tactfully navigates the realm of causal exploration, shedding light on the intricate connections between data analytics capability, business model innovation, and the intermediary function of knowledge acquisition.

3.3 Population of the study

This section delves into the comprehensive delineation of the study's population and the framework used to determine its sample. According to Etikan, Musa, and Alkassim (2016), the term "population" encapsulates the range of instances, individuals, or objects that constitute the focal point of investigation. In essence, the target population represents the specific group or individuals that the study aims to draw conclusions about. In a complementary vein, the target population encompasses a diverse array of individuals from which a representative sample is to be extracted (Shamsuddin et al., 2017).

In the context of this study, the population under scrutiny encompasses all enterprises involved in the domain of fast-moving consumer goods. Given the extensive nature of this overarching population, attempting to amass data from every entity is infeasible. Therefore, the study hones its focus on Small and Medium Enterprises (SMEs), effectively creating a sample frame to facilitate data collection. In this study, SMEs, whether engaged in manufacturing or service-oriented pursuits, form the nucleus of examination within the Eastern Region of Ghana.

The determination of the sample frame is pivotal in shaping the study's methodology and scope. While the population of firms operating in the fast-moving consumer goods sector is considerable, the study necessitates a strategic approach to data collection. Thus, the selection of SMEs as the primary constituents of the sample frame aligns with the pragmatic constraints of the study. This deliberate focus not only ensures that data collection remains manageable but also that the insights gleaned possess a degree of generalizability to the broader population of interest.

In sum, this section expounds upon the intricacies of the study's population and the judiciously crafted sample frame. By encapsulating the multifaceted realm of fast-moving consumer goods enterprises, the study fine-tunes its focus onto SMEs as the quintessential representation of this population within the Eastern Region of Ghana. This strategic selection serves as a cornerstone for data collection and subsequent analysis, embodying the intricate balance between comprehensiveness and feasibility.

3.4 Sampling techniques and sample size

Within the realm of academia, the issue of sample selection and sampling techniques stands as a subject of prolonged debate. This discourse arises from the profound impact that the choice of sample and the corresponding methodology wields on the outcomes of scholarly research. As elucidated by Kothari (2012), the sample embodies the researcher's strategic endeavor to ascertain the number of study participants to be encompassed within the sample. This pivotal decision reverberates throughout the research process, inherently shaping the robustness and validity of research findings.

The process of determining an appropriate sample size within a given population is underscored by three distinct methodologies, each characterized by unique attributes. First and foremost, researchers can employ formulas to derive the requisite sample size (Israel, 1992). Alternatively, the utilization of established statistical tables emerges as a viable approach, exemplified by renowned references like Krejcie and Morgan's (1970) and Cohen et al.'s (2013, 2009) published statistical tables. Lastly, the option of resorting to a census method, encompassing the collection of data from the entire population, is a conceivable avenue. In this context, the choice between these methodologies' hinges on the study's objectives, constraints, and inherent population dynamics.

For the current study, the determination of the sample size will be guided by the formula articulated by Singh and Masuku (2014) for sample size estimation. This selection is grounded in the compelling rationale that the actual population of Small and Medium Enterprises (SMEs) within the study region remains unknown to the researcher. This formula provides a strategic means to approximate an optimal sample size, effectively bridging the gap between the researcher's objectives and the inherent uncertainty concerning population metrics.

In essence, the process of sample selection and the application of pertinent sampling techniques occupy a pivotal juncture in the research journey. By judiciously determining the sample size through a well-justified formula such as that proposed by Singh and Masuku (2014), the study achieves a delicate balance between precision and practicality. This meticulous approach encapsulates the essence of methodological rigor, enhancing the credibility and potency of the research outcomes.

Hence the formula is given as

$$n = \frac{Z^2(P)(1-P)}{}\,C_2$$

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

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

C=Confidence interval

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

n=384.16 n~384

Sampling techniques are crucial components of research endeavors as they determine the subset of participants or data points that are included in a study. There are two main categories of sampling procedures: probability procedures and non-probability procedures (Taherdoost, 2016). In the following text, we will discuss the selection of a sample for a research study involving 384 firms and the rationale behind the chosen multistage sampling strategy. This approach allows for the utilization of various sampling techniques to achieve a comprehensive representation of the target population, specifically focusing on small and medium-sized enterprises (SMEs) in both manufacturing and service sectors. Probability procedures involve random selection, enabling each member of the population to have an equal chance of being chosen. Non-probability procedures, on the other hand, do not rely on randomness and might introduce bias into the sample. In this study, a multistage sampling strategy is adopted. This approach involves using multiple sampling techniques, allowing for a more nuanced and representative sample (Taherdoost, 2016). The strategy entails two main stages: the initial selection of SMEs and the subsequent purposive selection of knowledgeable staff within these firms. The first stage of the multistage sampling strategy involves selecting 384 SMEs to be included in the study. This selection will be conducted through a combination of stratified and cluster sampling. Stratified sampling involves dividing the population into distinct groups based on certain characteristics, ensuring proportional representation from each subgroup (Creswell, 2014). In this case, the SMEs will be divided into manufacturing and service sectors, as these represent different domains of business activities.

Within each stratum, cluster sampling will be employed, wherein clusters of SMEs will be randomly chosen, and all the SMEs within the selected clusters will be included in the sample. This method simplifies the process and makes data collection more feasible, especially when the target population is geographically dispersed (Creswell, 2014). After selecting the SMEs, the study aims to gather insights from staff who possess a deep understanding of the research issues. To achieve this, a purposive sampling technique will be employed. This non-probability technique involves deliberately selecting participants who have the desired knowledge and experience related to the study's focus (Palinkas et al., 2015). By targeting staff members with expertise in the investigated issues, the study can ensure that the collected data are rich and relevant. In summary, sampling techniques are fundamental to the success of a research study. The chosen multistage sampling strategy for this investigation involving 384 SMEs incorporates both probability and non-probability procedures. By utilizing a combination of stratified and cluster sampling to select SMEs and employing purposive sampling to choose knowledgeable staff, the study aims to achieve a well-rounded representation of the target population. This approach enhances the study's validity and the relevance of the collected data, ultimately contributing to the robustness of the research findings.

3.5 Data collection

A structured questionnaire will be used to source information from senior managers of firms dealing with fast moving consumer goods. This study dwells on the use of primary data that will be collected using primary data. The data will be gathered using a questionnaire. The questionnaire is designed in two parts. The first part contains the demographic information of the respondents. The second part contains questions on the variables used in this study. The measurement and operationalization of the variables are detailed below. In the survey, participants will be asked to choose a number from 1 to 5 that best represented their thoughts on each statement. The items used to measure the constructs are included in the appendix. Though the items were already validated and tested in previous studies, this study will also conduct different types of validity and reliability of the items to ensure the final results are reliable. To encourage participation, each questionnaire was accompanied by a cover note from the researcher clarifying the aim of the study as well as soliciting respondent involvement in the study; it as well assured the confidentiality y of the selected participants and briefly introduce the research work.

3.6 Data analysis

The significance of data analysis methods in research cannot be overstated, as the chosen approach directly impacts the quality of conclusions, recommendations, and insights drawn from the collected data. In this context, we delve into the critical role of data analysis methods within a quantitative research framework. The study employed various quantitative techniques to analyze data, aligning with the objectives set forth in the introductory chapter. The process involved meticulous data compilation, thorough scrutiny, and utilization of Statistical Package for Social Sciences (SPSS) version 26.0 for statistical analysis. This paper elaborates on the methodology applied and highlights the multifaceted quantitative techniques utilized to examine the relationship between data analytics capability and business model innovation, considering the mediating role of knowledge acquisition. Following data collection, a pivotal phase involved compiling the amassed data within an Excel spreadsheet. This step facilitated comprehensive scrutiny, ensuring data accuracy, completeness, and readiness for subsequent analysis. During this scrutiny, incomplete questionnaires were identified and excluded, thereby safeguarding the integrity of the data to be subjected to analysis. The study leveraged the advanced capabilities of the Statistical Package for Social Sciences (SPSS) version 26.0 to perform diverse analyses. SPSS is a widely recognized software tool renowned for its capacity to process and analyze data, particularly within the social sciences (IBM Corp, 2019). Its user-friendly interface and robust features make it a popular choice for researchers engaging in quantitative analyses. The quantitative analysis encompassed a range of techniques designed to uncover relationships and patterns within the data. Frequencies, means, and standard deviations were computed to provide a comprehensive understanding of the central tendencies and variabilities in the variables under investigation. Independent sample t-test was employed to discern any significant differences between groups, contributing to the exploration of factors impacting the research variables.

Furthermore, correlation analysis was conducted to assess the strength and direction of relationships between variables. This technique provided insights into the potential associations between data analytics capability and business model innovation, considering the mediating influence of knowledge acquisition. Correlation analysis is valuable for identifying potential connections between variables and forming the basis for more intricate analyses, such as mediation analysis. In summation, the method of data analysis constitutes a critical element in quantitative research, exerting a substantial impact on the validity and robustness of findings and recommendations. This study exemplified the careful consideration dedicated to data compilation, thoroughness, and the application of sophisticated quantitative techniques through SPSS. By employing methods such as frequencies, means, standard deviations, independent sample t-test, and correlation analysis, the research delved into the effect of data analytics capability on business model innovation, exploring the intermediary role of knowledge acquisition. This comprehensive approach enhances the credibility and depth of the research outcomes, contributing valuable insights to the realm of quantitative analysis.

3.7 Validity and reliability

Maintaining the credibility and trustworthiness of a research study is of paramount importance. This section discusses the strategies implemented to ensure external validity, content and construct validity, as well as reliability in the context of a research endeavor. The study's voluntary participation approach, dropout prevention measures, and meticulous attention to validity and reliability contribute to the study's robustness and the accuracy of its outcomes. To ensure the external validity of the study, participants' engagement was entirely voluntary. This approach aimed to encourage genuine interest and commitment from the participants, thereby enhancing the applicability of the study's findings to the broader population. Selected participants were also provided with a clear understanding of the study's benefits, emphasizing its relevance to their respective contexts. This strategy not only increased participant motivation but also worked to mitigate potential dropout rates, ensuring a comprehensive dataset for analysis. Both content and construct validity were meticulously addressed to bolster the study's integrity. Content validity refers to the alignment between the research instrument and the construct it intends to measure.

Construct validity, on the other hand, pertains to the accuracy of the interpretations drawn from the study's results (Straus, 2017). By meticulously crafting the study's questions and ensuring their relevance to the research objectives, content validity was upheld. Construct validity was maintained through careful design and execution to ensure that the study accurately captured the intended concepts and relationships. Validating the findings of a research study is fundamental to its credibility. The researcher undertook measures to eliminate logical inconsistencies and biases by focusing on both validity and reliability. This emphasis was integral to producing dependable results. To assess internal consistency and reliability, an alpha coefficient of 0.70 was employed as a benchmark. This coefficient is widely recognized for evaluating the consistency of research items and scales (Hair, Biasutti, & Frate, 2017). The researcher took comprehensive steps to eliminate potential issues and refine the research methodology. To this end, a pilot study involving 10 respondents was conducted. This preliminary phase allowed for the identification of any ambiguities, difficulties, or inconsistencies in the research instrument. Adjustments were made based on the pilot study's insights, enhancing the clarity and comprehensibility of the questions. By conducting this pilot study, the researcher validated the integrity of the research process and demonstrated a commitment to accurate results. Ensuring the validity and reliability of a research study is integral to generating credible and meaningful outcomes. This study adeptly navigated the challenges associated with external validity, content and construct validity, as well as reliability. Through voluntary participation, dropout prevention measures, attention to validity criteria, and a pilot study, the study's foundation was fortified. By implementing these strategies, the research enhanced the prospects of generating trustworthy results that contribute substantively to the field.

3.8 Ethical issues

Ethical considerations serve as the guiding principles in any research endeavor, ensuring the responsible and respectful treatment of participants. This section explores the ethical dimensions that underpinned the data collection process of the study, with a focus on informed consent, confidentiality, and anonymity. The study adhered to established ethical guidelines, drawing insights from Singh et al. (2015) and Fleming and Zegward (2018), to navigate the complexities of research ethics. Informed consent stands as a cornerstone of ethical research practice, exemplifying respect for participant autonomy. As advocated by Fleming and Zegward (2018), the study prioritized this principle by offering a comprehensive understanding of the research's purpose to all potential participants. This approach allowed individuals to make informed decisions regarding their participation, ensuring that only those who willingly agreed were included in the data collection process. By creating a transparent environment, the study respected participants' right to choose and reinforced ethical conduct. Another critical ethical dimension is maintaining confidentiality, minimizing potential harm by safeguarding participants' sensitive information. The study diligently upheld this tenet by adopting robust measures to protect the collected data. All data gathered through questionnaires were securely stored, limiting access exclusively to the research team. This practice assured participants that their responses would remain confidential, thus encouraging candid and accurate contributions without apprehension of unauthorized disclosure (Fleming & Zegward, 2018). Respecting participants' anonymity is vital for cultivating an environment where they feel safe sharing their perspectives. In alignment with ethical principles, the study took great care to ensure that no identifying information, such as names, addresses, and phone numbers, were included in the data collection instruments. This measure aimed to maintain the confidentiality of participants, further reinforcing the commitment to ethical research conduct. Voluntary participation serves as a foundational ethical principle, affirming participants' right to choose their level of involvement. In line with this, the study emphasized that participation was entirely voluntary, granting participants the liberty to withdraw from the data collection process at any stage without facing repercussions. This approach underscored the principle of respect for participants' autonomy (Fleming & Zegward, 2018). Ethical considerations represent a critical framework that shapes the ethical conduct of research studies. This paper elucidated the ethical facets that guided the data collection process, demonstrating the study's dedication to upholding the principles of informed consent, confidentiality, anonymity, and voluntary participation. By adhering to the ethical guidelines highlighted by Singh et al. (2015) and Fleming and Zegward (2018), the research fostered a trustworthy and respectful environment, ultimately enriching the study's validity and integrity.

3.9 Profile of organization

The chapter covered the research design and methodology followed to address the research issues. The sections gave the choices of methodologies and the justification for the choices. The chapter is organized under seven key headings. The chapter started with an introduction, followed by the research design and approach, study population, sample size, sampling technique, source of data, research instrumentation and data collection procedure, validity and reliability, and ethical consideration. The next section provides the analysis of the data collected using the methodology described in this chapter.

CHAPTER FOUR

DATA ANALYSIS, PRESENTATION AND DISCUSSION OF RESULT

4.1 Introduction

This chapter detailed the study's results. This research used descriptive statistics and confirmatory factor analysis. SmartPLS 4 was used to check the hypothesis. In the discussion section, the researcher puts the findings in perspective and makes connections to prior research.

4.2 Demographic Information

The demographic characteristics of the participants is captured in this section. The results are shown in the table 4.1 below. In terms of participants' gender, 53.4% were females and 46.6% were males. From the result also, 25.5% of the participants were within the age of 18-30 years, 44.0% were within 31-40 years, 27.1% were within 41-50 years and 3.4% of the remaining were above 50 years. The data also shows that 29.9% of the participants had bachelor's degree, 29.2% had diploma, 5.5% had master's/PhD and 11.2%, had junior high school certificate, 11.7% hold other certificates and 12.5% hold senior high school certificate. Also, the data shows that 16.4% of the participants were business owners, 34.1% were business owners and managers, 18.2% were managers, 6.3% hold other certificate and 25.0% of the remaining were production managers. Also, 25.5% of the participants indicated their organization has been operating for about 1-5 years, 20.8% indicated within 11-15 years, 8.9% also indicated above 16 years and 44.8% of the remaining indicated within 6-10 years. Again, 34.9% of the participants indicated 30-99 employees in their firms, 19.0% also indicated 5-29 employees, 16.7% indicated less than 5 employees and 29.4% indicated more than 100 employees. From the data 32.8% of the respondents indicated their firm is fully foreign owned, 45.6% indicated fully locally owned and 21.6% of the remaining also indicated jointly Ghanaian and foreign.

Table 4.1 Demographic Information

Variables	Frequency	Percent
Gender		
Female	205	53.4
Male	179	46.6
Age		
18-30 years	98	25.5
31-40 years	169	44.0
41-50 years	104	27.1
Above 50 years	13	3.4
Level of Education		
Bachelor Degree	115	29.9
Diploma	112	29.2
Graduate Studies (Master / Ph.D.)	21	5.5
Junior High School	43	11.2
Others	45	11.7
Senior High School	48	12.5
Your Position in the Firm Business		
Owner	63	16.4
Business Owner & Manager	131	34.1
Manager	70	18.2
Others	24	6.3
Production Manager	96	25.0
How many years have your firm been in operation 1		
- 5 years	98	25.5
11 – 15 years	80	20.8
16 years and above	34	8.9
6 - 10 years	172	44.8
How many employees are in the firm?		
30 – 99 employees	134	34.9
5 – 29 employees	73	19.0
Less than 5 employees	64	16.7
More than 100	113	29.4
Type of ownership Fully		
foreign owned	126	32.8
Fully locally owned	175	45.6
Jointly Ghanaian & foreign owned	83	21.6
Total	**384**	**100.0**

4.3 Descriptive Statistics

This analysis will tell the researcher whether the survey questions were correctly answered. Using descriptive statistics, a numerical value might be provided to each condition (such as the mean, median, maximum, standard deviation, excess kurtosis, and skewness, among others). The dispersion of data is quantified by its standard deviation. Data from Table 4.2. Averaging out at 4.05, 3.90, and 3.94, respectively, are data analytics capability, knowledge acquisition, and business model innovation. Standard deviation from the mean for data analytics capability was 0.799, knowledge acquisition was 0.846, and business model innovation was 0.816. The evidence clearly shows that the computed or statistical mean represents the usual value of all variables.

Table 4.2 Descriptive Statistics

Constructs	Mean	Standard Deviation
Data Analytics Capability	4.05	0.799
Knowledge Acquisition	3.90	0.846
Business Model Innovation	3.94	0.816

4.4 Measurement Model Assessment

The research assessed the accuracy of the measurement models by utilizing the criteria defined by Hair et al. (2019). This study was conducted using SmartPLS version 4, a program for developing partial least squares structural equation models (Ringle et al., 2015). The loadings were calculated for each item, and they were found to be more than 0.70 for every one. It's comforting to know that the construct is robust enough to account for more than half the variation in the indicator, suggesting that the components may be relied upon. According to table 4.3, all external loading factors with values below 0.700 were discarded.

4.4.1 Reliability

The researcher looked at the internal consistency of the constructs using methods like the Composite Reliability and the Cronbach Alpha. The result of reliability is provided in the table 4.3 below. Cronbach's alpha scores for this sample vary from 0.908 to 0.924, and composite reliability ratings fall in the 0.928 to 0.939, indicating that the data is reliable. Since every value was more than 0.7, there is a significant chance that this sample can be implemented (Hair, et al., 2019). The findings suggest the scale is unidimensional and if repeated would yield the same result.

4.4.2 Validity

The study then looked at the construct's convergent validity. A concept's convergent validity is determined by its ability to account for variances among its elements. Convergent validity for a group of variables may be assessed by calculating the AVE across all of the variables in the data set; a value of 0.50 or above indicates significant convergent validity. All of the AVE readings were properly contained within the specified limits of 0.647 and 0.721. The result is displayed in the table 4.3 below.

Table 4.3 Reliability and Validity

Constructs	Items	Loadings	CA	CR	AVE	VIF
Business Model Innovation	BMI1	0.825	0.924	0.937	0.652	2.950
	BMI2	0.806				2.835
	BMI3	0.780				2.302
	BMI4	0.815				2.729
	BMI5	0.825				3.022
	BMI6	0.816				2.962
	BMI7	0.767				2.167

	BMI8	0.825				2.630
Data Analytics Capability	DCA1	0.734	0.908	0.928	0.647	2.038
	DCA2	0.748				1.991
	DCA3	0.832				2.754
	DCA4	0.858				2.951
	DCA5	0.829				3.093
	DCA6	0.802				2.351
	DCA7	0.821				2.404
Knowledge Acquisition	KA1	0.791	0.923	0.939	0.721	2.186
	KA2	0.886				3.228
	KA3	0.830				2.446
	KA4	0.859				2.738
	KA5	0.868				2.817
	KA6	0.859				2.685

When comparing one independent variable to the others in the model, the level of discriminant validity was calculated. For a discriminant function to work, the input variables must have a correlation that is lower than the square root of the average variance (AVE) (Fornell & Larcker, 1981). Table 4.4 emphasizes the relationship between the variables by using non-diagonal values to contrast with the square roots of the AVE, which are shown with clear diagonals. The ideas have discriminant validity since diagonal values are greater than other diagonal values.

Table 4.4 Fornell-Larcker test

Constructs	**1**	**2**	**3**
Business Model Innovation	**0.808**		
Data Analytics Capability	0.645	**0.804**	
Knowledge Acquisition	0.608	0.623	**0.849**

By focusing only on associations between heterotraits and monotraits, the HTMT is an improvement over the problematic Fornell-Larcker criterion (Hair et al., 2019; Henseler et al., 2015; Voorhees et al., 2016). Scores on the HTMT below 0.90 have been demonstrated to be ideal in several studies. One way to do this is to calculate the geometric mean of the average value of the items' associations across all scales used to measure the same variable (Henseler et al., 2015). According to Table 4.5, the highest HTMT ever recorded was just 0.702, which is much lower than the expected threshold of 0.9.

Table 4.5 HTMT Test results

Constructs	1	2	3
Business Model Innovation Data			
Analytics Capability	0.702		
Knowledge Acquisition	0.654	0.678	

4.5 Model Fit Summary

Ranges and values for the Extracted-Index test, the Spectral Reconstruction Mean Ratio test, and the Chi-square test were examined, as well as the relative effectiveness of each (Table 4.6). The minimum necessary score is 0.9, which neither the Extracted nor the rare categories meet. If the residual has a square root or a common root, both of which have finite values, then it is not infinitesimally tiny. Therefore, future research must take into account all relevant data and points of view.

Table 4.6 Fit Summary

Indices	Saturated model	Estimated model
SRMR	0.054	0.054
d_ULS	0.680	0.680
d_G	0.383	0.383
Chi-square	903.823	903.823
NFI	0.860	0.860

4.6 Boot Trapping Resampling Technique

Developing a structural equation model, or internal model, may help researchers feel more certain in their findings and their ability to anticipate the behavior of one or more components of interest. The researcher accounts for standard error by resampling the data 5,000 times to verify the precision of the underlying model's coefficients (Hair et al., 2014). Collinearity, p-value, path coefficient, coefficient of determination, effect size (f2), and impact size are all measured within the framework of the structural model (g2). It is often used in the field of research to describe a situation in which two or more measurements have a tight connection with one another. The study quantifies the degree of collinearity between the regressors by using the variance inflation factor (VIF). As a result, it was decided that the (VIF) may be a helpful tool for examining these issues. Data in Table 4.4 indicate that the VIF values are lower than the cut-off value of 3.3 (Hair et al., 2019).

4.6.1 Coefficient of Determination and Predictive Power of the PLs Model

According to Henseler (2018), R2 values between 0.75 and 0.50 are considered to be very significant, whereas values below 0.25 are considered to be somewhat small. To the contrary, Chin et al. (2020) stresses the need of knowing R^2 in the related domain. Table 4.7 and Figure 4.1 show the model's R^2 value, which is within a respectable range for forecasting future business model innovation and knowledge acquisition at 0.485. and 0.388. This study shows that data analytics capability is responsible for 48.5% and 38.8% of the variations in business model innovation and knowledge acquisition. This means the model may be able to forecast future occurrences before they happen.

The PLS path model's predictive power may be estimated using a parameter called Q^2, the square root of the correlation (Geisser, 1974; Stone, 1974). When Q^2 rises over a certain point, it may be necessary to rely on a data-driven, in-house structural model efficiency in operating (Hair et al., 2019). Table 4.7 shows that the model is robust across those cut-offs with Q^2 scores of 0.410 and 0.381 for business model innovation and knowledge acquisition respectively. The results illustrate the model's ability to make predictions.

Table 4.7 Coefficient of Determination and Predictive Power Statistics

Endogenous Constructs	R-square	Q^2predict
Business Model Innovation	0.485	0.410
Knowledge Acquisition	0.388	0.381

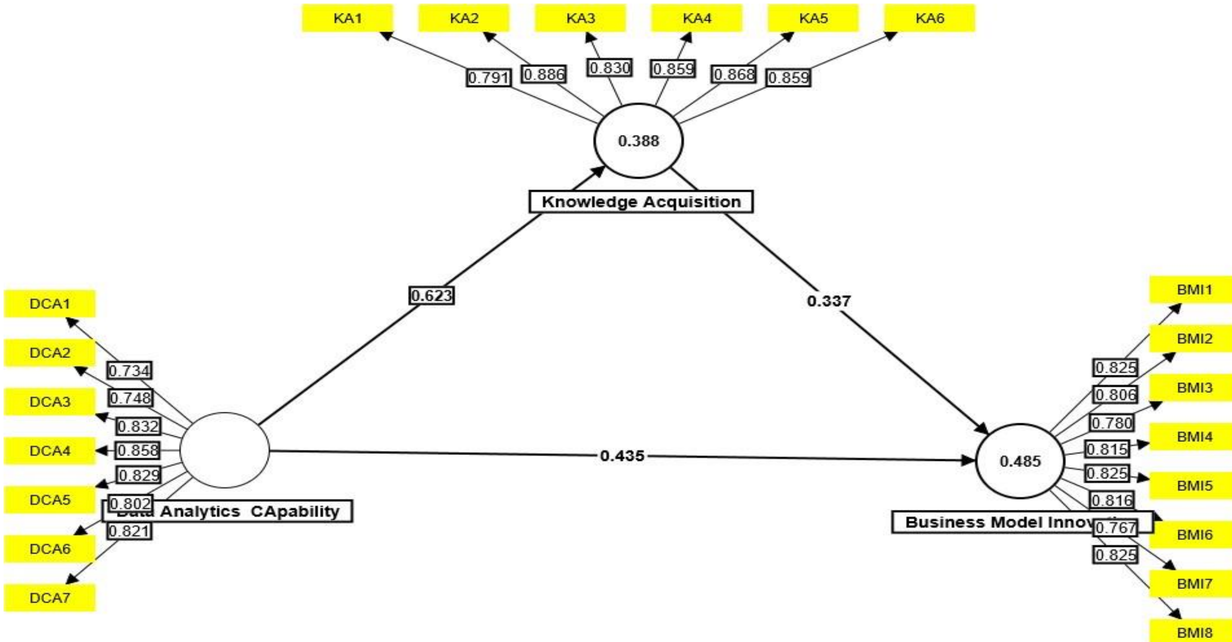


Figure 4.1 Measurement Model Assessment

4.7 Hypotheses for Direct and Indirect Relationship

SmartPLS 4 was used to verify the three assumptions this study examined. The purpose of this research was to analyze the interplay between data analytics and business model innovation in small and medium-sized enterprises (SMEs) in emerging markets via the mediating role of knowledge acquisition. The results are shown in Table 4.8 and Figure 4.2 down below.

The first objective of this study was to investigate how access to data analytics influences business model innovation in small and medium-sized enterprises (SMEs) in underdeveloped countries. Table 4.8 and Figure 4.2 display the study's data, which shows a positive and

significant relationship between SMEs' data analytics capability and their rate of business model innovation (B=0.435; t=8.566; p-value=0.001 <0.05). The results of this study corroborate the hypothesis that the factors under investigation are correlated. It also demonstrates that the extent to which data analytics capabilities are handled may account for variation in business model innovation across SMEs (43.5%), everything else being equal. The results suggested that small and medium-sized enterprises (SMEs) in emerging markets might benefit from enhancing their data analytics skills in order to better innovate their business models.

The study's second goal was to investigate the effects of data analytics skills on SME knowledge acquisition in emerging countries. The extent to which SMEs use data analytics skills is shown to have a significant impact on the extent to which SMEs acquire new knowledge, as shown in Table 4.8 and Figure 4.2 (B=0.623; t=15.992; p-value=0.000 <0.05). The findings of this research provide credence to the idea that the two factors are related. Data analytics capabilities were shown to be responsible for 62.3% of the variation in knowledge after accounting for other factors. To encourage wider use, small and medium-sized enterprises (SMEs) in emerging countries should highlight the benefits data analytics skills provide to knowledge development.

It was also a goal of the research to see whether the amount of knowledge acquisition by SMEs had any effect on their capacity to increase business model innovation. Table 4.8 and Figure 4.2 show that there is a statistically significant positive correlation between SME knowledge acquisition and business model innovation (B=0.337; t=6.211; p-value=0.000 <0.05). The results provide support to the idea that the two ideas are linked. This provides support for the hypothesis that the improvement in business model innovation among SMEs may be attributed to a change in knowledge acquisition. As a consequence, this accounts for 33.7% of the variation in business model innovation. These results give strong evidence that acquiring new information helps small and medium-sized enterprises (SMEs) in emerging markets innovate their business models.

The study's third objective was to determine whether or whether knowledge acquisition mediates the connection between data analytics capability and business model innovation among small and medium-sized enterprises (SMEs) in emerging economies. Figure 4.2 and Table 4.8 show that the connection between SMEs' data analytics capabilities and their propensity to innovate their business models is mediated by their level of knowledge acquisition (B=0.210; t=5.560; pvalue=0.000 <0.05). This study's findings are in line with those of the aforementioned studies, providing more evidence for the existence of the hypothesized relationship between the variables. An association between data analytics capability and business model innovation (22.2%, after adjusting for other factors) may be explained by knowledge gain. The findings of this study highlight the need for an organization-wide approach to knowledge acquisition in order to fully realize the benefits of data analytics capability and business model innovation.

Table 4.8 Hypotheses Statistics

Hypotheses	Original sample	Standard deviation	T statistics (|O/STDEV|)	P values	Decision
Data Analytics Capability -> Business Model Innovation	0.435	0.051	8.566	0.000	Supported
Data Analytics Capability -> Knowledge Acquisition	0.623	0.039	15.992	0.000	Supported
Knowledge Acquisition -> Business Model Innovation	0.337	0.054	6.211	0.000	Supported
Data Analytics Capability -> Knowledge Acquisition -> Business Model Innovation	0.210	0.038	5.560	0.000	Supported

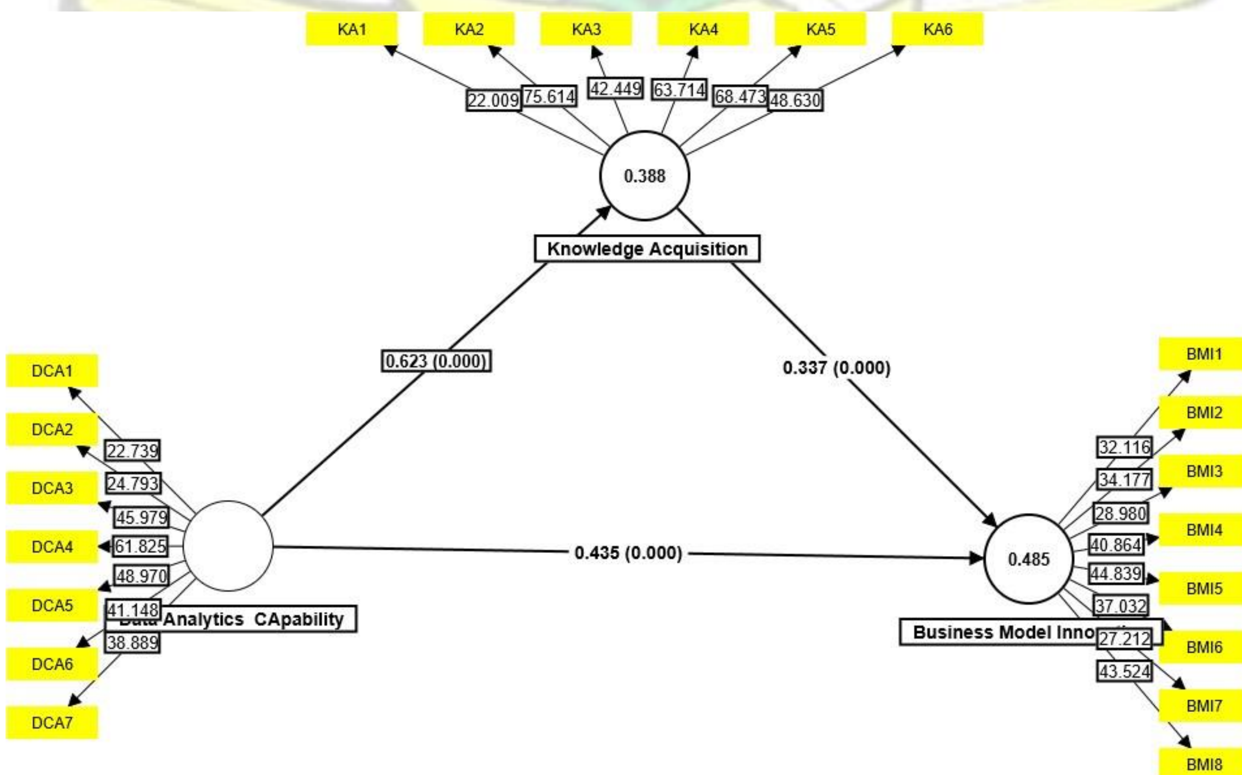


Figure 4.2 Structure Model Evaluation

4.9 Discussion of Results

This section provides a concise overview of relevant research, with a focus on the most salient findings. The purpose of this research was to analyze the interplay between data analytics and business model innovation in small and medium-sized enterprises (SMEs) in emerging markets via the mediating role of knowledge acquisition. The outcome is divided up into the components. The first objective of this study was to investigate how access to data analytics influences business model innovation in small and medium-sized enterprises (SMEs) in underdeveloped countries. The results showed a positive and significant relationship between SMEs' data analytics capability and their rate of business model innovation ($B=0.435$; $t=8.566$; p-value=0.001 <0.05). The results of this study corroborate the hypothesis that the factors under investigation are correlated. It also demonstrates that the extent to which data analytics capabilities are handled may account for variation in business model innovation across SMEs (43.5%), everything else being equal. The results suggested that small and medium-sized enterprises (SMEs) in emerging markets might benefit from enhancing their data analytics skills in order to better innovate their business models. The findings corroborate the contention of Bouncken et al. (2019), who draw on the dynamic capability theory to argue that businesses without DCs miss out on possibilities to profit from BDA and evolve their BMs for competitive advantage. The results back up Ciampi et al., (2021), who looked at how BDAC analytical capabilities affects business model innovation (BMI). The findings showed that there are beneficial effects of BDAC on BMI in two ways: directly and indirectly. This finding corroborates the findings of Minatogawa et al. (2019), who investigated the link between big data analytics capability and business model innovation and identified a significant relationship.

The study's second goal was to investigate the effects of data analytics skills on SME knowledge acquisition in emerging countries. The results showed that the extent to which SMEs use data analytics skills is shown to have a significant impact on the extent to which SMEs acquire new knowledge (B=0.623; t=15.992; p-value=0.000 <0.05). The findings of this research provide credence to the idea that the two factors are related. Data analytics capabilities were shown to be responsible for 62.3% of the variation in knowledge after accounting for other factors. To encourage wider use, small and medium-sized enterprises (SMEs) in emerging countries should highlight the benefits data analytics skills provide to knowledge development. The findings corroborate the work of Ferraris et al. (2019), who looked at how big data analytics skills and knowledge management affected company performance. The paper's results demonstrate that businesses with more technical and managerial BDA skills improved their performances, and that a knowledge management (KM) orientation significantly amplified the impact of BDA capabilities. The findings match the research of Obitade (2019), who looked at how the use of big data analytics might strengthen the connection between better knowledge management and cyber security. Cyber knowledge management skills were shown to be significantly enhanced in firms that used big data analytics. As a second point, the results corroborate the idea that big data analytics and cyber agility are inextricably linked.

The study's third objective was to determine whether or whether knowledge acquisition mediates the connection between data analytics capability and business model innovation among small and medium-sized enterprises (SMEs) in emerging economies. The result showed that the connection between SMEs' data analytics capabilities and their propensity to innovate their business models is mediated by their level of knowledge acquisition (B=0.210; t=5.560; p-value=0.000 <0.05). This study's findings are in line with those of the aforementioned studies, providing more evidence for the existence of the hypothesized relationship between the variables. An association between data analytics capability and business model innovation (22.2%, after adjusting for other factors) may be explained by knowledge gain. The findings of this study highlight the need for an organizationwide approach to knowledge acquisition in order to fully realize the benefits of data analytics capability and business model innovation. The findings are also corresponding the research of Parra-Requena et al. (2015), who investigated the mediating function of knowledge acquisition between external social capital and inventiveness. In line with Jiang et al. (2022), who investigate the moderating role of unconsumed slack in the relationship between the stability of innovation ecosystems (IES) and the innovativeness of businesses (through the intermediary of knowledge acquisition KA), the study found that KA plays a significant role in this relationship. The results also showed that IES has a beneficial effect on firms' innovation performance, and that KA helps to mediate this relationship to some extent. The findings demonstrated that the connection between external social capital and inventiveness is mediated by knowledge acquisition. The findings corroborate those of Shabbir and Gardezi (2020), who tested a model investigating the connection between the use of big data analytics (ABDA) and OP in SMEs (SMEs). Knowledge management practices (KMP) are also investigated as a potential mediator between the ABDA and the OP in this research. The study's findings revealed that big data analytics (ABDA) and organizational performance are connected through a mediating mechanism of knowledge management. The findings back up the work of Li et al. (2020), who investigated the effects of KAD on the innovation output of Chinese domestic firms and the conditions (in terms of technology gap and technology development pace) under which KAD is most likely to contribute. Both product-related innovation performance (NPS) and knowledge-related innovation performance (KIP) are negatively correlated with KAD (PAT).

CHAPTER FIVE

SUMMARY OF FINDINGS, CONCLUSION AND RECOMENDATIONS

5.1 Introduction

This chapter concludes the study by summarizing its findings and pointing to potential future research directions. Potential future research avenues and study limitations were discussed.

5.2 Summary of findings

The purpose of this research was to analyze the interplay between data analytics and business model innovation in small and medium-sized enterprises (SMEs) in emerging markets via the mediating role of knowledge acquisition. The study then presents a brief overview of its key findings, which were derived from the research and the existing literature. The findings are organized in a manner that is appropriate in light of the study's stated aims.

5.2.1 The relationship between Data Analytics Capabilities and Business Model Innovation among SMEs

The first objective of this study was to investigate how access to data analytics influences business model innovation in small and medium-sized enterprises (SMEs) in underdeveloped countries. The results showed a positive and significant relationship between SMEs' data analytics capability and their rate of business model innovation. The results of this study corroborate the hypothesis that the factors under investigation are correlated. It also demonstrates that the extent to which data analytics capabilities are handled may account for variation in business model innovation across SMEs, everything else being equal. The results suggested that small and medium-sized enterprises (SMEs) in emerging markets might benefit from enhancing their data analytics skills in order to better innovate their business models.

5.2.2 The relationship between Data Analytics Capabilities and Knowledge Acquisition among SMEs

The study's second goal was to investigate the effects of data analytics skills on SME knowledge acquisition in emerging countries. The results showed that the extent to which SMEs use data analytics skills is shown to have a significant impact on the extent to which SMEs acquire new knowledge. The findings of this research provide credence to the idea that the two factors are related. Data analytics capabilities were shown to be responsible for variation in knowledge after accounting for other factors. To encourage wider use, small and medium-sized enterprises (SMEs) in emerging countries should highlight the benefits data analytics skills provide to knowledge development.

5.2.3 The mediating role of Knowledge Acquisition in the relationship between Data Analytics Capabilities and Business Model Innovation among SMEs

The study's third objective was to determine whether or whether knowledge acquisition mediates the connection between data analytics capability and business model innovation among small and medium-sized enterprises (SMEs) in emerging economies. The result showed that the connection between SMEs' data analytics capabilities and their propensity to innovate their business models is mediated by their level of knowledge acquisition. This study's findings are in line with those of the aforementioned studies, providing more evidence for the existence of the hypothesized relationship between the variables. An association between data analytics capability and business model innovation may be explained by knowledge gain. The findings of this study highlight the need for an organization-wide approach to knowledge acquisition in order to fully realize the benefits of data analytics capability and business model innovation.

5.3 Conclusion

The study's goal was to examine the mediating function of knowledge acquisition between data analytics and business model innovation in SMEs in developing economies. Quantitative data was gathered using cross-sectional surveys with a view toward inference and analyzed using inductive logic. The study focused on small and medium-sized enterprises (SMEs) in the Eastern Region of Ghana, whether they were engaged in manufacturing or providing services. By using a purposive sampling technique, data was collected from 384 knowledgeable employees on the study's major topics. The study proved the hypotheses by using SEM (SmartPLS 4). The data was summarized using descriptive statistics. The findings revealed that data analytics capability has a positive and significant effect on business model innovation among SMEs. Knowledge acquisition was shown to have a significant influence on business model innovation, and it was also found to mediate the relationship between data analytics capabilities and business model innovation. Therefore, this suggests that business model innovation in SMEs should benefit from managers' greater openness to acquiring data analytics knowledge and skills.

5.4 Implications of the findings

The study's goal was to examine the mediating function of knowledge acquisition between data analytics and business model innovation in SMEs in developing economies. The findings revealed that data analytics capability has a positive and significant effect on business model innovation among SMEs. Knowledge acquisition was shown to have a significant influence on business model innovation, and it was also found to mediate the relationship between data analytics capabilities and business model innovation. Therefore, this suggests that business model innovation in SMEs should benefit from managers' greater openness to acquiring data analytics knowledge and skills. Below are some suggestions based on the findings.

According to the results, data analytics has a significant impact on the development of new business models. Based on the findings, SMEs may improve the efficiency of business model innovation by putting more focus on their data analytics capabilities. Therefore, it is crucial for company management for using internal information (e.g., orders, deliveries) to endorse production schedules, to use inner information to anticipate and inhibit production problems, to use inner data to predict malfunctions, they must collect data from equipment's and sensors and use it in products and services and use outer customer information (e.g., market research) to support going to plan Supplies.

The results demonstrated that the competence of data analytics has a considerable impact on knowledge acquisition. As a result, it's clear that SMEs need to concentrate more on developing their data analytics skills in order to greatly enhance their capacity for acquiring new knowledge. Therefore, decision makers in this field need to learn the landscape and choose an entry point for deployment, improve visualization skills to captivate people, establish a fact-driven mindset, and use right-fit metrics.

Knowledge acquisition was shown to be the "mediating" variable between data analytics capability and business model innovation, suggesting that boosting knowledge acquisition would increase the positive effect of data analytics on business model innovation. Therefore, this indicates that, for SMEs to innovate their business models, managers need be more receptive to learning data analytics. Managers in this area should have a strong interest in easing the exchange of information between the company and its external business environment. This is accomplished through open lines of communication with the company's key constituents and the systematic gathering, analysis, and incorporation of feedback from these conversations.

5.5 Limitations and Directions for Future Research

There are a few potential issues with this study's conclusions. DAC is still in its infancy, and the term "DAC capacity" is not yet defined anywhere in the literature. The analysis procedure and DAC technology are the main points of interest. More research is needed to confirm the conceptual model proposed in this study. The collection of data and the selection of a target sample also presents a challenge to the actualization of this research. Business managers make up the study's intended sample, thus contacting them is crucial for testing the model's assumptions. In addition, the size of the sample is still deemed to be low. Research into this area requires a much larger sample size before its results can be extrapolated to other sectors in Ghana. According to Bhatt and Grover, research into DAC is only getting started and will evolve with technological advances, making it impossible and laborious to account for every potential facet of DAC in the future. Once again, further research may help improve the DAC model by identifying more big data resources. Furthermore, testing the model developed in this work would need a more in-depth inquiry in Ghana. The study's conclusions are less reliable since the researcher used a quantitative research strategy and a cross-sectional design to gather data. Future researchers are encouraged to use a qualitative strategy, such as in-depth interviews, for data collection. Longitudinal data collection is also recommended for future studies to confirm these results.

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APPENDIX

Appendix I: Survey Questionnaire

Dear Sir/ Madam,

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

SECTION A: RESPONDENT'S BIOGRAPHY AND COMPANY PROFILE

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

Please answer the following questions:

Please answer the following questions:

1. *Gender*: Male ☐ Female ☐

2. *Age*

18-30 years ☐ 31-40 year's ☐ 41-50 years ☐ Above 50 years ☐

3. *Level of Education*

Junior High School ☐ Senior High School ☐ Diploma ☐ Bachelor Degree ☐ Graduate Studies (Master / Ph.D.) ☐ Others ☐ For Others, please specify……………………

4. *Your Position in the Firm*

Business Owner ☐ Business Owner & Manager ☐ Manager ☐ Production Manager ☐ Others ☐…………………………………………………………………………

5. *How many years have your firm been in operation?*

1 - 5 years ☐ 6 - 10 years ☐ 11 – 15 years ☐ 16 years and above ☐

6. *How many employees are in the firm?*

Less than 5 employees ☐ 5 – 29 employees ☐ 30 – 99 employees ☐ More than 100 ☐

7. Type of ownership:

[ ] Fully locally owned [ ] Fully foreign owned [ ] Jointly Ghanaian & foreign owned

SECTION B: Data Analytic Capability

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

Statement	**1**	**2**	**3**	**4**	**5**
We use internal data (e.g. orders, deliveries) to support production planning					
We use internal data to predict and prevent product failures					
We use internal data to predict machine failures					
We collect data from equipment's and sensors and use it in processes and services					
We use external customer information (e.g. market research) to support planning Sources:					
We use external information (e.g. price information) to support planning					
We use big data (external and internal) in business decisions					
We use external supplier information (e.g. vendor location information, credit information) for evaluating supplier risks					

SECTION C: Knowledge Acquisition

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

Statement	**1**	**2**	**3**	**4**	**5**
The organization is keen on facilitating knowledge flows between itself and the external business environment, by actively communicating with its most influential stakeholders					
Core team members are selected for their multiple ties and contacts, which enable them to access diverse and remote sources of information and knowledge					

The organization accesses, collects, and acquires new ideas and information from diverse external sources in its business environment, including its customers, suppliers, competitors, and partners					
The organization has in place internal routines and processes that allow its individuals to analyses, process, interpret, and understand the information obtained from external sources					
Individual members of the organization from different subunits hold discussions, interact, and communicate together, whenever there is a need to understand and comprehend certain information and knowledge acquired from outside the organization					
The organization is keen on seeking assistance from its highly skilled individuals to enrich its learning experience					

SECTION C: Business Model Innovation

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

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

Thank you for participating in the survey.