Antecedents, Outcomes, and Boundary Conditions of Disruptive Business Models

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The candidate confirms that the work submitted is her own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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ABSTRACT

Disruptive Business Models have received acclaimed attention in the literature due to their importance in explaining competitive advantages and positive performance outcomes for organisations. Even though past research examines their nature and how organisations can respond to disruptive business models, there is limited knowledge on the organisational capabilities that facilitate the development of disruptive business models and performance outcomes of disruptive business models. In addition, existing literature on disruptive business models is largely atheoretical and there are limited attempts at empirically measuring disruptive business models. Drawing on the Resource-based view of the firm and the literature on disruptive innovation, this thesis examines an integrated model of disruptive business model, its drivers, performance outcomes, and boundary conditions. The conceptual model examined in this study incorporates hypotheses pertaining to: (a) the factors influencing firms to develop a disruptive business model; (b) the relationship between disruptive business model and performance; and (c) the moderating role of big data analytics capability and adaptive marketing capability on the disruptive business model–performance relationship. The interview findings show that technological advancements, political uncertainty and government regulations, competitive pressures, the press and media, and consumer dynamism are linked to the development of disruptive business models. The conceptual model was empirically tested on a survey of 360 small, medium, and large organisations in the United Kingdom. Using seemingly unrelated regression, findings show that formalisation, top managerial risk-taking propensity, willingness to cannibalise, and management commitment to innovation are positively related to developing a disruptive business model. Regarding performance, disruptive business model is positively related to new product performance and market performance. Furthermore, both new product and market performance have positive relationships with anticipated financial performance. Findings further show that big data analytics capability has a positive moderating effect on the disruptive business model–performance relationship while adaptive marketing capability has a negative moderating effect on the disruptive business model–performance relationship. These results have significant implications for research and theory, management practice, managers, and policy making. Finally, the limitations of the study are considered in addition to future research directions on the subject matter.

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LIST OF ABBREVIATIONS

RBV – Resource-Based View

TCE – Transaction Cost Economies Theory

BDA – Big Data Analytics Capability

AMC – Adaptive Marketing Capability

EFA – Exploratory Factor Analysis

CFA – Confirmatory Factor Analysis

CRM – Customer Relationship Management

UK – United Kingdom

ROA – Return on Assets

ROI – Return on Investment

CHAPTER 1

INTRODUCTION

1.0 Introduction

In increasingly dynamic and competitive environments, disruption has become a buzz word because of its impact on firm survival and performance (Newman 2016). Organisations have come to terms with the reality of experiencing disruptive threats or initiating disruptive business models to meet emerging consumer needs, establish a foot hold in a market or industry, ensure survival, and achieve sustained competitive advantages by safeguarding and increasing organisational revenue, growth, and market share. The phrase 'disrupt or be disrupted' has been wide-spread in various ongoing conversations within different industries about the nature and impact of disruptive activities in general and disruptive business models in particular (Hessman 2014; Kotter 2013).

This has created the need for organisations to constantly monitor their internal and external environments, consumer needs, and competitive actions to remain competitive and survive in the marketplace (Beal 2000). As such, research on disruption has gradually increased over the years because of its growing importance and relevance to organisational strategies, survival, and performance (Shang, Miao, and Abdul 2019). This study draws on the disruptive business model literature (Habtay and Holmén 2014; Karimi and Walter 2016; Osiyevskyy and Dewald 2015) to propose and empirically test an integrated model of its drivers, outcomes, and boundary conditions.

This chapter starts with a discussion of the background of the study, problem definition and statement, and provides a rationale for examining the disruptive business model construct. It then identifies the gaps in current research which have necessitated this research and highlights the aims and objectives of the study. This is followed by a definition of the important concepts examined in this research and the potential value of the findings of this thesis to researchers, management practice, managers, and policy making is then discussed. This chapter ends with an outline of the organisation of the rest of this thesis.

1.1 Study Background, Problem Definition, and Statement

Various industries and organisations have experienced disruption caused by the introduction of disruptive business models, especially with the rise of technological advancements. Organisations such as Alibaba, WhatsApp, Uber, and Deliveroo are currently implementing disruptive business models in their respective industries (Dobbs, Manyika, and Woetzel 2015). Likewise, Spotify has introduced music subscription services, Netflix has introduced online movie/series subscription services in addition to providing their own content, and Amazon Go is currently disrupting the brick-and-mortar space through the provision of easy shopping to consumers (Keys 2017).

Dell Computer changed their traditional business model to a disruptive one where they customised their PCs, by-passed the middle-men such as retailers, and sold directly to consumers (Yovanof and Hazapis 2008). Furthermore, disruptions caused by Amazon in online retailing (Markides 2006) and Apple with the introduction of the iPod and iTunes (Burgelman and Grove 2007) can be credited to the introduction of disruptive business models that caused unprecedented changes in the ecosystem. A similar example is the disruptive business model introduced by Salesforce that disrupted the enterprise Customer Relationship Management (CRM) software ecosystem (Snihur, Thomas, and Burgelman 2018).

Business models provide a link between technologies and commercialisation of innovation (Yovanof and Hazapis 2008). As such, a disruptive business model provides a platform for the successful commercialisation of disruptive technologies in organisations but the question of 'how' to develop a disruptive business model and the boundary conditions of the disruptive business model–performance relationship remains elusive in extant literature. Past research has focused on case studies of organisations that have introduced disruptive business models, however, this is usually limited to industries such as ICT, communications, insurance, pharmaceutical, and airline industries (e.g., Yovanof and Hazapis 2008; Habtay and Holmén 2012; Sabatier, Craig-Kennard, and Mangematin 2012).

While these attempts at understanding disruptive business models are laudable, little is known about the mechanisms, resources, and capabilities needed for the successful development and implementation of disruptive business models across various industries. Furthermore, there is little attempt to measure the disruptive business model construct and empirically analyse its antecedents, performance outcomes, and boundary conditions.

A disruptive business model can be defined as "a tool in crafting strategy for the purpose of achieving sustainable innovation in the face of the reshaping of the industry and the market" (Yovanof and Hazapis 2008, p. 569). The ability of business models to reshape industry standards and market expectations can be attributed to the presence of disruptive technology which is a common characteristic of disruptive business models (Dewald and Bowen 2010). Thus, a disruptive business model changes customer perceptions and preferences, performance metrics, industry operations, existing business models, the basis for competition, organisational resources, and capabilities needed for business success (Christensen, Johnson, and Rigby 2002). Therefore, the core tenets of disruptive business models are "change" and "impact" because of the deviation from existing norms, target markets, and value creation mechanisms (Markides 2006).

Therefore, it has become expedient for organisations to remain competitive by introducing disruptive business models to ensure survival, profitability, and positive performance outcomes. This is because arguably, many firms fail because they continue doing the right thing for so long even when things have changed in their environment, are inflexible, and continually stick to their current business models (Doz and Kosonen 2010; DaSilva *et al.* 2013). This realisation has made disruptive business model development and implementation a crucial capability for organisations because it can open doors to new markets. Furthermore, some scholars argue that the refusal of organisations to implement disruptive business models can be detrimental to overall success (Casadesus-Masanell and Ricart 2011, 2010; Christensen 1997).

It must be noted however that developing and implementing disruptive business models is not without risk as they can also have high failure rates (Walsh 2004) which can be due to hasty and rigid decision making by incumbent organisations among others (Markides 2006). This emphasises the need to thoroughly understand how a disruptive business model can be successfully developed and the mechanisms that facilitate its success. Therefore, this research aims to shed light on the conditions under which a disruptive business model can be successfully implemented by organisations.

Having a thorough understanding of the nature of disruptive business models will provide much needed guidance to academics, organisations, and managers on how a disruptive business model can be developed, what factors enhance or inhibit its success, and the various performance outcomes that can be achieved by its introduction. This will help to increase the success rates of disruptive business models by providing information on its nature, drivers, contingencies, and performance effects. Knowledge on disruptive business models is therefore essential to ensuring that organisations remain competitive by successfully maneuvering the ever-competitive landscape (Teece 2010). Extant literature focuses mainly on external antecedents (e.g., Christensen 2006) and incumbent responses to disruptive business models (e.g., Habtay and Holmén 2014; Osiyevskyy and Dewald 2015). Thus, in-depth understanding on the nature of a disruptive business model is needed as there is limited research on its antecedents, contingency effects, and performance outcomes (for exceptions see Karimi and Walter 2016).

As such, this study addresses the knowledge gaps in the disruptive business model literature by empirically analysing an integrated model of the driving factors that enhance the development and implementation of disruptive business models, the contingency factors that enhance or inhibit the performance effects of disruptive business models, and the performance outcomes of disruptive business models.

1.2 Objectives and Research Questions of the Study

This study aims to develop and empirically test a model that examines the antecedents, contingency effects, and performance outcomes of disruptive business models using the resource-based view (RBV) as the theoretical underpinning for building the research model. This is crucial as extant research lacks strong theoretical foundations (Osiyevskyy and Dewald 2015). As such, the model identifies the major drivers of disruptive business models; establishes a link between disruptive business model and organisational performance metrics; and examines the critical moderating effects of organisational and marketing capabilities on the disruptive business model–performance relationship. Accordingly, the study seeks to achieve three key objectives, which are to: (a) identify major drivers of disruptive business models; (b) examine the organisational performance effects of disruptive business models; and (c) investigate the contingency effects of organisational and marketing capabilities on the disruptive business model–performance relationship.

Thus, the research questions to be examined in this study are: (a) what are the major drivers of disruptive business models; (b) what are the organisational performance effects of disruptive business models; and (c) what are contingency effects of organisational and marketing capabilities on the disruptive business model–performance relationship? Examining these research questions will advance existing research on disruptive business models and provide guidance to organisations, researchers, and managers on the nature of disruptive business models and how they can be successfully implemented. In addition, the answers to these research questions will contribute to the existing literature and address some of the gaps in the literature. Thus, this study will provide insight into the internal mechanisms, resources, and capabilities that need to be put in place in organisations to ensure the successful development and implementation of disruptive business models.

The first research question will shed light on the drivers of disruptive business models which will help organisations know what to pay attention to when developing disruptive business models. The second research question will expatiate on the performance outcomes of developing and implementing disruptive business models. This will provide organisations a blueprint that shows the path of success for disruptive business models and its benefits to organisations. The third research question will examine the impact of organisational capabilities on the disruptive business model–performance relationship and describe the complementary nature of organisational capabilities and disruptive business models.

1.3 Defining Important Concepts and Model Variables

The model of this study consists of drivers of disruptive business model, disruptive business model as the focal construct, moderators of the disruptive business model-performance relationship, and performance outcomes of disruptive business model. The *drivers* of disruptive business model include formalisation, managerial commitment to innovation, top managerial risk-taking propensity, and willingness to cannibalise.

Formalisation can be described as the extent to which rules and regulations are strictly followed, implemented, and adhered to in an organisation. Management commitment to innovation refers to the willingness of top management to identify innovative opportunities early on and invest in research and development, technological advancement, new product development, advertising for new products, and marketing for new products. Top managerial risk-taking propensity is the willingness of top managers to take financial and innovative risks even when success is uncertain. Willingness to cannibalise is the ability of an organisation to sacrifice existing sales, profits, infrastructure, assets, capabilities, and technical know-how to adopt an innovative product, service or business model.

The focal construct of this study, *disruptive business model*, can be defined as "a tool in crafting strategy for the purpose of achieving sustainable innovation in the face of the reshaping of the industry and the market." (Yovanof and Hazapis 2008, p. 569). It can also be described as a new combination of business model components or a new way of exploiting one or more of the business model components (Gambardella and McGahan 2010; Rivera-Camino 2007). Also, a disruptive business model aims to create "frame-breaking change within the industry or market" (Menon and Menon 1997, p. 57). Some disruptive business models are characterised by disruptive technologies (Dewald and Bowen 2010) that aim to change customer perceptions and preferences, performance metrics, industry operations, existing business models, basis for competition, organisational resources, and capabilities needed for business success (Christensen, Johnson, and Rigby 2002). Importantly, a disruptive business model can be introduced by any organisation irrespective of size or age in an industry.

The *moderators* examined in this study which have an impact on the disruptive business model–performance relationship are adaptive marketing capability and big data analytics capability. Adaptive marketing capability refers to "the extensible ability to proactively sense and act on market signals, continuously learn from market experiments, and integrate and coordinate social network resources to adapt to market changes and predict industry trends" (Guo et al. 2018, p. 3). Big data analytics capability refers to the ability of organisations to "collect large and complex data from different instruments at all stages of the process which go from acquisition, storage and sharing, to analysis and visualization" (Pisano, Pironti, and Rieple 2015, p. 191).

The *performance* outcomes of disruptive business model examined in this study consists of market performance, new product performance, and anticipated financial performance. Market performance refers to performance metrics that measure organisational market share, sales growth, market development, and product development (Sarkar, Echambadi, and Harrison 2001). New product performance can be described as the ability of managers and organisations to successfully create and generate new product ideas, introduce new products into a market, and engage in productive product development activities (Gatignon and Xuereb 1997; Im and Workman Jr 2004; Montoya-Weiss and Calantone 1994). Anticipated financial performance refers to organisations' projected performance for the next 12 months on metrics such as profit margin, return on assets, return on investment, and profit growth (Vorhies and Morgan 2005).

1.4 Value of the Study

The findings of this study will be beneficial to various parties such as researchers, management practice, managers, and policy makers. For *researchers*, this study builds on existing research on disruptive business models by employing both qualitative and quantitative research techniques to explicate the nature of disruptive business models, understand its main drivers, and the mechanisms at work in ensuring that adopting disruptive business models leads to positive performance outcomes.

Thus, the findings from this study will provide in-depth information through theoretical lenses on the drivers of disruptive business models, the performance outcomes of disruptive business models, and the contingency effects that influence the disruptive business model–

performance relationship. As such, this study builds on the resource-based view and literature on disruptive innovation to advance knowledge and understanding on the nature of disruptive business models, its drivers, performance effects, and boundary conditions. In addition, this study proposes a novel way of empirically measuring disruptive business models which is vital for future research on this subject.

For *management practice*, the findings of this study will provide guidance on how to ensure that a disruptive business model contributes positively to organisational performance by showing the mechanisms that enhance or hinder its success. Furthermore, the findings of this research will reveal the nature of disruptive business models in various industries and its major drivers which will provide insight to organisations on what to concentrate on when implementing a disruptive business model. This is in addition to discussing the various performance outcomes that can be accrued from adopting a disruptive business model.

For *managers*, the findings of this study will provide insight into the managerial attributes that are crucial to the successful development and implementation of disruptive business models. Hence, this study will provide guidance to managers on strategic decision making, resource allocation, and organisational strategies to put in place when developing, implementing or adopting disruptive business models. The findings of this study will provide an exposé on the perception of disruptive business models in various industries, the internal and external factors that facilitate its development, and the organisational capabilities that strengthen the disruptive business model–performance relationship.

In addition, the findings of this study will be applied to organisations operating in various industrial settings, irrespective of organisational size. On one hand, the analysis carried out in this study provide recommendations for small, medium-sized, and large organisations. On the other hand, analysis based on industry of operation classified into manufacturing firms, service firms, and manufacturing and services firms provide useful industry-specific insights into the successful development of disruptive business models.

For *policymaking*, the findings of this study will help to enhance the professional practices of strategic marketing decision making in relation to disruption caused by disruptive business models. The results of this study will unearth the nature of disruptive business models in various industries and thus provide guidance on the institutional dynamics at work which influence the success of disruptive business models in various industries. The findings from this research will provide contextual information on the mechanisms at work in ensuring that disruptive business models are successfully implemented and lead to positive performance outcomes.

In sum, the findings from this study will provide much needed guidance and information on the nature of disruptive business models and its major drivers. This will help to explain the nature of disruptive business models in addition to the role organisational capabilities play in facilitating or inhibiting the performance effects of disruptive business models. Furthermore, the results of this thesis will shed light on the performance outcomes of disruptive business models ranging from new product performance to market performance and anticipated financial performance. Thus, the findings of this study will build on existing literature and theoretical perspectives by extending these to the drivers, contingency effects, and performance outcomes of disruptive business models.

1.5 Organisation of the Study

This thesis consists of six chapters which are presented in Figure 1.1. *Chapter one* introduces the study and highlights the background of the study, problem definition, and statement. The main aims, objectives, and research questions of the study are presented. In addition, important concepts and model variables are defined and the potential value of the findings of the study to various parties is discussed. The organisation of the study on a chapter-by-chapter basis is then provided. *Chapter two* presents a review of existing literature on disruptive business models. It begins with an examination of theories used in previous research. The literature on disruptive business models, its antecedents, and outcomes are then discussed. The chapter ends with a critique of the literature and identification of the gaps in the literature.

Chapter three focuses on the research model of the thesis and the hypotheses development. The first part of the chapter provides an overview of the conceptual model of the study and discusses the constructs in the conceptual model. The second part of the chapter develops the study's hypotheses relating to the antecedents of disruptive business model, the outcomes of disruptive business model, and the boundary conditions of the disruptive business model–performance relationship. The third part of the chapter discusses the control variables and provides justifications for the control variables selected.

Chapter four discusses the research methodology adopted in this study. First, the scope of the research is discussed regarding geographic scope, industry coverage, unit of analysis, and key informants used in the study. Second, the data and data collection instruments including the qualitative and quantitative procedures used in the study are discussed. Third, the sampling procedures utilised in the study are examined and the research instrument is developed which includes the questionnaire layout, presentation of the questionnaire, cover letter, and questionnaire pre-testing. Fourth, the fieldwork procedures including steps taken to secure participation, enhance response rate, and ensure key informant quality are examined. The demographic characteristics of the sample are discussed and the test for non-response bias is presented. This is in addition to the procedures taken for the data editing, coding, and transcribing. Finally, the measures used in the thesis are discussed and the descriptive statistics are presented.

Chapter five concentrates on the test of hypotheses developed in the study. First, the purification of items is discussed including the selection of items using exploratory factor analysis and item-total correlation analysis. This is followed by the results of the confirmatory factor analysis for the antecedents of disruptive business model, organisational capabilities, and performance outcomes of disruptive business models. The results of the hypotheses testing are then presented. The robustness checks conducted are discussed consisting of slope test for interaction plots, additional analyses based on moderating, moderated mediation, industry, and organisational size effects.

Chapter six, the concluding chapter of the thesis provides the discussion of findings, theoretical contributions, implications, limitations, and future research avenues. First, the findings of the study are discussed in relation to paradigmatic theoretical findings, interview findings, and the conceptual model. Thereafter, the theoretical contributions and implications of the findings of the study to various stakeholders are discussed. This is followed by a discussion of some of the limitations of the study. The chapter concludes with a discussion of various avenues for future research based on the findings of the study.

Figure 1.1: Research Design

Chapter One
Introduction

- Provides a background to the thesis topic
- Presents recent debates on disruption
- Discusses the research questions, aims, and objectives
- Defines important concepts and model variables
- Provides the value of the study
- Presents the outline of the thesis

Chapter Two
Literature Review

- Critically reviews the theories used in past research
- Describes and defines disruptive business models
- Outlines the antecedents of disruptive business models
- Provides the outcomes of disruptive business models
- Reveals the gaps in the literature and critique of past literature

Chapter Three
Research Model and Hypotheses

- Provides an overview of the conceptual model
- Discusses the theoretical underpinnings of the model
- Develops the research hypotheses
- Provides the justification for control variables included in the conceptual model

Chapter Four
Resarch Methodology

- Examines the scope of the research
- Designs the research research and data collection instruments
- Explains the steps taken in data collection and fieldwork procedures
- Presents the measures and descriptive statistics

Chapter Five
Analysis and Results of the Empirical Study

- Provides the results of the exploratory and confirmatory factor analyses
- Presents the results of the hypotheses testing
- Presents the results of robustness checks and additonal analyses conducted

Chapter Six
Discussion, Contributions, Limitations, Direction for Future Research, and Conclusions

- Provides a summary of the study
- Discusses the findings of the study in relation to past research
- Derives implications from the findings
- Highlights the study limitations
- Proposes avenues for future research

1.6 Summary

This chapter introduces the study by discussing the background to the thesis topic and providing an overview of the concept of disruptive business models. Furthermore, the objectives and research questions of the study are presented. The key concepts and model variables are defined and the potential value of the study to potential stakeholders is discussed. An overview of each subsequent chapter in this thesis is provided and the research design of the study on a chapter-by-chapter basis is presented in Figure 1.1.

CHAPTER 2

LITERATURE REVIEW

2.0 Introduction

This chapter aims to provide a theoretical background on the nature of disruptive business models, its drivers, and outcomes. Current research on disruptive business models will be critically analysed with the aim of identifying gaps in the existing literature and exploring new research opportunities. The first section of this chapter examines the theories used in past research. This is followed by a review of the literature on disruptive business models, a discussion on its antecedents and outcomes, and a critique of existing research. The third and final section of this chapter provides a summary of all that has been discussed.

2.1 Critical Examination of Theories used in Previous Research

Various theories have been used in the Innovation and Business Model literature streams. They include the resource-based view (RBV), transaction cost theory (TCT), disruptive innovation theory, complexity theory, complementarity theory, innovation theory, entrepreneurship theories, leadership theories, and dynamic capabilities theory. A summary of these theories, their major assumptions, and weaknesses are provided in Table 2.1.

The RBV opines that organisations operate within industries and possess distinct attributes, resources, and capabilities that are within the control of the organisation, cannot be easily exchanged among firms, and lead to sustained competitive advantages (Barney 1991). However, a weakness of this view is its focus on internal mechanisms within organisations without considering external influences on organisational performance. The RBV can help to explain the internal mechanisms at work in the development of disruptive business models and highlight the role of organisational resources and capabilities that can facilitate the success of disruptive business models.

The dynamic capabilities theory extends the RBV by taking into account internal and external organisational competencies that can be restructured to match changing business conditions (Teece, Pisano, and Shuen 1997). Dynamic capabilities "are underpinned by organisational routines and managerial skills, are the firm's ability to integrate, build and reconfigure internal and external competences to address, or in some cases to bring about changes in the business environment" (Teece 2018, p. 40). Thus, dynamic capabilities theory can shed light on the internal and external factors that organisations can harness to successfully develop and implement disruptive business models and cause changes in their industries and business environments.

Complementarity can be described as when an activity works hand-in-hand and enhances another activity within an organisation. As such, the tenets of the complementarity theory argue that complementarities develop from a combination of individual factors / relationships within organisations and can facilitate superior organisational performance (Ennen and Richter 2010). Complementarity theory can provide insights into the internal mechanisms at work within organisations that develop disruptive business models. Specifically, complementarity theory can explain how some organisational capabilities work hand-in-hand to facilitate the development and success of disruptive business models.

Complexity theory examines the integral components of organisations and their environments and concludes that society consists of nonlinear relationships that are complex and can change dramatically over time (Levy 2000). Thus, simple actions within and outside organisations can collectively lead to unpredictable activities within organisations and their industries of operation. Hence, complexity theory emphasises the erratic and volatile nature of business environments and opines that it is difficult to make long-term forecasts and accurately measure the activities and their interactions that can affect business operations. In examining disruptive business models, complexity theory can only account for the impact caused by disruptive business models on the market/industry of operation but does not provide insight into the process of developing disruptive business models and their performance outcomes.

Transaction Cost Economics (TCE) has its roots in economics, organisational theory, and contract law (Song and Thieme 2009; Williamson 1981). TCE views the 'transaction' as the basic unit of analysis and posits that understanding transaction costs is crucial in research on organisations (Williamson 1981). TCE theory can help in explaining the characteristics of entrant firms that introduce disruptive business models. Specifically, Habtay (2012) examines the nature of an entrant's firm opportunistic behaviour using the TCE theory and argues that an entrant firm introducing disruptive business models can decide to engage in vertical integration to avoid being displaced or specialise in developing their capabilities through alliances. Therefore, firms that introduce disruptive business models by establishing collaboration, alliances, and partnerships to complement their resources and capabilities need to be aware of the transaction costs that might be incurred and the level of information processing that needs to be undertaken to maximise such relationships.

Disruptive business models can be viewed as a type of innovation. As such, innovation theory (Henderson and Clark 1990) can help to explain some ways that disruptive business models can be developed. This is essential as disruptive business models can displace existing business models and cannot be easily imitated by competitors and incumbents. It is therefore important to have knowledge of the components of a disruptive business model (component knowledge) and the integration of the components of a disruptive business model (architectural knowledge).

Similarly, disruptive business models can be viewed as a type of disruptive innovation. The disruptive innovation theory argues that organisations can introduce disruptive products, services, and business models that do not involve high-end technological advancements (Christensen 1997). However, these innovations possess attributes that are attractive to less demanding, emerging, or new market segments, and are perceived as inferior by incumbent organisations (Christensen, Johnson, and Dann 2002). Disruptive innovation theory can shed light on the nature of disruptive business models that do not involve significant technological advancements but cater to the needs of certain consumer segments that are unreached or ignored by existing business models. Furthermore, disruptive innovation theory can explain the performance outcomes of disruptive business models and how disruptive business models can eventually outperform existing business models.

For disruptive business models to be successfully developed, certain leadership qualities need to be present within organisational structures and settings. On one hand, entrepreneurship theories can elucidate the role of top managerial team members in ensuring the success of disruptive business models. Entrepreneurship theories propose that entrepreneurs create subjective interpretations based on objective data, are deliberate in their efforts, and combine resources and capabilities to satisfy consumer needs and wants (Foss and Klein 2017). A drawback of this theory which also applies to disruptive innovation theory is that results can only be known *ex post* and not *ex ante*. Thus, if applied to disruptive business models, the success of entrepreneurial/top-management decision making and resource allocation among others can only be known when they have been implemented based on consumer feedback and industry/market estimates.

On the other hand, leadership theories show that transformational leadership is positively related to performance, however, transactional and contingent reward leadership are negatively related to performance (Howell and Avolio 1993). The assumptions and tenets of leadership theories can be used to understand organisational settings and examine the leader–follower relationship and the management–employee relationship in organisations that introduce disruptive business models. Even though this will be an interesting avenue of research, it is beyond the scope of this study.

This study aims to examine the antecedents, outcomes, and boundary conditions of disruptive business models. Thus, it aims to examine the external factors that drive the development of disruptive business models and the internal mechanisms at work within organisations that develop and implement disruptive business models. The interview findings provide insight into these factors and the conceptual model examines the internal factors in more detail. As such, this study builds on the tenets of the RBV and the disruptive innovation theory to understand the nature, drivers, outcomes, and boundary conditions of the disruptive business model–performance relationship.

Table 2.1: Alternative Theories used in Past Research

Theory	Assumptions	Weaknesses
Resource-based View (Barney 1991)	i. Organisations that operate within an industry possess internal heterogeneous resources. ii. The internal resources under the control of organisations are not perfectly mobile and cannot be easily exchanged among firms. iii. Heterogenous organisational resources and capabilities can lead to sustained competitive advantages for organisations.	i. Focus on internal mechanisms within organisations. ii. Focus on competitive advantages. iii. Does not account for external influences on organisational performance.
Transaction Cost Theory (Williamson 1979, 1981)	i. Opportunism is the focal concept in understanding transaction costs, and it is crucial for economic activities that involve transactional investments in human and physical capital. ii. Transactions can be explained using three concepts: uncertainty, rate of transaction occurrence, and amount of investments into transactions.	i. Focus on organisational control mechanisms that need to be implemented to limit opportunism of partners. ii. Focus on internal organisational mechanisms (e.g., transactions and governance structures within organisations). iii. Internal-firm focus.
Disruptive Innovation Theory (Christensen 1997; Christensen, Johnson, and Dann 2002; Hart and Christensen 2002)	i. Disruptive innovations do not always have to involve high-end technological advancements. ii. Disruptive innovations possess distinct attributes that are attractive to over-served, less demanding, emerging, or new market segments. iii. Over time, disruptive innovations improve on performance and out-perform existing products, services, or business models.	i. Focus on successful disruptors. ii. Influence of other factors on the success of disruptive innovations (e.g., changing customer trends, regulatory bodies etc). iii. Not easily implementable by managers and organisations.

Theory	Assumptions	Weaknesses
Complexity theory (Levy 2000)	i. Organisations and their environments consist of nonlinear relationships that are complex and change dramatically over time. ii. Simple actions gradually and collectively lead to complex, dynamic, and unpredictable activities within organisations and their environments. iii. The social world consists of complex interaction of underlying subsystems and activities that exhibit patterns and can be predicted in the short-term.	i. Focus on industries as erratic and volatile. ii. Difficulty in making long-term forecasts that account for environmental changes that affect organisations. iii. Difficulty in measuring the activities and interactions that affect business operations.
Complementarity theory (Ennen and Richter 2010)	i. Complementarity is a situation where an activity enhances another activity within an organisation (i.e., working hand-in-hand). ii. Complementary relationships within organisations can facilitate superior performance outcomes in organisations. iii. Complementarities arise from a combination of individual relationships within an organisation.	i. Limited provision for the prediction of the relationships among specific organisational elements. ii. Elements/activities are individually measured, and interaction effects estimated. iii. Conclusions are usually made *ex post* iv. Complementarity theory can only provide limited guidance *ex ante* on the combination complementary activities/elements and the conditions that facilitate them within organisations.
Innovation theory (Henderson and Clark 1990)	i. The distinction between a product as a system and a product as a set of components facilitates successful product development. ii. Two kinds of knowledge are important: component knowledge (of each core concept of a product) and architectural knowledge (the integration of different components of a product). iii. Architectural innovation combines existing components of a product in a distinct way but does not change the core design and associated knowledge of each component	i. Assumption that organisations are limited by bounded rationality. ii. Focus on internal knowledge and information processing within organisations.

Theory	**Assumptions**	**Weaknesses**
Entrepreneurship theories (Foss and Klein 2017)	i. Entrepreneurs create subjective interpretations from objective data. ii. Entrepreneurs need to consciously put in effort in addition to other resources to satisfy consumer needs and wants. iii. It is difficult to forecast the result of entrepreneurial actions as these can only be known *ex post* and cannot be known *ex ante*.	i. Entrepreneurial success is determined by objective factors, consumer feedback, and other industry/market forces. ii. Entrepreneurial actions can only be known *ex post* and not *ex ante*. iii. Focus on the creation of subjective perceptions of objective realities.
Leadership theories (Howell and Avolio 1993)	i. Transformational leadership is positively related to performance. ii. Transactional and contingent reward leadership are negatively related to unit performance. iii. The level and support for innovation within an organisation moderates the relationship between transformational leadership and performance. iv. Locus of control is positively related to transformational leadership.	i. Little focus on the influence of external influences on leadership styles and organisational performance. ii. Assumptions and findings are limited to specific industrial settings and contexts. iii. Limited ability to actively observe leader-follower relationships (i.e., observational data) to corroborate survey findings. iv. Little information on the needs and capabilities of followers.
Dynamic capabilities theory (Teece, Pisano, and Shuen 1997)	i. Firms are able to restructure their internal and external competencies to match the changes in their business environments. ii. Focus on organisational and competitive survival in response to changing business conditions.	i. Focus on organisational ability to adapt to changing market conditions. ii. Introspective and internally focused on organisational resources and capabilities.

2.1.1 Resource-Based View

Resources can be described as anything that can either be a strength or weakness of a firm (Wernerfelt 1984) and includes “assets, capabilities, organisational processes, firm attributes, information, and knowledge” which are at the disposal of a firm (Barney 1991, p. 101). Resources can also consist of physical capital (e.g., plant and machinery), human capital (e.g., employee training and insight), and organisational capital (organisational structure and relationship with other firms in its environment) (Barney 1991). The RBV posits that organisations achieve superior competitive advantages because they possess valuable, rare, imperfectly imitable, non-substitutable, heterogeneous, idiosyncratic, and immobile resources that provide stable differences over time (Barney 1991).

The basic assumptions of the RBV are that (i) organisations that operate within an industry possess internal heterogeneous resources; and that (ii) the internal resources under the control of organisations are not perfectly mobile and cannot be easily exchanged among firms (Barney 1991). Hence, the differences among organisations operating within the same industry or in the same environment can be sustained over time. These two assumptions provide the basis for the achievement of competitive advantages within organisations against competitors operating in the same industry.

An organisation is said to have a competitive advantage over rivals when it implements a strategic plan that is not being executed by competitors (current or potential) while sustained competitive advantage is gotten when an organisation implements a strategy not executed by current or potential competitors and when other competitors are not able to replicate the benefits of the strategy (Barney 1991). Thus, the RBV seeks to explain reasons why organisations gain sustained competitive advantages and as a result, superior performance outcomes by maximising the value gotten from their unique bundle of resources and capabilities (Grant 1996). As such, organisations aim to maintain competitive advantages in their industries by developing and implementing strategic plans that maximise opportunities through the exploitation of strengths on one hand and minimise the threats faced by avoiding inherent weaknesses on the other hand (Barney 1991).

The RBV has been used to explain the development and implementation of disruptive business models in past research. For instance, Yovanof and Hazapis (2008) argue that disruptive technologies lead to organisations adopting disruptive business models and this forces organisations to shift from their traditional business models to business models that take advantage of disruptive technologies. As such, this shift enables organisations move from an internal resource-based view to an external view that involves developing dynamic capabilities through alliances. Furthermore, the strategy development process for implementing disruptive business models focuses on how firms can achieve sustainable competitive advantages over time (Habtay 2012). Arguably, the disruptive business model literature builds on the RBV to show how organisations can achieve differential advantages over competitors.

The RBV can aid in the prediction of competitive advantages that organisations can enjoy based on available resources, competencies, and capabilities (Barney 1991). This knowledge is crucial when developing disruptive business models as they involve the development of strategic plans, capabilities (e.g., procurement, R&D, production, marketing, and sales capabilities), and competencies accessed through collaborations and alliances (Habtay 2012). Also, disruptive business models can enable organisations achieve superior performance if their benefits cannot be easily imitated by competitors. The ability of organisations to introduce disruptive business models that cannot be easily copied can be a differentiating, rare, invaluable, and imperfectly immobile resource at the disposal of organisations.

Furthermore, the RBV can be used to understand the heterogenous capabilities that organisations possess which enable them to achieve competitive advantages when implementing disruptive business models. Some of these capabilities include innovation capabilities reflected in organisational abilities to introduce disruptive business models, knowledge capabilities reflected in the presence of big data analytics capabilities, and knowledge on environmental occurrences reflected in adaptive marketing capabilities. Thus, the RBV can help in explaining the internal mechanisms at work in the successful development and implementation of disruptive business models.

2.2 Disruptive Business Model

Disruptive business models have been discussed in extant literature from various perspectives. Asides the use of the term ‘disruptive business model’, some studies have examined similar concepts using terms such as ‘disruptive business model innovation’ (e.g., Habtay 2012) and ‘disruptive innovation’ (e.g., Christensen and Raynor 2003). Thus, a review of the literature shows that existing research on disruptive business models builds on the innovation, disruptive innovation, business model, and business model innovation literature streams.

Business models can be defined as “sets of structured and interdependent operational relationships between a firm and its customers, suppliers, complementors, partners and other stakeholders, and among its internal units and departments (functions, staff, operating units)” (Doz and Kosonen 2010, pp. 370–71). These relationships are usually documented in official company documents and translated into organisational routines and actions. Additionally, a business model depicts the way in which a firm believes it should interact with its internal stakeholders and external environment (Doz and Kosonen 2010). Thus, business models “stand as cognitive structures providing a theory of how to set boundaries to the firm, of how to create value, and how to organise its internal structure and governance” (Doz and Kosonen 2010, p. 371).

All organisations have business models (obvious or implied) which are conceptual prototypes that guide business operations and describe in detail how value is created by the organisation (Teece 2010). A business model explicitly states the target market, their needs and wants, and how value can be provided to consumers at suitable prices to ensure organisational profitability (Magretta 2002; Teece 2010; Yunus, Moingeon, and Lehmann-Ortega 2010).

Amit and Zott (2001) opine that the business model of an organisation provides a platform for firm innovativeness which should result in the creation of value for all relevant stakeholders of the firm. Winter and Szulanski (2001, p. 731) define a business model as a "complex set of independent routines that is discovered, adjusted, and fine-tuned by doing." Thus, a business model is a blueprint which provides a detailed overview of the major aspects of a business and its strategic projections for value creation.

Disruptive business models have been defined in various ways. Yovanof and Hazapis (2008, p. 569) define a disruptive business model as "a tool in crafting strategy for the purpose of achieving sustainable innovation in the face of the reshaping of the industry and the market." They argue that the introduction of disruptive business models is a strategic choice taken by organisations when faced with paradigm shifts caused by disruptive technologies such as Voice-over-IP and is aimed at developing sustainable innovations. As such, organisations use disruptive business models to challenge dominant industry logics and create "frame-breaking change within the industry or market" (Menon and Menon, 1997, p. 57).

A disruptive business model can also be described as a new combination of business model components or a new way of exploiting one or more components of a business model (Gambardella and McGahan 2010; Rivera-Camino 2007). Some disruptive business models are characterised by disruptive technologies (Dewald and Bowen 2010) that aim to change customer perceptions and preferences, performance metrics, industry operations, existing business models, basis for competition, organisational resources, and capabilities needed for business success (Christensen, Johnson, and Rigby 2002).

Importantly, a disruptive business model can be introduced by any organisation irrespective of size or age in an industry. Furthermore, disruptive business models have also been defined as “value propositions and the opportunities to satisfy customer needs at a profit; cost structure, revenue model, processes, resources; or the interactions between the firm and its key stakeholders in order to measure resource, transactive, and value structures dimensions of the new business model” (Karimi and Walter 2016, p. 356).

From a business model innovation perspective, disruptive business models can be seen as a type of business model innovation (Yovanof and Hazapis 2008). This is buttressed by Osiyevskyy and Dewald (2015) who argue that “disruptive business model innovation draws heavily on identification and exploitation of gaps in the industry positioning, often addressing the needs of unserved customers through low-cost offerings that may ultimately overtake established markets” (p. 60). Furthermore, Velu and Stiles (2013) posit that some business model innovations can be disruptive as they can involve transitioning from one business model to a new business model. An illustrative example is Dell computers who changed their business model by customising their PCs and bypassing middle men such as retailers by selling their customised PCs to consumers directly (Yovanof and Hazapis 2008).

Habtay (2012) conceptualises disruptive business model as ‘disruptive business model innovation’ introduced by new entrants which can either be technology-driven or market-driven and result in varying levels of disruptiveness. On one hand, a technology-driven disruptive business model innovation is defined as “an innovation where R&D experimentation precedes market opportunities and a business model development that will over time affect the incumbent firm’s established market” (Habtay 2012, p. 291). Thus, a technology-driven business model innovation is initiated through continuous market experiments using insights from research and technological advancements which has an impact on incumbent firms within an industry.

On the other hand, a market-driven disruptive business model involves a change in product or service value offerings to customers which has an impact on the industry at large. A market-driven disruptive business model innovation is “a less sophisticated technological business model innovation that results from radical changes in the established value propositions to the existing customer or altering the firm’s role in the existing value chain or both that will over time affect the established market” (Habtay 2012, p. 291). Thus, a market-driven disruptive business model is based on consumer needs and how the firm decides to change its value proposition to consumers over time.

A similarity between technology-driven disruptive business model and market-driven disruptive business model is the potential impact on established markets including incumbents’ practices and market share. It is however unclear where to draw the line between a highly sophisticated and a less-sophisticated technological business model innovation in order to distinguish between a technology-driven disruptive business model and a market-driven disruptive business model based on the definition proposed by Habtay (2012).

Karimi and Walter (2016) also conceptualise disruptive business model as ‘disruptive business model innovation’ that involves the replacement of an “old business model with a new one for offering products or services not previously available” (pg. 343). Habtay (2012) proposes a conceptual model for disruptive business model innovation development process that consists of five stages and is based on three assumptions. The stages identified for developing a disruptive business model innovation include: (i) the identification of customer value propositions; (ii) the establishment of a customer base for whom value will be created and delivered to; (iii) the creation of a value network configuration which includes procurement, R&D, production, marketing, and sales activities; (iv) the development of organisational strategy to achieve competitive advantages; and (v) the creation of a revenue model that comprises of cost structures and pricing strategies among others. The assumptions include the customer-centric nature of business model innovation, the likelihood that customer value innovation may not be accurately predicted, and the path dependence of business model innovation.

Sabatier, Craig-Kennard and Mangematin (2012, p. 949) posit that technological discontinuities defined as “rare, unpredictable innovations which advance a relevant technological frontier by an order-of-magnitude and which involve fundamentally different product or process design” work hand-in-hand with disruptive business models to challenge industry dominant logics, reshape value chains, and initiate industry evolution. This can lead to an increased number of competitors entering the industry to take advantage of the changes in industry dominant logic and value chains by developing new ways of creating, capturing, and delivering value to consumers (Sabatier, Craig-Kennard, and Mangematin 2012).

The dominant logic within an industry refers to “a general framework within which firms conceive what their customers want and define how to best serve their needs, and thus design their strategies and business models” (Sabatier, Craig-Kennard, and Mangematin 2012, p. 953). The industry dominant logic comprises of value context, value creation, and value capture. The relationship between dominant industry logics and organisational strategy is intertwined as the former determines managerial perceptions about the environment, consumers, competitors, and industry forecasts (Hodgkinson and Wright 2002; Doz and Kosonen 2010). As such, disruptive business models in addition to other factors can lead to a change in the dominant logic within an industry.

From a disruptive innovation perspective, a disruptive business model can be viewed as a type of disruptive innovation that incorporates disruptive technologies which are strategically combined to achieve maximum impact (Christensen and Raynor 2003). Also, disruptive business models can be described as "activity systems that include new partners and activities configured in a way that is unprecedented in comparison to existing incumbents" (Snihur, Thomas, and Burgelman 2018, p. 1279).

Extant literature argues that disruptive innovations can be introduced by creating a disruptive business model targeted at the low end of the market (Christensen, Johnson, and Dann 2002; Christensen, Johnson, and Rigby 2002). Christensen and colleagues also propose the use of two litmus tests to facilitate the introduction of disruptive business models. The litmus test for developing low-end disruptive business models involve answering the following questions:

> "(a) Are there over-served customers that will happily buy a good-enough product that's cheaper than those currently available? (b) Can we create a different business model that unattractive to incumbent leaders?"
>
> (Christensen, Johnson, and Dann 2002, p. 46; Christensen, Johnson, and Rigby 2002, pp. 24–25)

Regarding the antecedents of disruptive business models, the review of literature shows that disruptive technologies are crucial drivers in developing and successfully implementing disruptive business models (Christensen, 2006; Markides, 2006; Osiyevskyy and Dewald, 2015). Specifically, Yovanof and Hazapis (2008) argue that disruptive technologies such as VoIP changed the business models, strategies, and industry dynamics of telecommunications operators. As such, disruptive technologies provide the platform to render "existing business models obsolete and force a business model revaluation and innovative redesign" (Yovanof and Hazapis 2008, p. 580).

Disruptive technologies such as Information and Communications Technologies (ICT) convergence and Voice-over-IP (VoIP) provide platforms for organisations to introduce disruptive business models. ICT convergence comprises of "computing, communications and content" and examples of converged technologies are the Internet and VoIP (Yovanof and Hazapis 2008, p. 570). Another example is Salesforce.com, an organisation that introduced a disruptive business model that leveraged on technological advancements in the 1990s and disrupted the CRM software ecosystem (Snihur, Thomas, and Burgelman 2018).

Similarly, Habtay (2012) argues that disruptive business models are birthed when radical or disruptive technological innovations attain maturity and influence the competitive actions taken by rival organisations in an industry or market. This is buttressed by Sabatier, Craig-Kennard and Mangematin (2012) who examine the drug industry and find that technological discontinuities cause disruptive business models to emerge and they work hand-in-hand to change the dominant industry logic and established industry value chains. Additionally, disruptive technologies enable organisations to develop capabilities that enhance the development of disruptive business models (Yovanof and Hazapis 2008). Thus, disruptive technologies and organisational capabilities play significant roles in ensuring the success of disruptive business models.

Karimi and Walter (2016) find that autonomy, risk-taking, and proactiveness have positive relationships with the development of disruptive business models. Autonomy can be described as the ability of organisational members to introduce new ideas and execute them successfully (Lumpkin, Cogliser, and Schneider 2009). Risk taking involves decision making in spite of environmental uncertainty and the ability of organisations to make investments without having total knowledge of the possible outcomes (Rauch et al. 2009). Proactiveness relates to the ability of an organisation to mobilise resources ahead of competitors, examine market signals, monitor changing consumer preferences, anticipate future demand, and conduct extensive forecasts (Barclay and Benson 1990; Lumpkin and Dess 1996; Wright et al. 1995). Therefore, the ability of organisations to have autonomous cultures, encourage risk-taking activities, and proactively make decisions is positively related to the development of disruptive business models.

Regarding the outcomes of adopting a disruptive business model, Karimi and Walter (2016) examine the U.S. newspaper industry and find that disruptive business model has a strong and positive relationship with business model performance. Specifically, disruptive business models that utilise distinct product, price, distribution, and promotion strategies can provide organisations with significant profits and ensure that crucial partnerships are formed with suppliers to meet the needs of various customer segments profitably (Christensen and Raynor, 2003; Karimi and Walter, 2016).

Yovanof and Hazapis (2008) argue that the introduction of disruptive business models helps organisations reshape their innovation strategies based on insights gotten by examining the Voice-over-IP (VoIP) market and Skype technology and service. Thus, disruptive business models enable organisations achieve sustainable innovation and help to reshape industries and markets. Additionally, disruptive business models can enable organisations achieve performance outcomes such as increased growth, profitability, and market share in addition to the creation of new market spaces, increased competition, and customer value which in turn affect consumer behaviour (Yovanof and Hazapis 2008).

Additionally, disruptive business models alongside technological discontinuities challenge the dominant industry logic and change established value chains within an industry (Sabatier, Craig-Kennard, and Mangematin 2012). As such disruptive business models change patterns of competition, design new value chains, and encourage new entrants into an industry. Table 2.2 provides an overview of relevant studies in extant literature.

Table 2.2: Summary of Relevant Literature

Paper	Theory	Sample and Method	Antecedents	Outcomes	Moderators / Mediators	Aim of the study	Findings	Limitations
Christensen (1997)	Disruptive innovation	Technical and performance specifications of disk drives between 1975 and 1994.	Cannibalisation, disruptive technologies	Business survival, profitability	N/A	• To identify why great firms fail • To identify the reasons for the success of disruptive innovations • To examine the causes of failure of established firms	• New firms were more successful in introducing disruptive innovations than incumbent firms. • Incumbent firms were scared of introducing disruptive technologies and cannibalising existing products.	Use of case-studies within a single industry context.
Hart and Christensen (2002)	Disruptive innovation	Conceptual	Investments in disruptive innovation	Disruptive Business Models	N/A	• To identify how disruptive business models can be developed and sustained	• Organisations do not invest in disruptive innovations because of existing investments in sustaining innovations. • Developing countries can have emerging markets that can pave the way for new business growth and business model innovations.	Conceptual findings on how disruptive business models succeed are made ex *post* and not *ex-ante*.
Gilbert and Bower (2002)	Disruptive innovation	Conceptual	Separation from parent organisation, financial investments	Disruptive innovation	N/A	• To identify how firms can effectively respond to disruption	• The way organisations frame a disruptive threat will determine their response in relation to resource allocation. • The optimal way of framing disruption is to view it as a threat for resource allocation and opportunity for strategy to discover and respond to new markets. • Successful organisations separate disruptive innovations from the rest of the organisation and simultaneously compete with two business strategies.	Findings from the study based on conceptual discussions of organisations in a limited number of industries.

Paper	Theory	Sample and Method	Antecedents	Outcomes	Moderators / Mediators	Aim of the study	Findings	Limitations
Christensen, Johnson, and Dann (2002)	Disruptive innovation	Conceptual	Aggregate project planning, employee training, resource allocation and investments for disruptive innovations, presence of a Chief Information officer, perception of disruptive innovation as opportunities and not threat	Disruptive innovations	N/A	To identify how new and established organisations can successfully introduce disruptive innovations.	• To succeed at introducing disruptive innovations, established firms need to create an internal process of identifying, evaluating, and creating disruptive business ideas. • Disruptive innovations need to be viewed as opportunities and not threats.	Findings are based on conceptualisations of existing disruptive innovations and has limited ability to predict future success of disruptive innovations.
Christensen, Johnson, and Rigby (2002)	Disruptive innovation	Conceptual	Creation of a new market base for disruption; disrupt the business model from the low end	Disruptive innovation	N/A	To identify how firms can successfully introduce disruptive innovations	Organisations can create disruptive innovations by: • Creating a new market base for disruption and competing against non- consumption • Introducing disruptive innovations by targeting the low end of the market • Using an aggregate project plan for resource allocation • Training employees to distinguish between sustaining and disruptive innovations.	Findings do not include organisational capabilities needed for the success of disruptive innovation
Charitou and Markides (2003)	Disruptive innovation	10 companies were interviewed, 115 survey responses from 98 companies	Disruptive Strategic Innovations .g., direct banking, home ordering and delivery	Response to disruptive strategic innovations	Company position in the industry, organisational resources and competences, and the nature of disruption	To find out how organisations successfully respond to disruptive innovations	Organisations can respond to disruptive innovations in the following ways: • Focus and invest in the traditional business • Ignore the disruptive innovation • Attack and try to disrupt the disruptor • Adopt the innovation and play both games at once • Embrace the innovation and invest in it in order to scale it up completely.	Focus on the internal organisational characteristics that facilitate the success of disruptive innovations

Paper	Theory	Sample and Method	Antecedents	Outcomes	Moderators / Mediators	Aim of the study	Findings	Limitations
Yovanof and Hazapis (2008)	RBV/dynamic capabilities	1 Case-study, Voice-over-IP (VoIP) market, Skype	Disruptive Technologies	Sustainable innovation, increased growth, profitability and market share	N/A	• Application of disruptive business model to the VoIP market and the Skype technology and service	• Disruptive technologies such as ICT convergence make existing business models obsolete and lead to the development of disruptive business models. • Disruptive technologies change industry dynamics, influence the nature of market competition, affect organisational revenue flows, and affect established industry-wide regulatory frameworks	Inadequate theoretical application of the resource-based / Dynamic Capabilities theories to disruptive technologies and the development of disruptive business models
Habtay (2012)	Business model concept Disruptive innovation	Multiple case deductive study using 4 case-studies	Radical or disruptive technological innovation	Retention of profitable markets, new product success, retention of investments, processes, routines and values, obsolescence of current business models	Moderators: • Technological and market uncertainties • Low-end market foothold • Core capabilities, economic feasibility and differential resources endowments	• To evaluate the disruptiveness potential between technology-driven and market-driven disruptive business model innovations from entrants' perspective • To examine the enablers and inhibitors of disruptive business models innovation	• Technology-driven disruptive business model innovations are first relatively unsuccessful and gradually become successful while market-driven disruptive business model innovations are successful rapidly and then their growth starts to reduce over time.	Lack of clarity on the definitions and differentiation between technology-driven and market-driven disruptive business model innovations.
Sabatier, Craig-Kennard and Mangematin (2012)	Industry Lifecycle theory	Case-study of 7 bioinformatics companies	New technologies / technological discontinuities	Change in dominant industry logic and value chains	NA	• Identification of the factors created by biotechnologies and bioinformatics that trigger the development of disruptive business models	• New technologies / technological discontinuities enable disruptive business models to emerge which then challenge the dominant industry logics and established value chains.	Examination of a single industry – drug industry
DaSilva *et al.* (2013)	Implied RBV	Case study of firms in the Cloud computing industry (Siebel, Amazon, Salesforce.com)	Disruptive technologies	Business Success/failure	N/A	• To identify the response of incumbents to disruptive technologies and the creation/adoption of disruptive business models.	• The inability of organisations to adopt business models that incorporate disruptive technologies leads to failure.	Case studies of organisations in a single industry

Paper	Theory	Sample and Method	Antecedents	Outcomes	Moderators / Mediators	Aim of the study	Findings	Limitations
Velu and Stiles (2013)	N/A	In-depth longitudinal case-study of a US bank	Willingness to cannibalise	Customer satisfaction	N/A	• To examine management decision making on cannibalisation when running two business models (old and new) simultaneously.	• The bank successfully introduced a disruptive business model (trading bonds on the Internet) that replaced their existing business model (telephone-based trading) by balancing rationality and politics.	Single industry context
Osiyevskyy and Dewald (2015)	Strategic agency perspective, prospect theory, behavioural theory of the firm	241 Canadian realtors	Disruptive technologies	Intention to innovate	N/A	• To evaluate organisational decision making when faced with disruptive business models	• Incumbents can respond to disruptive threats by either adopting a disruptive business model or strengthening their existing business models.	Single industry context
Karimi and Walter (2016)	N/A	148 respondents from the Newspaper industry	Autonomy Risk-taking Proactiveness Innovativeness	Business model performance	NA	• To identify the corporate entrepreneurship attributes that have an impact on business model innovation adoption • Identification of the extent to which disruptive business model innovation influences business model performance	• Autonomy, risk-taking, and proactiveness have a positive relationship with disruptive business model innovation but innovativeness does not. • Disruptive business model innovation has a nonlinear association with business model performance	Research limited to a subsection of the newspaper industry
Snihur, Thomas and Burgelman (2018)	Disruption theory	Longitudinal case study – Salesforce disruption for Siebel	N/A	N/A	Targeted customer groups	• An investigation into the eco-system of a start-up business model disruptor • To identify how a disruptive business model innovator aligns framing and adaptation of its business model during disruption	• A disruptor's gambit is when the disruptor indicates their plans early and then quickly adapt its business model to meet ecosystem needs. • Framing helps disruptors shape new ecosystems through business model innovation by decreasing uncertainty and gaining competitive advantages over incumbent firms.	Single case study

2.3 Disruptive Business Model Critique, Gaps, and Conclusions

There is a plethora of literature streams from which disruptive business model literature draws from and this can be a two-edged sword. One implication is the number of varying conceptualisations, definitions, and descriptions of disruptive business models in the literature. It can be observed that there is a lack of clarity and ambiguity in defining disruptive business models. A plausible reason for this can be the fact that in the business model literature, there is no universally accepted definition of a business model (Markides 2013). Thus, studies that examine and build their arguments of disruptive business models from the business model literature encounter similar issues in defining disruptive business models.

Additionally, it appears that in some studies, references to theories are implied and as such, there are limited theoretical foundations and underpinnings used in extant literature while in some other studies, many theories are used to explain the conceptual model under examination. This is buttressed by Osiyevskyy and Dewald (2015) who argue that the literature on disruptive business models largely lacks theoretical groundings. This makes it difficult to pinpoint the specific theoretical underpinning common to previous studies on disruptive business models. A reason for this could be that past research draws from various literature streams and encounters difficulties in settling for suitable theoretical foundations.

Furthermore, the literature on disruptive business models is yet to provide a "valid and widely agreed upon operational construct of the concept that is useful for empirical research" (Habtay 2012, p. 300). As such, studies that have attempted to empirically measure disruptive business models usually use measures for business model innovation. For instance, Karimi and Walter (2016, p. 348) examine disruptive business models as 'business model innovation adoption' and measure the construct as "the extent to which the business model innovation adoption has resulted in changes over the last three years in the revenue model, value proposition, pricing structure, cost structure, resources for selling noncore products, and new formal or informal arrangement for information exchange with partners.” However, this measure does not entirely capture the nature of disruptive business models and only measures the impact of business model innovation adoption.

In addition, most of the studies on disruptive business models are based on case-studies of specific industries, contexts, and organisations. As such, there are limited studies that empirically test conceptual models comprising of the antecedents, outcomes, and boundary conditions of disruptive business model. Therefore, this research aims to contribute to the literature on disruptive business models by empirically testing an integrated model of its drivers, outcomes, and contingency effects.

2.4 Summary

This chapter has presented an overview of the literature on disruptive business models. Specifically, the major theories predominant in past research were discussed and an explanation of the antecedents and outcomes of disruptive business models was provided. The next chapter discusses the conceptual model of the study, provides its theoretical underpinnings, and develops the research hypotheses for the study.

CHAPTER 3

RESEARCH MODEL AND HYPOTHESES

3.0 Introduction

This chapter provides an overview of the research model to be examined and the hypotheses based on the conceptual model that will be tested in this study. The chapter begins with an overview of the conceptual model, thereafter, the hypotheses relating to the antecedents of disruptive business model are discussed. The next section presents the hypotheses development based on theoretical arguments and previous findings for the outcomes of disruptive business model and the moderating effects on the disruptive business model–performance relationship. The control variables selected for this study are then examined and this chapter concludes with a summary of the research hypotheses that have been formulated and the definitions of the key constructs used in the research model.

3.1 An Overview of the Conceptual Model

Research on disruptive business models is dominated by the RBV and Disruptive Innovation theories. The RBV argues that organisations make use of their assets (tangible and intangible) to provide sustained competitive advantages to the firm (Barney 1991; Wernerfelt 1984). An assumption of the RBV is that “strategic resources are heterogeneously distributed across firms and that these differences are stable over time” (Barney 1991, p. 99). Thus, organisations have distinct internal assets and resources that they can use to achieve competitive advantages that are sustained over time. As such, the RBV places emphasis on and examines the relationship among the internal assets, features, characteristics, and performance of a firm (Barney 1991).

Disruptive innovation theory argues that disruptive innovations possess distinct attributes that are attractive to over-served, under-served or new market segments, do not necessarily involve high-end technological advancements, and out-perform existing innovations as they improve over time (Christensen 1997; Christensen, Johnson, and Dann 2002). Furthermore, disruptive business models can be viewed as a form of disruptive innovation because they involve the introduction of disruptive products, services, technologies, and business models.

The research model examined in this study focuses on the internal organisational mechanisms at work in organisations that develop and introduce disruptive business models. In addition, this study examines the organisational resources and capabilities that facilitate the successful development and implementation of disruptive business models. Thus, the *RBV* was chosen as the predominant theoretical base of the research model (Barney 1991; Grant 1996) for two major reasons: (a) the RBV emphasises the role of internal resources and capabilities which are central to the adoption and implementation of disruptive business models; and (b) the RBV provides a rationale for creating and maintaining sustainable competitive advantages which is the aim of developing disruptive business models.

The RBV can also explain the capabilities utilised by organisations in developing disruptive business models that capitalise on technological advancements. An example of this is Salesforce.com who disrupted the CRM industry by incorporating technological advancements within their product and service offerings (DaSilva et al. 2013). Therefore, organisations that develop and implement disruptive business models need to possess crucial organisational resources and capabilities to facilitate their success.

Figure 3.1 shows the research model of this thesis which comprises of the antecedents, moderators, and performance outcomes of disruptive business models. The **antecedents** refer to the internal aspects of the organisation that influence the development and creation of disruptive business models. They consist of four factors: (a) formalisation, which is the extent to which organisations follow strict procedures, rules, and regulations (Aiken and Hage 1966;

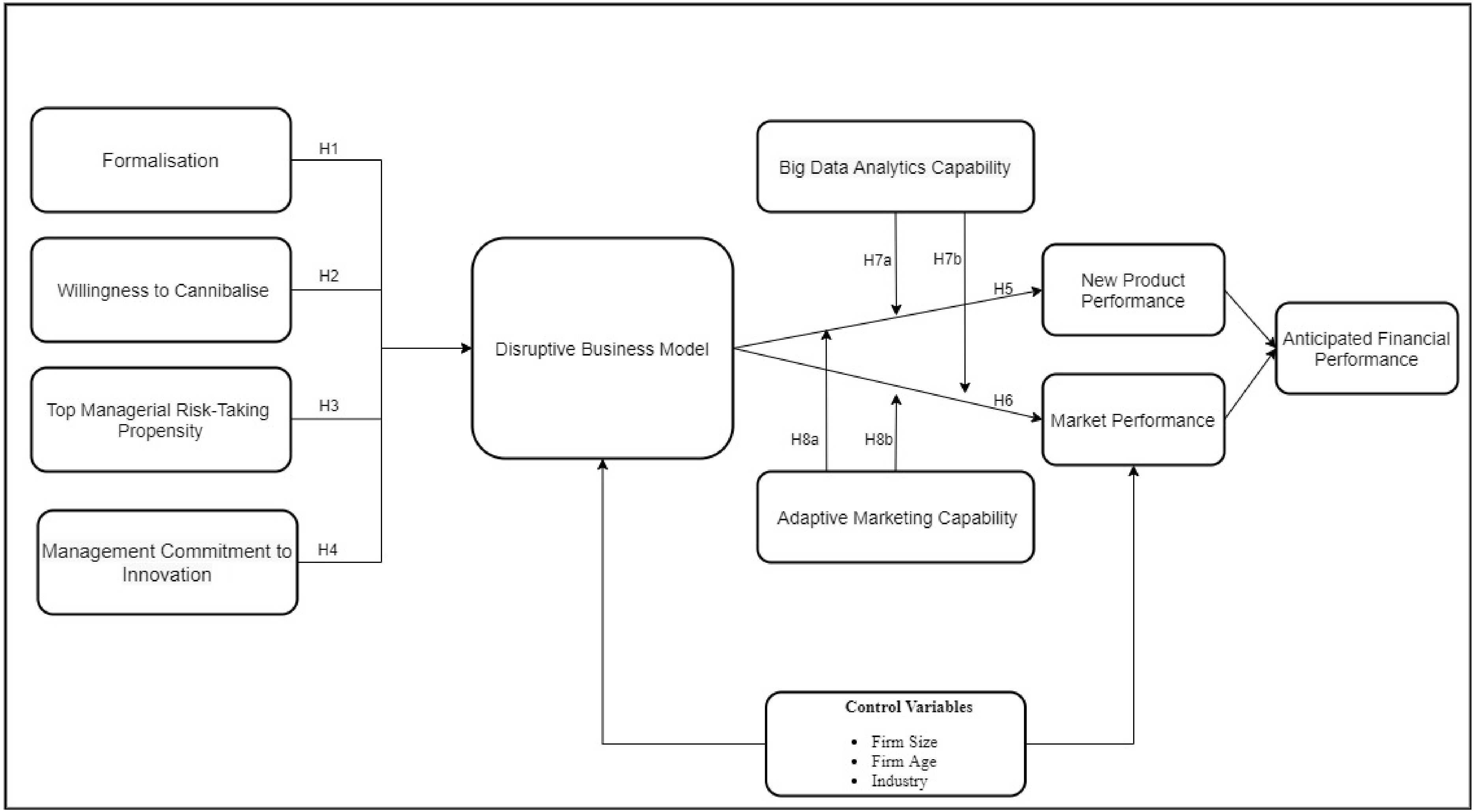
Raymond, Paré, and Bergeron 1995); (b) management commitment to innovation, which looks at the manner in which an organisation makes significant financial commitment to innovative activities (Heavey, Simsek, and Fox 2015; Hitt, Hoskisson, and Ireland 1990); (c) top managerial risk-taking propensity, which is the willingness to make strategic financial commitments in the face of uncertainty (Rauch et al. 2009; Tellis, Prabhu, and Chandy 2009); and (d) management willingness to cannibalise existing resources, assets, profits, products, and capabilities (Chandy and Tellis 1998).

The model proposes that these four factors have a relationship with **disruptive business model**, which “draws heavily on the identification and exploitation of gaps in the industry positioning, often addressing the needs of unserved customers through low-cost offerings that may ultimately overtake established markets” (Osiyevskyy and Dewald 2015, p. 60). The disruptive business model introduced by organisations will have certain outcomes for the organisation with regard to its **performance** (Christensen, Johnson, and Dann 2002).

The term ‘product’ is used as an all-encompassing term comprising of physical goods, intangible services, and processes. New product performance refers to the ability of an organisation to successfully introduce new products into its industry (Im and Workman Jr 2004); market performance refers to the ability of an organisation to increase its overall market share, sales growth, market development, and product development processes (Sarkar, Echambadi, and Harrison 2001); and anticipated financial performance refers to expected firm financial performance for the next 12 months based on measures such as profit growth, return on investment, return on assets, and profit margin (Katsikeas, Samiee, and Theodosiou 2006; Vorhies and Morgan 2005).

The model also proposes that various organisational capabilities act as **moderators** of the disruptive business model–performance relationship. These are: (a) **adaptive marketing capability**, which refers to the ability of organisations to engage in market experimentation of various ideas before commercialisation, develop partnerships and alliances, and engage in vigilant market learning to continuously monitor environmental, industry, and competitive changes (Guo et al. 2018), and (b) **big data analytics capability,** which refers to the ability of organisations to access a wide range of sources of consumer data, analyse consumer data speedily, have large amounts of consumer data at their disposal (Johnson, Friend, and Lee 2017). Overall, the study argues that adaptive marketing capability and big data analytics capability are enablers of the economic performance outcomes of disruptive business models.

Figure 3.1: Conceptual Model of the Study



3.2 Antecedents of Disruptive Business Model

Disruption can be defined as "fundamental changes that disturb or re-order the ways in which organisations and ecosystems operate" (Zietsma, Ruebottom, and Slade Shantz 2018, p. 1242). Disruptive business models can be described as "activity systems that include new partners and activities configured in a way that is unprecedented in comparison to existing incumbents" (Snihur, Thomas, and Burgelman 2018, p. 1279). The introduction of disruptive business models is synonymous with high levels of uncertainty in the business environment ranging from concerns about changing consumer needs to technological advancements and long-term sustainability (Dattée, Alexy, and Autio 2018; Ozcan and Eisenhardt 2009; Suarez and Lanzolla 2005).

Having in-depth understanding of the nature of disruptive business models in a multi-industry context is crucial as this provides insight into the mechanisms at work when introducing, adopting, and implementing disruptive business models. As such, there is a need to examine the antecedents, consequences, and contingencies of disruptive business models across various industrial contexts. This section will discuss the proposed drivers of disruptive business models including formalisation, management commitment to innovation, top managerial risk-taking propensity, and willingness to cannibalise.

Formalisation can be described as the extent to which rules and regulations are strictly followed, implemented, and adhered to within an organisation. Management commitment to innovation refers to the willingness of top management to identify innovative opportunities early on and invest in research and development, technological advancement, new product development, advertising for new products, and marketing for new products. Top managerial risk-taking propensity is the willingness of top managers to take financial and innovative risks even when success is uncertain, and willingness to cannibalise is the ability of an organisation to sacrifice existing sales, profits, infrastructure, assets, capabilities, and technical know-how to adopt an innovative product, service or business model. These antecedents are discussed in greater detail subsequently.

3.2.1 Formalisation

Formalisation can be described as an element of organisational structure and can be defined as “the degree of work standardisation and the amount of deviation that is allowed from standards” (Aiken and Hage 1966, p. 499). It is an inherent aspect of organisational structure and reflects the way the top managerial team want to conduct and handle organisational activities and processes. Formalisation can also be described as the use of official representations of systems and processes within an organisation (Raymond, Paré, and Bergeron 1995).

Highly formalised structures require the use of sophisticated management techniques that guide the behaviours, attitudes, codes, and conduct within organisations. This implies the presence of strict rules, regulations, and standards that employees must adhere to. Also, formalisation has been described as the level to which regulations, rules, guidance, procedures, and activities are written down (Pugh et al. 1969) and implemented to guide employee behaviour.

Furthermore, high formalisation levels means that rules are made, clearly specified, maintained, and enforced (Aiken and Hage 1966; Williams 2005) and this is more common in larger organisations than smaller ones (Pugh et al. 1969). One down side of formalisation is that the rules and regulations can restrict employee behaviour and result in dissatisfied employees, low levels of solidarity among employees, employees feeling that the work being done is meaningless, and reduced employee motivation (Gross 1953; Worthy 1950).

Therefore, formalisation can influence the level of creativity and creativeness within organisations which can affect organisational ability to develop and introduce disruptive business models. Organisations with highly formalised structures involving the observance of strict rules and regulations are less likely to encourage employees to present creative ideas and develop disruptive business models. Therefore, it is expected that organisations with highly formalised structures will most likely introduce incremental innovations at best or reproduce existing products, services, and business models (Le Roy and Yami 2007).

On the other hand, organisations with less formalised structures are more likely to encourage innovativeness and creativity which helps in the development of disruptive business models. This is because employees are encouraged to be deliberate in creativity and develop "an attitude of continuous questioning" (Le Roy and Yami 2007, p. 434) which enhances the development of disruptive business models. This implies that organisations that aim to develop and implement disruptive business models need to create enabling environments that encourage employees to question the status quo.

In addition, informal arrangements and strategic decision-making processes within organisations should facilitate firm innovativeness and the development of disruptive business models that are different from the norm and are not reproductions of existing business models (Hamel 1996, 1998; Le Roy and Yami 2007). Similarly, for disruptive business models to be successfully created and implemented, a two-way communication flow is required among organisational members between employees and top level managers as this facilitates creativity and innovativeness (Hamel 1998, 2001).

By way of illustration, Karimi and Walter (2016) find that autonomy has a positive relationship with the development of disruptive business models. Autonomy can be described as the flexibility to take actions, make decisions, present new ideas, successfully develop new ideas, and implement the ideas presented (Lumpkin, Cogliser, and Schneider 2009). As such, autonomy is crucial for the development and implementation of disruptive business models (Markides and Oyon 2010). It is expected that the more autonomous organisational members are, the higher the likelihood that they will effectively express creative ideas and develop disruptive business models (Karimi and Walter 2016).

Drawing on the disruptive innovation theory, new entrants who might be relatively smaller than incumbent organisations can easily introduce disruptive business models because of their organisational culture. This implies that high levels of formalised structures, set rules, and regulations can have a negative impact on the development of a disruptive business model. Organisation that can overcome this limitation because of their size can easily and quickly make decisions without going through levels of decision making based on organisational procedures. As such, it is expected that high levels of formalisation within an organisation will be negatively related to the development of disruptive business models.

Hence, it is hypothesised that formalisation is negatively related to the creation and implementation of disruptive business models.

Hypothesis 1: Formalisation is negatively related to disruptive business model

3.2.2 Willingness to Cannibalise

Willingness to cannibalise has been viewed as a component of organisational culture which can have a significant effect on innovative activities within organisations (Tellis, Prabhu, and Chandy 2009). It has been described as "an attitude that puts up for review and sacrifices current profit-generating assets, including current profitable and successful innovations, so that the firm can get ahead with the next generation of innovations" (Tellis, Prabhu, and Chandy 2009, p. 8). Cannibalisation occurs when the introduction of a new product, service or business model negatively affects existing organisational operations, tangible assets, and intangible assets (Velu and Stiles 2013). Cannibalisation can also be a reduction in sales, profits or market share of existing products when a new product is introduced (Van Heerde, Srinivasan, and Dekimpe 2010).

In broad terms, willingness to cannibalise can be defined as the ability of an organisation to introduce new products, services or business models that can erode the sales, profits, and revenues of existing products, services or business models. Furthermore, an organisation's willingness to cannibalise can be reflected in the introduction of new processes, infrastructure or technologies that make existing processes, technologies, infrastructure, and assets go obsolete. Thus, willingness to cannibalise is "the extent to which a firm is prepared to reduce the value of its own prior investments" (Tellis, Prabhu, and Chandy 2009, p. 11).

In line with the construction of the disruptive innovation theory, disruptive business models require a unique combination of resources and capabilities that are different from those of existing business models. Organisations that already have a business model in operation might find that the disruptive business model utilises a different set of assets, processes, and procedures. Therefore, it becomes imperative for organisations to let go of existing resources, capabilities, and infrastructure that are not compatible with the disruptive business model.

Furthermore, the commercialisation of a disruptive business model can erode the existing sales from previous business models. This is because consumers might switch from purchasing products and services compatible with an existing business models to the products and services of the disruptive business model. Hence, there might be a need for organisations to forgo the sales and profits gotten from existing business models when implementing a disruptive business model.

Disruptive business models often result in high levels of uncertainty and can bring about unprecedented changes in the industry and ecosystem (Dattée, Alexy, and Autio 2018; Snihur, Thomas, and Burgelman 2018). As such, it is expected that organisations whose top management teams are willing to cannibalise existing sales, profits, products, processes, business models, assets, and infrastructure are more likely to introduce and implement disruptive business models than organisations whose top management teams are hesitant to do so.

Organisations can be reluctant to change their business models especially if there is a high level of uncertainty surrounding the new business model (Velu and Stiles 2013). Organisations that are fearful of implementing disruptive business models can end up losing their consumers, market share, and industry positioning to competitors who decide to develop and implement disruptive business models. An example is Siebel who was reluctant to change its existing business model for fear of losing its clientele. However, this move backfired as their clients were forced to consider competitive alternatives (DaSilva et al. 2013).

Due to the nature of disruptive business models, there might be a need for organisations to completely forgo existing business models, processes, and strategies. However, this can be a barrier to implementing disruptive business models for organisations that are reluctant to take this decision in the face of uncertainty about the viability of the disruptive business model. Thus, it is hypothesised that willingness to cannibalise is positively related to the development and implementation of disruptive business models.

Hypothesis 2: Willingness to cannibalise is positively related to disruptive business model

3.2.3 Top Managerial Risk-Taking Propensity

Top managerial risk-taking propensity refers to the willingness of managers within organisations to undertake financial and investment risks to exploit business opportunities. It is therefore a fundamental aspect of corporate culture that can significantly influence the ability of firms to engage in innovative practices, processes, and activities (Tellis, Prabhu, and Chandy 2009). It has also been defined as “taking bold actions by venturing into the unknown, borrowing heavily, and/or committing significant resources to ventures in uncertain environments" (Rauch et al. 2009, p. 763).

Managers who are risk-taking and see the failure of some innovative activities as normal are likely to have employees who make innovative suggestions to satisfy consumer needs (Kohli and Jaworski 1990). On the other hand, if managers are risk and failure averse, employees can be discouraged from making innovative suggestions (Jaworski and Kohli 1993). However, it should be noted that sacrificing a current profit and revenue stream for one that is uncertain is not a decision that comes easily for managers. Hence, most managers are risk-averse and prefer to focus on short-term profitable investments instead of long-term uncertain investments (Burgelman and Välikangas 2005; McGrath, Keil, and Tukiainen 2006).

In spite of this, developing a risk-taking mentality is important to encouraging vital innovations within an organisation (Gilman 1995; Kuczmarski 1996; Tellis, Prabhu, and Chandy 2009). Developing and introducing disruptive business models involves a certain amount of risk as they are usually new and relatively unknown in a given market or industry. As such, they are not usually assured of success upon implementation. Thus, organisations that develop and introduce disruptive business models should be willing to take risks to achieve organisational goals and objectives even though they know that failure is a possibility (Tellis, Prabhu, and Chandy 2009).

Drawing from the disruptive innovation theory, disruptive business models do not always involve high technological advancements and can initially be seen as inferior to existing business models in operation. They can be targeted at over-served, less demanding, emerging, or new market segments whose viability has not been established. Thus, disruptive business models by nature involve a high level of risk because their success is not guaranteed, and customer value propositions might not be accurately predicted. As such, it is expected that high levels of managerial risk-taking propensity will facilitate and enhance the development of disruptive business models within organisations.

Karimi and Walter (2016) find that risk-taking behaviour has a positive influence on the development of disruptive business models. Risk taking behavior involves making commitments in uncertain environmental conditions without knowing the possible outcomes (Rauch et al. 2009). Thus, they find that the higher the extent of risk-taking in a firm, the higher the extent to which the firm can adopt a disruptive business model because of the level of risk involved in identifying and adopting a completely different business model. Similarly, DaSilva *et al.* (2013) find that organisations that introduced disruptive business models such as Amazon and Salesforce.com needed to take significant risks by diverting from their current business models to disruptive business models.

Thus, organisations that take financial risks and make significant investments in innovative strategies despite the possibility of failure are more likely to develop and implement disruptive business models than organisations who are risk-averse. Furthermore, past research indicates that managers who are more risk taking develop a larger number of internally generated innovations than their risk-averse counterparts (Pérez-Luño, Wiklund, and Cabrera 2011). This is because managers who like to 'play-it-safe' are likely to prefer developing business models that involve little or no risks instead of disruptive business models that involve high risks. Thus, it is expected that top managerial risk-taking propensity will have a positive relationship with the development of a disruptive business model. As such, this study hypothesises that:

Hypothesis 3: Top managerial risk-taking propensity is positively related to disruptive business model

3.2.4 Management Commitment to Innovation

Management commitment to innovation can be described as the proactive nature of managers within business organisations to engage in innovative pursuits and activities (Heavey, Simsek, and Fox 2015). It is the "managerial willingness to allocate resources and champion activities that lead to the development of new products, technologies, and processes consistent with marketplace opportunities" (Hitt, Hoskisson, and Ireland 1990, pp. 29–30). In these situations, managerial teams can proactively make commitments to maximise innovative opportunities and minimise threats in their internal and external environments.

The ability of managers to proactively identify and respond to business opportunities is vital to their willingness to make investments by using part of organisational revenue on innovative activities (Doz and Kosonen 2010). These investments can be financial resources deployed to creative opportunities, research and development, technological advancements, new product development, advertising for new products or marketing, and marketing for new products or markets (Daellenbach, McCarthy, and Schoenecker 1999; Gamble 2000; Heavey, Simsek, and Fox 2015).

Disruptive business models can be viewed as a type of innovation because it involves the development of a business model that has not been implemented in the past. It can be described as the replacement of an old business model with a new one that offers different combinations of products, services, and processes that were not previously available. Disruptive business models involve a unique combination of value propositions and organisational strategies that are different and new to an industry, organisation, and market. Therefore, it is vital that organisations that want to successfully introduce disruptive business models pay close attention to activities, systems, and procedures that can facilitate innovation.

Hence, management commitment to innovation is especially crucial for the development and implementation of disruptive business models. This is because for organisations to continually innovate and develop disruptive business models, they need to have a unified management team, be strategically sensitive, and possess resource fluidity (Doz and Kosonen 2010). Commitment to innovation also shows the ability of an organisation to adopt new technologies, ideas, processes, and practices (Kitchell 1995; Salavou 2004) which is expected to have a positive influence on the development of disruptive business models.

Furthermore, commitment to innovation is not limited to product innovations, process innovations or disruptive business models but also involves the ability to develop key organisational capabilities to exploit available opportunities (Cohen and Levinthal 1994). As such, the ability of organisations to engage in creative activities through the introduction of new products, services, and processes is expected to have a positive relationship with disruptive business model development (Karimi and Walter 2016).

Organisations whose managers are committed to innovative activities and reflect this by investing in research and development, technologies, new product development, marketing for new products, marketing for new markets, advertising for new products, and advertising for new markets are more likely to develop and implement disruptive business models. This is buttressed in extant literature that argues that significant financial investments in innovative activities and innovation facilitates the development of disruptive business models (Gilbert, Clark and Bower 2002; Hart and Christensen 2002). An example is Amazon.com who developed a web-service business model that incorporated innovative computing infrastructural facilities (DaSilva et al. 2013).

Therefore, it is expected that that management commitment to innovation has a positive influence on the development and implementation of a disruptive business model within an organisation. As such, this study hypothesises that:

Hypothesis 4: Management commitment to innovation is positively related to disruptive business model

3.3 Marketing Performance Outcomes of Disruptive Business Model

Christensen, Johnson, and Dann (2002) opine that one of the ways in which organisations can cause disruptions is by introducing a disruptive business model that targets low-end and over-served customers who are not attractive to incumbents in an industry and are willing to purchase cheaper alternatives than existing product and service offerings. As such, when an organisation introduces a disruptive business model into the market, it is with the aim of meeting consumer needs and achieving positive performance outcomes by carefully selecting the target market. Disruptive business models incorporate disruptive technologies, products, services, and information (Christensen 2006; Markides 2006; Yovanof and Hazapis 2008). As such, it is expected that organisations that regularly introduce disruptive business models can gain superior and sustained competitive advantages over other firms in their industry of operation.

One of the expected outcomes of introducing a disruptive business model is to ensure that there is an increased likelihood of new product performance for the organisation. This can be achieved by introducing a disruptive business model that incorporates new products, services, and processes. As such, the introduction of a new product within a disruptive business model can increase the likelihood of new product performance. This is crucial as new product performance reflects the success of the disruptive business model introduced into a market. New product performance is evident in managerial ability to successfully introduce new products into a market, obtain positive outcomes of new product development activity, and generate new product ideas (Gatignon and Xuereb 1997; Im and Workman Jr 2004; Montoya-Weiss and Calantone 1994).

In addition, firms have come to the realisation that new product performance is a necessity to ensure competitive advantages (Najafi-Tavani et al. 2018). In order to ensure sustained competitive advantages, it is expected that organisations will aim to successfully develop disruptive business models to facilitate their ability to produce and commercialise innovative product ideas. This study argues that organisations that successfully develop and implement disruptive business models will enjoy new product success and performance.

This line of reasoning is buttressed by past literature (e.g., Christensen, Johnson, and Rigby 2002; Gilbert, Clark and Bower 2002) who argue that disruptive innovations (such as disruptive business models) lead to great strides with regard to new product development. These studies show that once firms master the art of developing disruptive innovations in general and disruptive business models in particular, they succeed in the marketplace by displacing existing innovations and business models. Thus, disruptive business models help in the creation of new markets and serve as an opportunity for organisations to cater to the needs of emerging, less demanding, and new market segments through the introduction of innovative products, services, and processes.

The new product and service offerings embedded in the disruptive business model initially appeal to emerging customer segments and eventually appeal to mainstream customer segments due to constant improvements in the business model. Thus, disruptive business models open new doors of opportunities and markets to organisations above and beyond their initial target market segments. This increase in number of consumers served will result in increased sales and profitability from the new product and service offerings provided to consumers based on the disruptive business model. Therefore, the introduction of a disruptive business model is expected to have a positive relationship with new product performance.

Additionally, the first mover advantages that accrue to firms for introducing disruptive business models can influence their market performance outcomes. Importantly, disruptive business models incorporate disruptive innovations, disruptive technologies (Snihur, Thomas, and Burgelman 2018), and new products that are competitive in nature and appealing to customers. Hence, this can influence other industry players to make attempts to imitate the disruptive business model. As such, competitive imitation is increased when the disruptive business model is very profitable and attractive to consumers.

Consequently, organisations that develop and introduce disruptive business models will have high levels of market performance outcomes reflected in their market share, sales growth, market development, and product development (Sarkar, Echambadi, and Harrison 2001). This is because a disruptive business model can help to increase an organisation's market share and sales due to increased consumer patronage. Furthermore, introducing a disruptive business model can help organisations establish a foothold in the market in addition to commercialising new product ideas. As such, it is expected that a disruptive business model will enhance a firm's market performance outcomes.

Furthermore, extant literature argues that organisations that invest in developing and introducing disruptive business models are more successful than those who do not (Christensen 1997). A plausible reason for this can be the fact that disruptive business models open up new markets not previously available to an organisation. This can result in increased number of consumers which can lead to increased sales, profits, and market share compared to competitors. Thus, disruptive business models help organisations introduce disruptive products and services that outperform and displace existing products and services which leads to competitive advantages evident in increased market share, profits, and sales.

In line with the tenets of the RBV, disruptive business model can be conceptualised as a unique bundle of resources and capabilities at the disposal of organisations which can lead to sustained competitive advantages. Thus, it is expected that organisations that possess the capability of developing and introducing disruptive business models will outperform their competitors and this will result in positive performance outcomes for the organisation.

Therefore, it is hypothesised that disruptive business model is positively related with market performance. As such, this study hypothesises that:

Hypothesis 5: Disruptive business model is positively related to new product performance.

Hypothesis 6: Disruptive business model is positively related to market performance.

3.4 Boundary Conditions of the Disruptive Business Model–Performance Relationship

3.4.1 Big Data Analytics Capability

Big data refers to "a collection of large and complex data from different instruments at all stages of the process which go from acquisition, storage and sharing, to analysis and visualisation" (Pisano, Pironti, and Rieple 2015, p. 191). Big data can also refer to a dataset (Lin and Kunnathur 2019) or large volumes of various types of data (McAfee et al. 2012). As such, big data analytics capability can be defined as "operational routines of identifying, collecting, storing, and analysing big data, which consist of an interplay of resources, assets, skills, and competencies" (Lin and Kunnathur 2019, p. 50).

Big data analytics capability can also be described as the ability of an organisation to identify market opportunities and offer high value product and service offerings to customers through insights gotten from analysing a large variety and amount of consumer data (Johnson, Friend, and Lee 2017). Thus, big data analytics capability provides a platform for managers to ensure a fit between strategic plans and consumer needs on one hand (Pisano, Pironti, and Rieple 2015) and provide competitive advantages to the firm on the other hand (Marshall, Mueck, and Shockley 2015).

Big data analytics capability consists of three component elements: big data volume, big data variety, and big data velocity (McAfee et al. 2012). Big data volume refers to the ability of an organisation to analyse large amounts of customer data and use these in strategic decision making (Johnson, Friend, and Lee 2017). Understanding consumer behaviour is very important for the success of disruptive business models because they aim to meet consumer needs. As such, the ability to analyse large amounts of consumer data helps in identifying trends and making market forecasts. This in turn provides insight into consumer decision-making processes which can offer crucial guidance to organisations on how to successfully develop and implement disruptive business models.

Big data variety is the extent to which an organisation has different sources and types of consumer data to analyse (Johnson, Friend, and Lee 2017). These data sources can range from primary data to secondary data using sources such as surveys, interviews, and focus groups. They can also come in the form of customer databases as sources of accessing consumer data. An organisation that possesses the ability to access different sources of consumer data will have a way of triangulating findings using different sources to make the best strategic decisions and choices on how to successfully develop a disruptive business model. On the other hand, an organisation that does not possess big data variety might experience limitations in making accurate predictions about consumer purchase behavior which can deter the successful development of a disruptive business model.

Big data velocity is the speed at which an organisation analyses consumer data once it is received (Johnson, Friend, and Lee 2017). The ability of an organisation to analyse customer data quickly can be the difference between the success and failure of a disruptive business model. Once a disruptive business model has been introduced, consumers might respond in a different way than projected thereby necessitating quick organisational decision making and adjustments to the business model. Thus, it is expected that organisations that possess the capability of analysing consumer data quickly will be more successful at developing and introducing successful disruptive business models that provide positive performance outcomes than their counterparts who do not possess this capability.

Therefore, it is likely that organisations that possess data analytics capabilities are more likely to maximise their ability to develop and introduce disruptive business models and this will enhance their new product and market performance. This is exemplified in Uber and Netflix who have utilised big data analytics to disrupt the transportation industry and traditional movie industry respectively by providing cheaper alternatives to consumers than local taxi services on one hand and providing low-cost online streaming content to consumers on the other hand (Johnson, Friend, and Lee 2017).

This study draws on the tenets of the RBV and conceptualises big data analytics capability as an organisational resource at the disposal of an organisation which can be used to achieve superior competitive advantages. Big data analytics capability is a valuable, rare, idiosyncratic, and immobile resource that can provide significant differences among organisations over time. Thus, it cannot be easily exchanged among firms and can be the differentiating factor between organisations that successfully introduce disruptive business models and those who do not.

It is expected that the effect of disruptive business models on organisational performance will be strengthened in organisations that possess high levels of big data analytics capabilities. As such, organisations that have high levels of big data variety, big data velocity, and big data volume will maximise these to ensure that the disruptive business models introduced result in superior new product and market performance compared to organisations who do not possess these capabilities.

Hence, this study hypothesises that big data analytics capability will strengthen the positive relationship between disruptive business model and new product performance on one hand, and between disruptive business model and market performance on the other hand.

Hypothesis 7a: Big data analytics capability strengthens the positive relationship between disruptive business model and new product performance.

Hypothesis 7b: Big data analytics capability strengthens the positive relationship between disruptive business model and market performance.

3.4.2 Adaptive Marketing Capability

Adaptive marketing capability can be described as the ability of an organisation to "identify and capitalise on emerging market opportunities" (Polat and Akgün 2017, p. 1139). It can also be defined as the ability of a firm to "reconfigure resources and coordinate processes promptly and effectively to meet rapid environmental changes" (Zhou and Li 2010, p. 225). In addition, adaptive marketing capability refers to "the extensible ability to proactively sense and act on market signals, continuously learn from market experiments, and integrate and coordinate social network resources to adapt to market changes and predict industry trends" (Guo et al. 2018, p. 3). Thus, adaptive marketing capability involves the ability of an organisation to collaborate with other organisations, actively conduct market experiments, and proactively monitor environmental changes.

Adaptive marketing capability consists of open marketing capability, adaptive market experimentation, and vigilant market learning (Guo et al. 2018). Organisations that possess open marketing capability can liaise and partner with other firms to deliver superior value to their consumers. The partnership can provide complimentary resources and capabilities to both firms and maximise customer satisfaction through the introduction of innovative products, services, and business models.

This is illustrated by Sabatier, Craig-Kennard and Mangematin (2012) who find that new patterns of collaborations triggered the development of disruptive business models that led to a change in the drug industry's dominant logic. This is also evident in the pharmaceutical industry where alliances and partnerships pave the way for both small and large organisations to access innovations and markets (Bianchi et al. 2011; Bradfield and El-Sayed 2009; Mittra 2007). Thus, partnerships and collaborations enable organisations to develop innovation capabilities (Najafi-Tavani et al. 2018), external competencies (Gassmann and Reepmeyer 2005), and disruptive business models (Sabatier, Craig-Kennard, and Mangematin 2012).

In addition, Yovanof and Hazapis (2008) argue that organisations can establish dynamic capabilities across their value networks through alliances with other organisations. Thus, organisations that possess open marketing capabilities can take advantage of insights from research and development and consumer analysis that can enhance the success of disruptive business models. As such, organisations that do not possess open marketing capabilities might find it more difficult to successfully introduce and implement disruptive business models because of changing industry landscapes, competitive activities, and customer preferences.

Also, organisations that constantly engage in market experimentation are likely to know which business model will be disruptive and explore ways of maximising its benefits. Adaptive market experimentation is the ability of organisations to explore various ideas before commercialisation (Guo et al. 2018). This capability is crucial for the success of disruptive business models as it is possible that firms are not always certain that a business model will be well received by consumers and meet their needs adequately (Nidumolu, Prahalad, and Rangaswami 2009). Additionally, disruptive business models involve the creation of customer value innovation that requires constant market experimentation (Chesbrough 2010; Habtay 2012; McGrath 2010). DaSilva *et al.* (2013) also find that organisations need to constantly experiment and develop business models which incorporate disruptive technologies and technological advancements.

Engaging in market experimentation will provide a firm with higher chances of successfully developing a disruptive business model which can result in positive new product and market performance outcomes for the firm. As such, extant research shows that experimentation can help in fine-tuning a new business model (Sosna, Trevinyo-Rodríguez, and Velamuri 2010). For instance, Sony developed the capability of designing and introducing different variations of their electronics products at a very fast rate which helped them meet their customers' needs (Yovanof and Hazapis 2008). Also, Karimi and Walter (2016) argue that developing a disruptive business model involves constant exploration of alternatives as the right business model to adopt is not always apparent. Another illustration of this is provided by Yovanof and Hazapis (2008) who argue that developing a disruptive business model requires modifications and adaptations by organisations.

In a similar vein, organisations that possess vigilant market learning capabilities can closely monitor the environment, consumer behaviour, competitors, technological advancements, and industry shifts. This can provide the firm with a viable platform to enhance the performance outcomes of disruptive business models. Vigilant market learning can enable an organisation select the right target market, determine the best pricing strategy, and ensure that the disruptive business model is successfully commercialised. Therefore, organisations that are receptive to market signals, conscious of changing consumer needs, able to conduct forecasts, and involved in environmental scanning are more likely to engage in proactive strategies (Barclay and Benson 1990; Lumpkin and Dess 1996; Wright et al. 1995).

Karimi and Walter (2016) argue that the ability of organisations to be proactive in identifying market signals, anticipating future demand, conducting environmental scanning, and conducting extensive feasibility research has a positive influence on the development of disruptive business models. This is buttressed by DaSilva *et al.* (2013) who highlight the importance of keeping abreast of competitive behavior and industry trends in examining disruptive business models.

In line with the RBV, this study conceptualises adaptive marketing capability as an internal heterogenous resource under the control of an organisation. As such, adaptive marketing capability can provide organisations with distinct competitive advantages because it is one of the strengths of an organisation. Therefore, it is expected that the disruptive business model–performance relationship will be strengthened in organisations that have high levels of adaptive marketing capabilities.

On the other hand, the disruptive business model–performance relationship will be weakened in organisations that do not have adaptive marketing capabilities at their disposal. This is because the presence of adaptive marketing capabilities as a valuable organisational resource can facilitate the success of disruptive business models due to its differentiating nature. In addition, adaptive marketing capabilities are non-substitutable and immobile resources that organisations possess which can reinforce the positive relationship between disruptive business models and performance.

Thus, it is expected that organisations that possess adaptive marketing capabilities are more likely to successfully introduce and implement disruptive business models that lead to positive new product and market performance than organisations that do not possess these capabilities. As such, adaptive marketing capability should strengthen the positive relationship between disruptive business model and new product on one hand and strengthen the positive relationship between disruptive business model and market performance on the other hand. This study hypothesises that:

Hypothesis 8a: Adaptive marketing capability strengthens the positive relationship between disruptive business model and new product performance.

Hypothesis 8b: Adaptive marketing capability strengthens the positive relationship between disruptive business model and market performance.

3.5 Control Variables

Various control variables were used in this study. Past research has found that the size of a firm can have an effect on disruptive business models. Karimi and Walter (2016) find that large organisations have abundant resources and capabilities because of their size and this has a positive relationship with disruptive business models. However, some research shows that small firms are likely to introduce disruptive business models faster than larger incumbents (Christensen 1997; Ghezzi et al. 2016). In addition, some research shows that entrant firms are proficient in introducing disruptive business models. Specifically, Christensen (1997) found that new entrants were more likely to successfully introduce disruptive business models than incumbent firms.

As such, it was vital to include firm size as a control variable in this study. Firm size was measured as the number of employees in the firm in this study. Similarly, firm age was included as a control variable in this study in order to account for new entrants and incumbent firms in various industries. Firm age was measured as the number of years the organisation has been in operation. This will enable the researcher to clearly distinguish between small firms, medium-sized firms, and large firms in understanding their ability to successfully develop and implement disruptive business models.

The last control variable included in this study was the firm’s industry of operation to account for the differences between Business-to-Business (B2B) and Business-to-Consumer (B2C) firms on one hand and between Manufacturing and Services firms on the other hand. This distinction based on industry of operation will help to account for differences that can occur based on the idiosyncrasies and peculiarities of different industries and estimate their impact on the ability of organisations to successfully develop and implement disruptive business models.

Therefore, firm age, firm size, and industry of operation were included in order to account for the various organisations that are capable of introducing disruptive business models irrespective of their age, size, or industry of operation.

3.6 Summary

This chapter has provided an overview of the conceptual model to be examined and the hypotheses to be tested in this study. Four major drivers of disruptive business model were discussed including formalisation, management commitment to innovation, top managerial risk-taking propensity, and willingness to cannibalise. The development and implementation of disruptive business models is hypothesised to lead to new product performance and market performance for organisations. Additionally, organisations that possess adaptive marketing capability and big data analytics capability are more likely to succeed at introducing disruptive business models and achieving positive performance outcomes than organisations that do not possess these capabilities. Table 3.1 provides a summary of the hypothesised associations for the research model while Table 3.2 provides the definitions of key constructs of the research model.

Table 3.1: Summary of the Hypothesised Associations

Hypothesis 1	Formalisation is negatively related to disruptive business model
Hypothesis 2	Willingness to cannibalise is positively related to disruptive business model
Hypothesis 3	Top managerial risk-taking propensity is positively related to disruptive business model
Hypothesis 4	Management commitment to innovation is positively related to disruptive business model
Hypothesis 5	Disruptive business model is positively related to new product performance
Hypothesis 6	Disruptive business model is positively related to market performance
Hypothesis 7a	Big data analytics capability strengthens the positive relationship between disruptive business model and new product performance
Hypothesis 7b	Big data analytics capability strengthens the positive relationship between disruptive business model and market performance
Hypothesis 8a	Adaptive marketing capability strengthens the positive relationship between disruptive business model and new product performance
Hypothesis 8b	Adaptive marketing capability strengthens the positive relationship between disruptive business model and market performance

Table 3.2: Definition of Key Constructs

Set of Variables	Construct	Definition
Antecedents	Formalisation	Refers to "the degree of work standardisation and the amount of deviation that is allowed from standards" (Aiken and Hage 1966, p. 499).
	Management Commitment to Innovation	Refers to "managerial willingness to allocate resources and champion activities that lead to the development of new products, technologies, and processes consistent with marketplace opportunities" (Hitt, Hoskisson, and Ireland 1990, pp. 29–30).
	Top Managerial Risk-Taking Propensity	Refers to the willingness of managers within organisations to undertake financial and investment risks to exploit business opportunities.
	Willingness to Cannibalise	Refers to "an attitude that puts up for review and sacrifice current profit-generating assets, including current profitable and successful innovations, so that the firm can get ahead with the next generation of innovations" (Tellis, Prabhu, and Chandy 2009, p. 8).
Performance	Market performance	Refers to performance reflected in an increase in market share, growth in sales volume of the organisation, product development and market development.
	New product performance	Refers to the managerial ability to successfully introduce new products into a market, engage in new product development activity and the capability of creating and generating new product ideas.
	Anticipated Financial Performance	Refers to the expected performance for the next financial year measured as return on assets, return on investment, profit growth, and profit margin.
Moderators	Adaptive Marketing Capability	Refers to "the extensible ability to proactively sense and act on market signals, continuously learn from market experiments, and integrate and coordinate social network resources to adapt to market changes and predict industry trends " (Guo et al. 2018, p. 3).
	Big Data Analytics Capability	Refers to the ability of organisations to "collect large and complex data from different instruments at all stages of the process which go from acquisition, storage and sharing, to analysis and visualization" (Pisano, Pironti, and Rieple 2015, p. 191).
Controls	Firm Age	Refers to the number of years the organisation has been in operation.
	Firm Size	Refers to the number of employees in the firm.

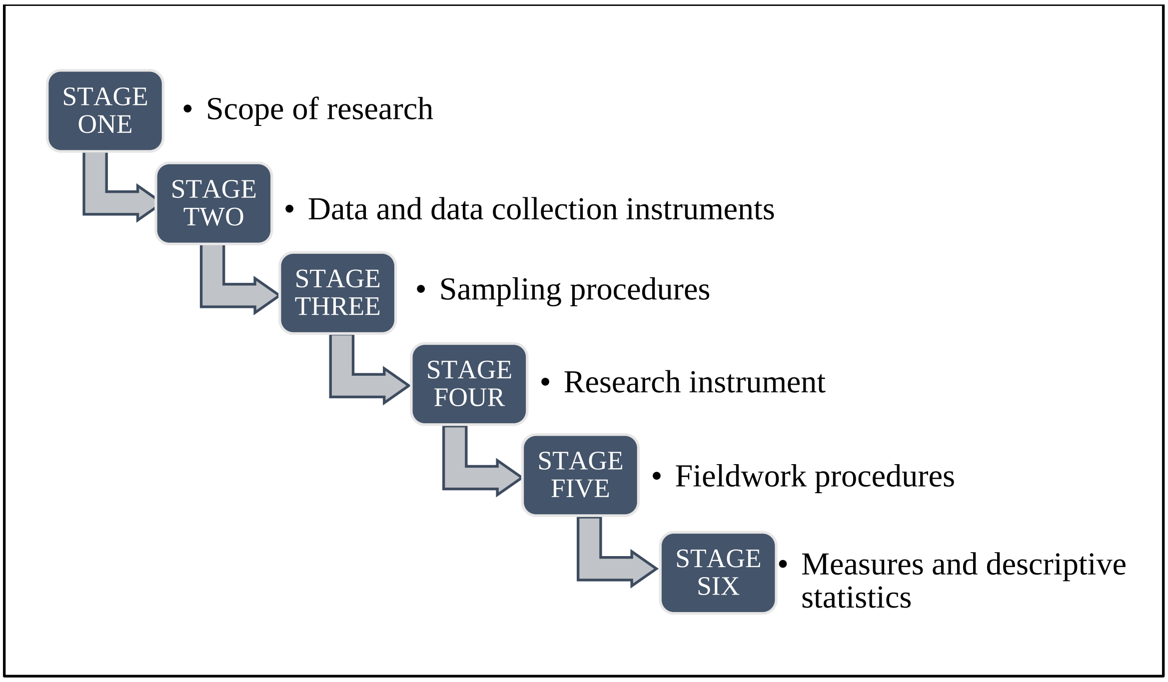
CHAPTER 4

RESEARCH METHODOLOGY

4.0 Introduction

The aim of this study is to examine the antecedents, performance outcomes, and contingency effects of disruptive business models. This chapter explores the methodology undertaken to test the hypotheses developed in the previous chapter. The research process is divided into six stages and is illustrated in Figure 4.1.

Figure 4.1: Stages of the Thesis Research Process



Stage one examines the scope of the research including the geographic scope, industry coverage, unit of analysis, and key informants in this study. *Stage two* deals with the data and data collection instruments. Specifically, the qualitative and quantitative approaches undertaken in this study will be discussed. *Stage three* examines the sampling procedures and sampling frame used for the study. *Stage four* looks at the research instrument while *stage five* describes the method used to collect the data. Finally, *stage six* examines the measures used in the study and the descriptive statistics of the constructs.

4.1 Scope of Research

This section examines the geographic scope of the study, industry coverage, unit of analysis, and the processes through which the key informants for this study were selected.

4.1.1 Geographic Scope

This study was undertaken in the United Kingdom (UK) for several reasons. *First*, the UK is an advanced economy that has highly competitive industries that are open to external pressures which can lead to innovative practices within organisations. An example of an external pressure is the Brexit vote in March 2019 which initially had some adverse effects on the UK economy. However, economic activities and employment rates have peaked at 75% for people between 16 and 64 years of age in addition to an increase in the number of hours worked mainly because of immigration from the European Union (OECD 2020).

Second, the UK is among the top 10 competitive countries in the world and the fourth most competitive economy in Europe (Schwab 2018). This implies that the level of competition within industries can promote and facilitate the development of disruptive innovations in general and disruptive business models in particular. Competitive pressures can drive organisations to develop disruptive business models as a way of ensuring survival in the marketplace and positive performance outcomes for the organisation.

Third, the UK is one of the top three most "promising countries in the world to introduce technological breakthroughs which will have a global impact" (KPMG 2019, p. 3). *Fourth*, findings from the UK context can provide insights into other contexts that share similar characteristics. As such, the UK context provides relevant insights into the workings of similar developed economies in Europe and countries in the European Union. *Fifth*, the UK was a suitable selection because of the author's acquaintance with the country's environment.

Sixth, the UK boasts of being one of the strongest economies in Europe. The economic growth rate of the UK has risen steadily between 2016 and 2019 and this coincides with the time when this research was conducted. Thus, the UK provides an avenue to make insightful discoveries on innovative activities in general and disruptive business models in particular.

4.1.2 Industry Coverage

Data was obtained from a wide range of industries due to the varying levels of disruptive business model development undertaken based on industry of operation. Specifically, the organisations selected were grouped into manufacturing firms, service firms, and firms that combine both manufacturing and services in their business operations. This will help to provide a holistic view of disruptive business model activities in these three contexts. Thus, it was crucial to distinguish between industry of operation to account for the unique peculiarities of different industrial settings.

In addition to grouping based on manufacturing, service, or both manufacturing and services firms, an option was provided to respondents to classify their business operations based on their target market. As such, respondents were requested to indicate if their business activities were targeted at consumers (business-to-consumer), at organisations (business-to-business), or a combination of both consumers and organisations (business-to-consumer and business-to-business). This helped to differentiate between organisations that were involved in providing product and service offerings to other organisations and organisations that offered product and service offerings to final consumers.

Another measure that was undertaken in this study was differentiating firms based on the scope of their business operations. This is because some organisations operate locally within the borders of the UK while some are involved in international business operations. Thus, the respondents were asked to indicate the nature of their business operations to show whether they were operational in national or international markets.

4.1.3 Unit of Analysis

The *unit of analysis* for this study is 'organisational level disruptive business model' relating to products, services, and processes. This accounts for the unique internal organisational characteristics and distinct external influences that can influence decisions to develop and implement disruptive business models. Small, medium, and large organisations with a minimum annual sales turnover of £5,000 were preferred for this study because all organisations of varying sizes have the capability of introducing disruptive business models.

While Christensen (1997) and Ghezzi *et al.* (2016) find that small organisations can use their size to introduce disruptive innovations faster than larger incumbents, Karimi and Walter (2016) find that large organisations that had abundant resources and capabilities were more likely to successfully develop and implement disruptive business models. Thus, the selection of small organisations helped minimise the potential bias of examining only medium and large organisations that are likely to possess financial resources and capabilities that can facilitate introduction of disruptive business models.

4.1.4 Key Informants

The key informants were carefully selected to ensure their suitability to complete the research instrument in an accurate manner. Thus, criteria such as position in the organisation, expertise on innovation, and knowledge about organisational activities were used in screening the respondents for this study (Bagozzi, Yi, and Phillips 1991).

In order to address the measurement problems commonly associated with single informants, various steps were taken including the key informant method proposed by Phillips (1981). These included asking questions about respondents' position within their organisation, level of knowledge about organisational business model activities, and their confidence in answering the survey questions. These questions were included at the end of the survey as pre-coded statements.

4.2 Data and Data Collection Instruments

Extant literature argues that qualitative research should precede quantitative studies because of its ability to make valuable contributions to the development of research questions, refine conceptual models, and aid in data collection and analysis (Malhotra, Birks, and Wills 2012). The exploratory nature of qualitative research makes it invaluable to quantitative research which is principally confirmatory and deductive in nature (Trochim 2006). Thus, a mixed methods approach was adopted which will be discussed in this section. Additionally, the data collection instruments such as interview protocol and survey questionnaire will be described.

4.2.1 Qualitative Procedure

The first stage of the data collection process was the use of qualitative methods to understand the conceptual domain of disruptive business models. In order to gain in-depth understanding of the nature of disruptive business models, the researcher organised face-to-face interviews with 23 organisations in the UK. Given the need to sample a wide range of participating organisations, small, medium, and large organisations were contacted to participate in the interviews. Their employees ranged from five to 32,000 and were operating in various industries including business software and IT, fast-moving consumer goods

(FMCG), education, pharmaceuticals, airline, and automotive among others. These industries were selected because they are among those identified as having the fastest rate of disruption in the UK. Specifically, industries like FMCG and automotive have higher rates of technology adoption (EY 2018).

To ensure high rates of participation in this study, company websites were examined to identify managerial level employees who were likely to possess significant insights about organisational business model strategies. Thus, phone calls and emails were made as potential respondents were informed about the purpose of the study and invited to participate. All respondents were assured of confidentiality and anonymity and appropriate measures were taken to ensure privacy and data confidentiality. As such, pseudonyms are used to protect the identities of the respondents. Thus, participants were selected based on criterion sampling which enabled the selection of interviewees and archival sources based on knowledgeability and seniority (Patton 2002).

The interviewees were asked open ended questions to encourage discussions within the parameters of the research questions of this study. The participants were asked to discuss in detail the activities related to the development of disruptive business models within their organisations, how these were implemented, and their performance outcomes. The interviews lasted between 45 minutes and one hour. All interviewees except one agreed to be recorded, thereafter, the recordings were transcribed verbatim while notes were made after the single non-recorded interview. In all, the transcripts and summaries were approximately 94,000 words in total.

The interviewees had job titles such as chief executive officer, managing director, marketing manager, chief technology officer, head of strategy, sales officer, and marketing officer among others. The diversity in organisations and the positions of key informants helped to identify the potential drivers of developing a disruptive business model, its performance, and contingency effects. In sum, in-depth interviews were conducted with 23 different individuals representing various organisations in different industries and Table 4.1 contains the sample characteristics of managers interviewed.

Table 4.1: Sample Characteristics of Managers Interviewed

Firm	Manager	Position	Industry	Size	No of Employees	Years in Business
A	Alex	CEO	Business Software and IT	Large	3,000+	38
B	Gary	Managing Director	Pharmaceuticals	Medium	250	18
C	Annie	Marketing Manager	FMCG	Large	3,000+	15
D	Ben	Chief Technology Officer	Business Software and IT	Small	10–20	11
E	Alfred	Head of Strategy	Automotive	Large	32,000	22
F	Anderson	CEO	Management Consulting	Small	5	10
G	Catherine	Marketing Manager	FMCG	Medium	50–100	50
H	Derek	Marketing Manager	FMCG	Large	2,000+	15
I	Henry	Sales and Managing Director	Marketing Services	Medium	150–200	11
J	Jane	CEO	Marketing Services	Small	5	6
K	Sharon	Marketing Manager	Education	Medium	200+	21
L	Charles	Director	Management Consulting	Large	13,000+	31
M	Jeffery	CEO	Marketing Services	Small	5	7
N	Ethan	Sales Manager	FMCG	Large	14,000+	173
O	Frederick	CEO	Pharmaceuticals	Small	25–50	18
P	Eric	Director	Business Software and IT	Small	14	28
Q	Jeremy	Global Brand Manager	FMCG	Large	2,500+	15
R	Lisa	Manager	Management Consultancy	Large	22,000+	169
S	Laura	Manager	Management Consultancy	Large	13,000+	31
T	Douglas	Director	Airline	Large	10,000+	23
U	Alvin	Director	Management Consultancy	Large	22,000+	169
V	Kate	Head of Marketing	Education	Medium	200+	21
W	Austin	Managing Director	Manufacturing	Small	31	29

4.2.1.1 Interview Protocol and Administration

An interview protocol was designed to guide the interviews with key informants. The interviews were semi-structured as the interviewees could express their answers within the boundaries of the research questions of this study. The interviews began with an introduction of the research topic by the researcher in addition to assurances of anonymity and confidentiality given to every interviewee. Permission was sought from the interviewees for the interviews to be recorded to ensure concentration on the topic of discussion and facilitate transcribing.

Regarding the structure of the interviews, interviewees were first asked about their job title, position within their organisation, and how long they had been in that position. They were then told to provide a general overview of their roles and responsibilities within their organisations in addition to previous experience in strategy development and implementation. This was followed by a description of organisational and industry peculiarities. This helped to provide a background for the researcher to guide the interview and ensure that the interviewees were knowledgeable about strategic decision making within their organisations.

The next set of questions focused on the activities related to disruptive business model development and implementation within the organisation in addition to various market shifts that had occurred in their industries. This enabled the researcher to probe into the nature of disruptive business model activities undertaken within the organisation and the major motivating factors. Interviewees were also asked about the ways in which disruptive business models were evaluated and their relationship with organisational performance.

Furthermore, interviewees were asked about factors that facilitate the development of disruptive business models within their organisations. This provided the researcher with the opportunity to understand the internal and external mechanisms influencing the creation of disruptive business models. During the interviews, the researcher ensured that answers which needed further elaboration were probed.

4.2.2 Quantitative Procedure

The second phase of this study was the adoption of a quantitative approach based on the findings of the exploratory interviews to ensure that the study's conceptual framework was tested empirically. This section describes the processes undertaken and the cross-sectional research design used to answer the research questions discovered during the qualitative phase.

Cross-sectional design can be described as a process where data is collected from many respondents at a single time. Cross-sectional design was selected as it is the most common method used in management, business, marketing, and marketing strategy studies due to its strength of using large sample size to make inferences (Jap and Anderson 2004).

Time considerations also necessitated the choice of a cross-sectional design as longitudinal designs take considerably more time to complete and require higher financial commitments than cross-sectional designs (Rindfleisch et al. 2008). However, the adoption of a cross-sectional design is not without criticism. Specifically, adopting a cross-sectional design can lead to the occurrence of common method bias in the data (Podsakoff et al. 2003) and issues in making causal inferences between independent and dependent variables (Rindfleisch et al. 2008).

Several steps were taken to reduce the impact of common method bias on the data collection, analysis, and findings. These included both procedural and *post-hoc* remedies proposed by Podsakoff *et al.* (2003). A procedural remedy which was undertaken was the use of different response formats for the scales of predictor and criterion variables as different common-scale anchors were used (Lindell and Whitney 2001; Podsakoff et al. 2003). Also, all respondents were assured of anonymity in written form via the cover letter provided and on the first page of the online questionnaire (Podsakoff et al. 2003). Additionally, the variables (independent and dependent variables) in the questionnaire were mixed to ensure that respondents could not easily guess the relationships under examination (Podsakoff et al. 2003).

Following Lindell and Whitney's (2001) marker variable technique, a marker variable that had no theoretical links to any of the constructs examined was included in the questionnaire (i.e., Negative Affectivity). Furthermore, it also showed good reliability (mean = 3.9, standard deviation [SD] = 1.53, Cronbach's alpha = .833). In addition, the questionnaire asked respondents to answer questions retrospectively with a focus on actual behaviours and not belief systems (Golden 1992). Furthermore, several statistical *post-hoc* remedies and tests were conducted during the data analysis and these are presented in chapter five.

4.3 Sampling Procedures

The quantitative approach adopted in this study involved a large-scale mail and online survey which was conducted in the UK. Questionnaires were used to elicit detailed information from respondents. Using questionnaires provided numerous advantages including the ability to collect data from a large number of respondents, ease of coding and analysis, accurate data based on the parameters provided, and the reduction of bias due to the specific alternatives provided to respondents (Malhotra, Birks, and Wills 2012).

4.3.1 Sampling Frame

The main aim of this study is to examine the antecedents, outcomes, and boundary conditions of disruptive business models. Thus, the sample frame included small, medium, and large organisations operating in a multi-industry context in the UK. The researcher developed the study's sample frame from two sources. First, by compiling data from FAME, *Bureau van Dijk*, a database of over 11 million companies in the UK and Ireland which provides detailed information about each firm’s financials, industry descriptions, organisational profile, directors, managers, and up-to-date contact details. Second, a panel was used from Qualtrics.

The organisations selected had to satisfy the following criteria: (a) be involved in either manufacturing or service industries; (b) have sales turnover in excess of £5,000; (c) have total assets in excess of £10,000; and (d) be operational in the UK. Based on the aforementioned criteria, 7,585 firms were identified in the directory and 1,450 firms were randomly selected.

4.4 Research Instrument

4.4.1 Questionnaire Layout

To improve the questionnaire layout and presentation, leading academics and scholars in the field gave valuable feedback on the structure and format of the questionnaire. The questionnaire was prepared in both print and online versions and was divided into six sections. *Section one* contained questions about the organisation’s disruptive business model activities. The questions also covered the industry of operation and nature of business operations. *Section two* focused on the internal operations of the organisation including formalisation, top managerial risk-taking propensity, management commitment to innovation, and willingness to cannibalise existing products, resources, and technologies.

Section three focused on the core competencies within the organisation including data analytics capability and adaptive marketing capability. *Section four* contained questions on current organisational performance reflected in current new product performance, current market performance, and anticipated financial performance for the next 12 months.

Section five contained questions about the organisation and the respondent. The questions about the organisation included the number of years the organisation has been in operation and the number of full-time employees. Questions relating to the respondent included questions on the level of knowledgeability, confidence about the answers provided, negative affectivity (marker variable), position held, number of years in position, and number of years in industry. The respondents were also given the opportunity to provide their email addresses, phone numbers, and the option on whether to receive a summary of study findings.

4.4.2 Presentation of the Questionnaire

The questionnaire was prepared in both print and online formats to enhance accessibility and provide added convenience to respondents. For the print version of the questionnaire, attention was paid to the layout and format of the document to positively influence response rates and ensure accurate responses from respondents. The online version of the questionnaire was created with Qualtrics and was customised to ensure that it was mobile-friendly. This helped to provide an alternative option for respondents to complete the questionnaire on their mobile devices. The format of the online version was identical to the print version to minimise differences in the data collection through both methods. The data from both the print and online versions were coded into a single database and used for the data analysis.

4.4.3 Cover Letter

The cover letter stated the title of the study, a brief description of the study to the respondents, and the ethical approval received from the university. Instructions were provided to respondents to guide the completion of the questionnaire and respondents were assured of anonymity and confidentiality. The cover letter also provided contact details of the researcher and names of the supervisory team for this study.

4.4.4 Questionnaire Pre-testing

A pre-test of the questionnaire was conducted in order to ensure that the questionnaire developed was well understood by the respondents. 25 respondents completed the questionnaire and provided feedback on the clarity of words and general comments on how the questionnaire could be improved upon. To facilitate the response rate for the pre-test, a monetary incentive of the donation of £1 per completed questionnaire to Children's Aid was offered to potential respondents. This process provided some corrections to be made regarding the flow, content, and structure of the questionnaire. Thus, there were no major problems identified during the pre-test process.

The results from the pre-test enabled the researcher to make some modifications and corrections to the questionnaire. For instance, the reference for the items on performance was changed from comparison with 'major competitors' to comparison with 'major competitor'. This is because organisations have different major competitors and performance outcomes can be larger or smaller than those competitors. The change helped to remove any ambiguity and confusion on the items relating to performance.

4.5 Fieldwork Procedures

4.5.1 Securing Participation and Enhancing the Response Rate

For the qualitative phase of the study, company websites were searched to identify the names and contact details of key informants including managing directors and top managerial team members. This process resulted in getting the phone numbers, email addresses, and names of key informants for 105 companies. The organisations were then contacted by phone and email to introduce the study, its aims and objectives, and request for participation in the interviews. This resulted in a total of 23 positive responses for participation in the interview.

For the quantitative phase of the study, a panel was used from Qualtrics in addition to the Financial Analysis Made Easy (FAME) database to ensure that the right respondents were secured for participation based on the criteria specified in section 4.3.1. The initial search using FAME with all the criteria specified resulted in a total of 7,585 manufacturing and services companies and 1,450 of these companies were randomly selected.

First, the names, office addresses, phone numbers, and email addresses of the top management team of each organisation were gotten from the FAME database. This process helped to identify 174 organisations that either had repeat entries, bad and inadequate records, were closing or in administration. Thus, after the initial screening process, 1,276 companies were left in the sample.

Second, each organisation was called to identify the key informants, get contact details, and verify that they still work in that capacity within the organisation. An option was provided to either complete the survey online or for a paper copy to be sent through the post. From the telephone screening process, 57 organisations declined to participate in the research because of company policies of not participating in academic research or surveys; 63 organisations had a no-name policy; 76 organisations stated that the key informant was not available or had voicemail policies and so access was denied; 49 organisations had no key informants based in the UK; 14 organisations declined to participate in the research because of incompatibility between the research topic and the nature of their business operations; and 148 organisations refused to participate in the study without providing specific reasons.

Thus, the telephone screening process eliminated 432 organisations from the sample leaving a total of 844 companies available after all the screening procedures were completed. The telephone contact process is in line with academic conventions as a viable means of ascertaining that each organisation meets the criteria stipulated for a research study (Hultman, Robson, and Katsikeas 2009).

The data collection process was undertaken by sending emails to all potential respondents who asked to complete the survey online and sending questionnaires by post to all respondents who requested for paper copies. The emails contained a brief description of the research, assurance of confidentiality and anonymity, the survey link, and contact details of the researcher and supervisory team. The questionnaires sent by post included the contact details of the researcher, a cover letter providing information about the study, and a pre-paid return envelope to facilitate the returning of completed questionnaires.

To further enhance the response rate, respondents who had not completed the questionnaire after 2 weeks were reminded to complete the survey through phone calls, emails containing the link to the questionnaire, and via LinkedIn. The reminder phone calls, emails, and LinkedIn messages helped to identify issues such as delayed delivery of the questionnaire by post and answer general questions about the study and specific questions about the questionnaire. Based on the feedback gotten from respondents, replacement questionnaires were sent to respondents who requested for this and this helped to further enhance the response rate. After this, final reminders were sent to all potential respondents who had not completed the survey reminding them about completing the questionnaire within the stipulated timeframe of the study.

The various factors taken into consideration to enhance the response rate are summarised in Table 4.5. *First*, ethical approval was gotten from the University before the commencement of the data collection process and details of this were included in the cover letters and emails sent to potential respondents. *Second*, a cover letter was designed to provide general information about the research such as sponsorship from the University of Leeds, assurance of confidentiality and anonymity, and contact details of the researcher and supervisory team.

Third, a pre-paid envelope was included in the questionnaires sent by post to minimise the costs associated with returning the questionnaire. This provided respondents with an easy way of returning completed questionnaires. *Fourth*, respondents were incentivised to complete the survey by getting an option to request for a summary of the research findings. *Fifth,* an online version of the survey was created based on requests from potential respondents during the screening process. The online version was mobile friendly and easy to use enabling respondents to complete the survey at their convenience using their laptops, personal computers, and other mobile devices.

At the end of the data collection process, a total of 458 questionnaires were received (30 questionnaires received by post and 428 questionnaires completed online). Of the 30 questionnaires received by post, 5 had excessive missing data and were unusable for the data analysis. Of the 428 questionnaires completed online, 35 had excessive missing data and 58 failed to meet up with the competency requirements and attention checkers included in the survey. This provided a total of 335 usable questionnaires completed online. In all, the final sample consisted of 360 usable survey responses for the data analysis.

Figure 4.2 shows the step-by-step survey contact process while Table 4.2 provides a summary of the preliminary and initial telephone screening process undertaken. Table 4.3 shows the questionnaire distribution results while Table 4.4 provides the breakdown of questionnaires received.

Figure 4.2: The Survey Contact Process

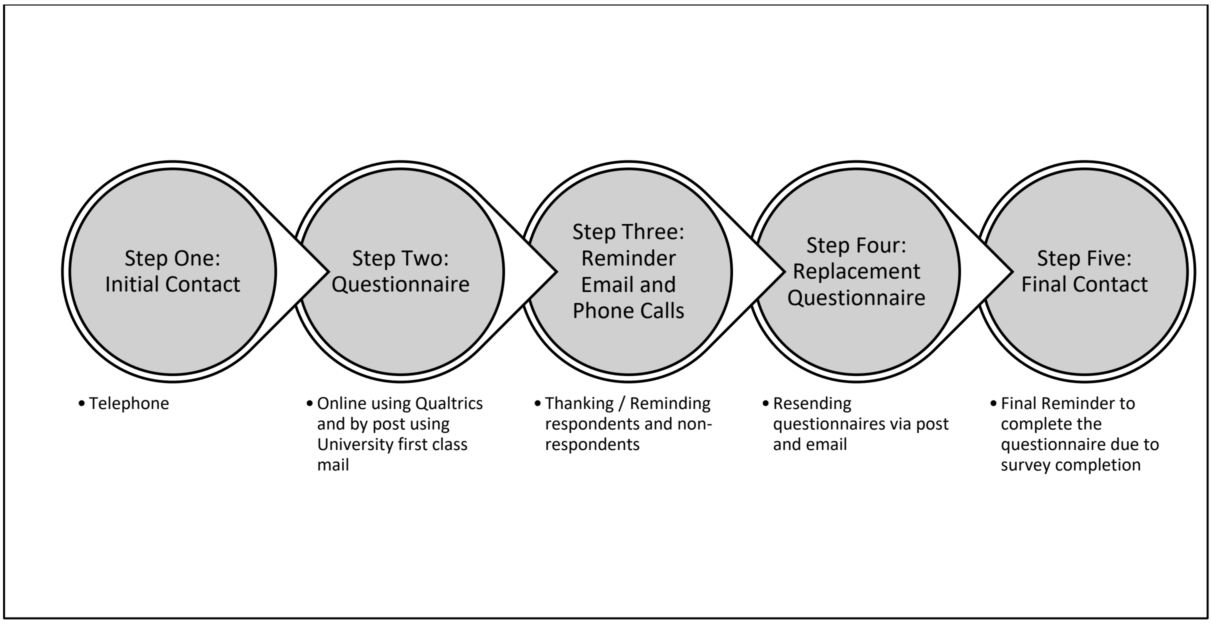


Table 4.2: Preliminary and Initial Telephone Screenings

Details	**Individual number**	**Total number**
Total Sample (derived from manufacturing and service industries with £5,000 annual sales turnover as criteria)		**1450**
Entries classified as bad records (e.g., wrong telephone number and address)	78	
Double and repetitive entries	67	
Company closed, closing or in administration	29	-174
Total available companies after pre-screening		**1276**
Non-participation due to company policy of not completing surveys	57	
Non-participation due to no-name policy	63	
Non-participation due to unavailability (e.g., managing director absent, voicemail policies)	76	
Non-participation due to lack of key informants (e.g., top management based outside the UK)	49	
Non-participation due to lack on congruence between research topic and nature of business operations	14	
Companies used in the pre-test	25	
Companies not willing to participate	148	-432
Companies available after screening procedures		**844**

Table 4.3: Questionnaire Distribution Results

Details	**Percentage rate (%)**	**Individual number**
Total questionnaires returned by post	3	30
Total questionnaires completed online	51	428
Companies not responding	46	386
Total number of questionnaires sent out (post and online)		**844**

Table 4.4: Breakdown of Questionnaires Received

Details	**Percentage rate (%)**	**Individual number**
Total questionnaires received by post	3	30
Unusable questionnaires		
Excessive missing data	17	5
Total usable questionnaires received by post	**83**	**25**
Total questionnaires received online	51	428
Unusable questionnaires		
Excessive missing data	8	35
Failure of competency test and attention checkers	14	58
Total usable questionnaires received online	**78**	**335**
Final sample	**43**	**360**

Table 4.5: Summary of Important Survey Considerations

Survey consideration	**Motivation for potential respondents**	**Used in the study**
Ethical approval	This study was approved by the faculty research ethics committee, University of Leeds, Leeds University Business School (Ethics Reference: LTLUBS-211).	Yes
Study sponsorship	This study was sponsored by the Marketing Division, Leeds University Business School and Leeds Anniversary Research Scholarship, University of Leeds.	Yes
Cover letter	The cover letter accompanying the questionnaire contained contact details of the researcher (including email address, phone number, and link to university online profile) and contact details of the supervisory team.	Yes
Questionnaire	The language used in the questionnaire was easy to read and the questionnaire was divided into sections to prevent a long flow of questions to potential respondents.	Yes
Postage	A pre-paid return envelope was enclosed with the cover letter and questionnaire to facilitate ease of posting. A copy of the researcher's business card was also enclosed.	Yes
Anonymity and Confidentiality	All respondents were assured of anonymity and confidentiality and this was reflected in the cover letter.	Yes
Monetary incentives	The donation of £1 per completed questionnaire to Children's Aid was used for the pre-test but not for the main data collection process.	Yes – for pretest; No – for main data collection
Non-monetary incentives	All respondents were given the option of requesting for a summary of the research findings to be sent upon completion of the study	Yes
Online version of Survey	An online version of the questionnaire was created using Qualtrics and is available at: **https://leedsubs.eu.qualtrics.com/jfe/form/SV_5Ayzb0ttRFtmoaV**	Yes

4.5.2 Key Informant Quality

Direct contacts were made with key decision makers and members of the top management team within organisations to ensure that they were knowledgeable on the core concepts and variables examined in this study. As such, only managerial level respondents were targeted for this study. Furthermore, only responses with high levels of competence and knowledgeability about the issues discussed in the questionnaire were used for the data analysis. As such, the overall key informant competency variable had a mean of 5.98 and standard deviation of 0.896 as shown in Table 4.6.

A question was included in the questionnaire to get information on the position of the respondents within their organisations and the number of years of experience that each of them had. Over half of the respondents were top managerial team members in their organisations. 50% of the respondents were CEOs/Owners of their organisations or businesses, 16% were Managing Directors and 15% were Marketing Directors as shown in Table 4.7. Respondents had been in their current position in their organisations for an average of 6 years and approximately 70% of the respondents had held their current position for more than 3 years (see Table 4.8).

Table 4.6: Descriptive Statistics for Key Informant Competency and Knowledgeability

		Descriptive Results	
Item Code	**Items**	**Mean**	**S.D**
COMP	Key Informant Competency		
COMP_1	The questionnaire deals with issues I am very knowledgeable about	5.08	1.034
COMP_2	I am completely confident about my answers to the questions	6.02	1.058
COMP_3	I am confident that my answers reflect the firm’s situation	6.12	.911
COMP		**5.98**	**.896**

Table 4.7: Key Informant Position

Informant Job Title	**Frequency**	**% of total companies**
CEO / Owner	179	49.7
Managing Director	59	16.4
Marketing Director	56	15.6
Sales/Strategy/Marketing/Operations Manager	38	10.6
Other Manager	28	7.7
Total	360	100

Table 4.8: Key Informant Experience

Years in position	Frequency	% of total companies
1 – 3 years	111	30.8
4 – 6 years	122	33.8
7 – 9 years	47	13.1
10 – 12 years	41	11.4
13 - 15 years	18	5
16 years and above	19	5.3
Not specified	2	0.6
Total	360	100

Note: The mean score was 6.59 years (s.d. = 6.04).

4.5.3 Demographic Characteristics of the Sample

All the respondents for both the interviews and the survey were top managerial team members working in a wide range of industries broadly classified as manufacturing and services operating in the UK. The demographic characteristics of the sample are presented in Table 4.9. Regarding company size, most of the organisations had annual sales turnover of more than £500,001 (45%), this was by followed organisations whose annual sales turnover was between £50,0001 and £500,000 (38.9%), and organisations whose annual sales turnover was between £5,000 and £50,000 (14.2%). Additionally, the average number of full-time employees was 10,919 employees (s.d. = 41,961), with 56.7% of the companies having below 1,000 employees and 43.3% of the companies having above 1,000 employees. The companies in the sample had been in operation for an average of 45 years (s.d. = 116 years) with 26.3% of the companies operating for more than 45 years.

Regarding the nature of business operations, 28.6% of the companies had only domestic business operations, 46.1% had only foreign business operations, and 15.3% of the companies had both domestic and foreign business operations. In terms of industry of operation, 36.1% of the sample were operational in only manufacturing industries, 48.6% of the sample operated in only service-related industries, and 15.3% of the sample had business operations in both manufacturing and service industries.

In terms of the consumer markets, 34.7% of the sample engaged in only B2B operations, 33.1% of the sample were involved in only B2C operations, and 32.2% of the sample conducted both B2B and B2C operations. Regarding the educational qualifications of the respondents, over 80% of the respondents had at least an undergraduate degree, professional qualification or diploma. 64.4% of the respondents were male while 34.2% of the respondents were female.

Table 4.9: Demographic Characteristics of the Sample

Demographic characteristics	**Frequency**	**% of total companies**
Annual Sales Turnover		
£5,000 - £50,000	51	14.2
£50,001 - £500,000	140	38.9
Above £500,001	162	45
Not specified	7	1.9
Number of Full Time Employees [Mean: 10,919 employees (s.d. = 41,961)]		
1 – 99 employees	89	24.6
100 – 249 employees	32	8.9
250 – 499 employees	42	11.7
500 – 999 employees	42	11.7
1,000 – 4,999 employees	77	21.4
5,000 – 9,999 employees	24	6.7
10,000 – 14,999 employees	14	3.9
15,000 – 19,999 employees	7	1.9
20,000 employees and above	33	9.2
Company Age [Mean: 45 years (s.d. = 116)]		
1 – 9 years	59	16.4
10 – 19 years	89	24.7
20 – 29 years	76	21.1
30 – 39 years	30	8.3
40 – 49 years	25	7
50 – 99 years	37	10.3
100 and above	44	12.2
Market Chosen		
Domestic	139	38.6
Foreign	166	46.1
Both Domestic and Foreign	55	15.3

Demographic characteristics	Frequency	% of total companies
Gender		
Male	232	64.4
Female	123	34.2
Not specified	5	1.4
Industry of Operation		
Manufacturing	130	36.1
Services	175	48.6
Both Manufacturing and Services	55	15.3
Nature of Business Operations		
Business to Business (B2B)	125	34.7
Business to Consumer (B2C)	119	33.1
Both B2B and B2C	116	32.2
Educational Qualification		
Less than high school	2	0.6
High school graduate	31	8.6
Some college	38	10.6
Bachelor’s degree	155	43.1
Masters (MSc / MBA)	92	25.6
Educational Qualification		
Doctorate	26	7.2
Professional Courses	11	3.1
Other (e.g., ACCA, CIMA, Diploma)	5	1.4

4.5.4 Controlling for Non-Response Bias

One of the criticisms of mail surveys is the possibility of nonresponse bias. Non-response bias can be described as when the answers of respondents is significantly different from those who do not respond (Armstrong and Overton 1977). As such, nonresponse bias can be evaluated by comparing answers provided by early respondents to the answers provided by late respondents. This is because late respondents are similar to non-respondents. It is expected that there will be no significant differences between both samples to eliminate the presence of non-response bias.

Two groups were created that comprised of early respondents (25% of the sample) and late respondents (25% of the sample). These groups were then compared based on key constructs in the study. Using independent sample t-test, the t-values were compared, and they showed no difference at the 0.05 level. For instance, the comparison of the two groups yielded the following results: formalisation ($t = -1.2$, $p = .232$), market performance ($t = -1.755$, $p = .081$), big data analytics capability ($t = -1.411$, $p = .160$), and new product performance ($t = -1.859$, $p = .065$). Therefore, the results indicate that nonresponse bias does not pose a problem by threatening the interpretation of the findings of this study.

4.5.5 Data Editing, Coding, and Transcribing

For the in-depth interviews, all interviewees except one agreed to be recorded. After each interview, the recordings were transcribed verbatim while notes were made after the single non-recorded interview. This process helped to identify central themes in the responses provided by the managers across industrial settings. In all, the transcripts and summaries were approximately 94,000 words in total. The coding for the qualitative data analysis was conducted using the NVivo qualitative software package. The first process involved open coding and the extraction of significant parts of the interviews relevant to the research questions examined in this study. This initial coding process resulted in 877 significant pieces of texts that were labelled and placed into various categories.

Similarly, for the quantitative data collected, all the questionnaires received by post and online were coded. Once the responses started coming in, they were individually checked to ensure that responses where the respondents provided gibberish answers, had a pattern in answering all the questions, and were not very knowledgeable about the questions asked in the questionnaire were removed from the final dataset. Afterwards, the questionnaires gotten from respondents over the post were coded in SPSS while the coding for the questionnaires that were completed online was automatically generated using Qualtrics.

In addition, some variables were reverse coded based on the nature of the statements in the questionnaire. The variables that were reverse coded include Formalisation 4 (In our firm the employees are constantly being checked on for rule violations); Formalisation 5 (In our firm people feel as though they are constantly being watched to see that they obey all the rules); Willingness to Cannibalise 4 (In our firm we find it difficult to change established procedures to cater to the needs of a new product); Willingness to Cannibalise 5 (In our firm we tend to oppose new technologies that cause our manufacturing facilities to become obsolete); and Risk 4 (In our firm, top managers like to implement plans only if they are very certain that they will work). Furthermore, management commitment to innovation was logarithmically transformed as the initial scale asked respondents to indicate the percentage of their firm's total sales revenue that was committed to innovative activities.

4.6 Measures and Descriptive Statistics

Most of the measures used in this study were adapted from existing scales in the literature and were measured with a 7-point Likert-type scale ranging from strongly disagree (1) to strongly agree (7) except where stated. Regarding the antecedents of disruptive business model, formalisation was measured with a five-item scale adapted from Aiken and Hage (1966); willingness to cannibalise was measured with a five-item scale adapted from Chandy and Tellis (1998) and Tellis, Prabhu and Chandy (2009); and top managerial risk-taking propensity was measured with a four-item scale adapted from Jaworski and Kohli (1993). Management commitment to innovation was measured with seven items adapted from Heavey, Simsek and Fox (2015) which evaluated the percentage of the firm's total sales committed to various innovative activities. The five-item measure of disruptive business model was created using Zott and Amit's (2007) scale of business model innovation as a guide.

Adaptive marketing capability was measured with a 15-item scale adapted from Guo *et al.* (2018) while big data analytics capability was measured with a 12-item scale adapted from Johnson, Friend and Lee (2017). For all performance measures, respondents were told to evaluate their firm’s performance relative to a major competitor with responses ranging from much worse than competitors (1) to much better than competitors (7). Market performance was measured with a five-item scale adapted from Sarkar, Echambadi and Harrison (2001) while new product performance was measured with a six-item scale adapted from Menguc, Auh and Yannopoulos (2014).

In addition, respondents were told to evaluate the anticipated performance of their firm for the next 12 months relative to their major competitor. Thus, anticipated financial performance was measured with a four-item scale adapted from Katsikeas, Samiee, and Theodosiou (2006) and Vorhies and Morgan (2005). The marker variable, negative affectivity was measured with a three-item scale adapted from Menguc, Auh and Yannopoulos (2014). All the measures used in the study and their descriptive statistics are provided in Table 4.10.

Table 4.10: Descriptive Results

Item Code	Items	Mean	SD
DIS_BM	**Disruptive Business Model**		
DIS_BM_1	Our business model offers new combinations of products, services and information that are disruptive	4.41	1.77
DIS_BM_2	This firm is the pioneer of the current business model in the industry	4.79	1.69
DIS_BM_3	This firm has continuously introduced disruptive innovations in its business model	4.41	1.69
DIS_BM_4	This firm's disruptive business model has been imitated by competitors	4.42	1.75
DIS_BM_5	This firm's business model depends on disruptive technologies	4.19	1.79
FORMAL	**Formalisation**		
FORMAL_1	In our firm people feel that they are their own boss in most matters	4.13	1.67
FORMAL_2	In our firm a person can make his/her own decisions without following established rules	3.57	1.74
FORMAL_3	In our firm most people make their own rules on the job	3.32	1.80
FORMAL_4	In our firm the employees are constantly being checked on for rule violations	4.01	1.89
FORMAL_5	In our firm people feel as though they are constantly being watched to see that they obey all the rules	4.25	1.89
CANIB	**Willingness to Cannibalise**		
CANIB_1	In our firm we are very willing to sacrifice sales of our existing products to improve sales of our new products	4.23	1.65
CANIB_2	In our firm we tend to support new innovations that could take away from sales of our existing products and investments	4.49	1.59
CANIB_3	In our firm we easily replace one set of abilities with a different set of abilities to adopt a new technology	4.71	1.46
CANIB_4	In our firm we find it difficult to change established procedures to cater to the needs of a new product	4.11	1.70
CANIB_5	In our firm we tend to oppose new technologies that cause our manufacturing facilities to become obsolete	4.26	1.76
RISK	**Top Managerial Risk-Taking Propensity**		
RISK_1	In our firm top managers believe that higher financial risks are worth taking for higher rewards	4.77	1.53
RISK_2	In our firm top managers like to take big financial risks	4.23	1.72
RISK_3	In our firm top managers encourage the development of innovative marketing strategies, knowing well that some will fail	4.94	1.52
RISK_4	In our firm top managers like to implement plans only if they are very certain that they will work	3.20	1.47

Item Code	Items	Mean	SD
MCI	**Management Commitment to Innovation[a]**		
MCI_1	The development of new technologies	1.37	0.44
MCI_2	New product (service) development	1.42	0.39
MCI_3	R&D activities devoted to new products (services)	1.34	0.44
MCI_4	Marketing for new products (services)	1.40	0.43
MCI_5	Marketing for new markets	1.35	0.48
MCI_6	Advertising for new products (services)	1.35	0.51
MCI_7	Advertising for new markets	1.35	0.49
BDA	**Big Data Analytics Capability**		
BDA_1	We analyse large amounts of data about our customers	5.49	1.44
BDA_2	The quantity of data we explore about our customers is substantial	5.36	1.46
BDA_3	We use a great deal of customer data	5.44	1.48
BDA_4	We scrutinize large volumes of customer data	5.23	1.58
BDA_5	We use several different sources of customer data to gain customer insights	5.40	1.39
BDA_6	We analyse many types of customer data	5.38	1.50
BDA_7	We have many customer databases from which we can run data	5.20	1.58
BDA_8	We examine customer data from a multitude of sources	5.30	1.51
BDA_9	We analyse customer data as soon as we receive it	4.91	1.55
BDA_10	The time period between when we get and analyse customer data is short	4.88	1.54
BDA_11	We are lightning fast in exploring our customer data	4.68	1.66
BDA_12	We analyse customer data very quickly	4.89	1.61
AMC	**Adaptive Marketing Capability**		
AMC_1	Our firm is highly sensitive to the market environment	5.31	1.22
AMC_2	Our firm is able to detect market signals (even the weak ones) timely and accurately	5.12	1.30
AMC_3	Our firm actively collects extensive marketing information through all social networks and media	4.99	1.54
AMC_4	Our firm is able to forecast market trends based on past histories of customer demand	5.29	1.27
AMC_5	Our firm shares and distributes new market information to different divisions in a timely manner	5.20	1.35
AMC_6	Our firm is willing to actively conduct market experiments or tests based on our own market forecast	5.15	1.41

Item Code	Items	Mean	SD
AMC	**Adaptive Marketing Capability**		
AMC_7	Our firm explores future market trends through trial-and-error and experimenting	4.94	1.49
AMC_8	Our firm develops potentially successful business models through trial-and-error experimenting	5.03	1.43
AMC_9	Our firm takes advantage of emerging technologies, such as the Internet, quick-response technologies, and database technologies to track market changes	5.23	1.42
AMC_10	Our firm takes advantage of emerging technologies, such as the Internet, quick-response technologies, and database technologies to learn from market experiments	5.21	1.45
AMC_11	Our firm actively learns from a wider range of peer companies, market leaders, and channel partners	5.30	1.24
AMC_12	Our firm actively seeks a strategic partnership with companies that are complementary with our firm in terms of resources and capabilities	5.14	1.43
AMC_13	Our firm is able to achieve synergy in effectively and quickly responding to market signals (even the weak ones) through coordination and collaboration with our partners	5.06	1.31
AMC_14	Our firm gains the capabilities for continuous product and technology innovation through resource integration with our partners	5.14	1.36
AMC_15	Our firm improves the capability of developing innovative strategies and tactics through collaboration and coordination	5.18	1.35
MRK_PER	**Market Performance**		
MRK_PER1	Market share	4.78	1.38
MRK_PER2	Market share growth	4.81	1.31
MRK_PER3	Sales volume	4.87	1.44
MRK_PER4	Sales growth	4.89	1.34
MRK_PER5	Product development	4.86	1.32
NP_PER	**New Product Performance**		
NP_PER1	Sales of new products	4.89	1.33
NP_PER2	Profitability of new products	4.99	1.25
NP_PER3	Sales growth of new products	4.97	1.30
NP_PER4	Market share growth of new products	4.87	1.29
NP_PER5	Growth in profit from new products	4.91	1.24
NP_PER6	Return-on-investment from new products	4.91	1.27

Item Code	Items	Mean	SD
AFP	**Anticipated Financial Performance**		
AFP_1	Profit margin	5.01	1.25
AFP_2	Return on assets (ROA)	4.99	1.25
AFP_3	Return on investment (ROI)	5.00	1.22
AFP_4	Profit growth	5.13	1.24
NEG_AFF	**Negative Affectivity**		
NEG_AFF_1	Minor setbacks tend to irritate me too much	3.96	1.75
NEG_AFF_2	Often, I get irritated at little annoyances	3.77	1.75
NEG_AFF_3	There are days when I am “on-edge” all the time	3.98	1.80

[a] Logarithmically transformed

4.7 Summary

The research for this study employed both qualitative and quantitative procedures as the research method. In-depth interviews were conducted to examine the nature of disruptive business models while the survey technique was used with a structured questionnaire. The constructs used in this study were adapted from existing literature and scales. All the constructs were operationalised using a seven-point Likert scale and were included in the questionnaire. The survey contact process took place between three to five steps depending on how soon the responses were received and various procedures were undertaken to enhance the response rate. In sum, this chapter seeks to link the discussion of concepts and theories in chapters two and three with the data analysis, findings, and discussion in chapters five and six. Specifically, this chapter has established the scope of the research, discussed the sampling frame employed and research instruments used, explained the fieldwork procedure and the measures used, and provided the descriptive results for all the constructs used in the study.

CHAPTER 5

ANALYSIS AND RESULTS OF THE EMPIRICAL STUDY

5.0 Introduction

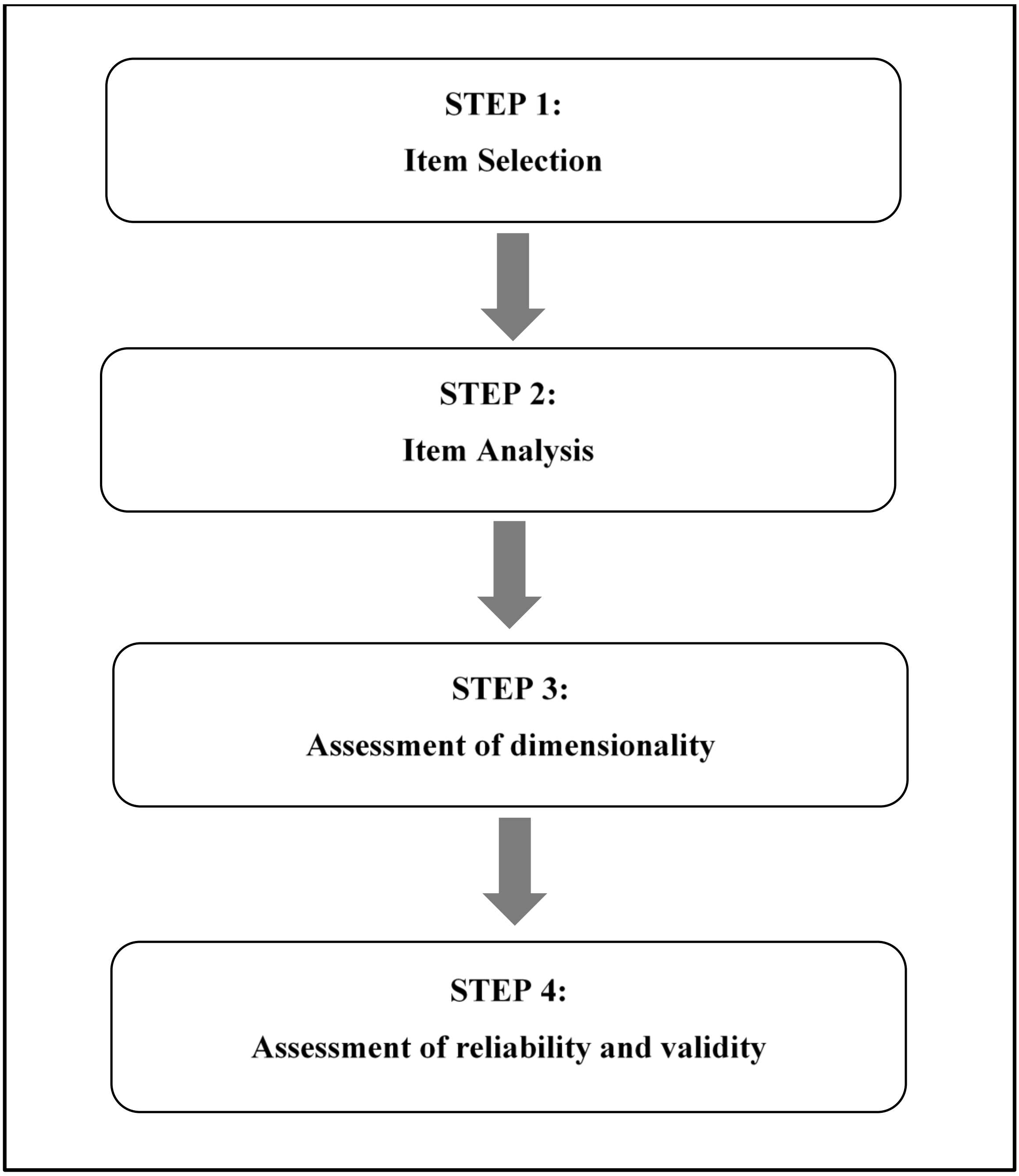
This chapter provides the results of the data analysis in relation to the hypotheses developed in Chapter 3. The first section of this chapter examines the scale purification and item selection conducted through both exploratory factor analysis, item-to-total correlation analysis, and confirmatory factor analysis. The second section provides the correlation matrix and model fit while the fourth section provides an assessment of construct validity and reliability and common method bias. The fifth section presents the results of the hypotheses testing, robustness checks, and additional analyses. The chapter concludes with a summary of results.

5.1 Scale Development and Measurement Assessment

In order to ensure scale purification in preparation for hypotheses testing, a missing value analysis was conducted. Questionnaires that had a high amount of missing values were removed and the mean value replacement technique was used for the non-problematic data (Hancock and Mueller 2013; Limaj and Bernroider 2019). To ensure that thorough statistical analyses were carried out, the researcher adopted the psychometric procedure for scale selection and purification proposed by various scholars (e.g., Bagozzi, Yi and Phillips 1991; Netemeyer, Bearden and Sharma 2003).

Figure 5.1 provides an overview of the processes taken in the scale selection and purification process. The first step was the selection of items through exploratory factor analysis. The second step involved item analysis using reliability tests and inter-item correlations. This was followed by an assessment of the dimensionality of items in each scale (where applicable). The fourth and final step included an assessment of the reliability and validity of measures used in this study. Each of these steps will be examined in detail subsequently.

Figure 5.1: Scale Development Procedure



5.1.1 Selection of Items using Exploratory Factor Analysis

Factor analysis has been widely acclaimed to be the best statistical procedure to examine the relationship between observed and latent variables (Byrne 2001). The two basic types of factor analysis are exploratory factor analysis (EFA) and confirmatory factor analysis (CFA). EFA is generally used when the relationship and links between the manifest variable and the unobserved variable are unknown or uncertain (Byrne 2001). Thus, EFA helps to examine and identify "the extent to which item measurements are related to latent constructs" (Byrne 2001, p. 6).

All the items in the study were analysed using the SPSS statistics 26 software and were allowed to be estimated freely without restrictions in order to identify the number of factors (Anderson and Gerbing 1988). The model examined in this thesis consists of 68 items which make up ten latent constructs. Of the ten constructs, two are multi-dimensional (adaptive marketing capability and big data analytics capability). Adaptive marketing capability consists of three dimensions: vigilant market learning, open marketing capability, and adaptive marketing experimentation. Similarly, big data analytics capability consists of three dimensions: big data volume, big data variety, and big data velocity. The other factors include: formalisation, management commitment to innovation, top managerial risk-taking propensity, willingness to cannibalise, disruptive business model, new product performance, market performance, and anticipated financial performance.

Principal component analysis and varimax rotation were used as the methods for factor extractions and items with factor loadings ≤ 0.40 were not selected for further EFA analysis (Hair et al. 2013). The items were divided into three categories: antecedents, moderators, and outcomes (Leonidou 2009) and the results showed that most of the items loaded on their respective constructs and were thus unidimensional. However, some items presented in Table 5.1 showed low loading and were therefore excluded from further analysis.

Alternative steps that can be undertaken to evaluate the items for each measurement scale include an examination of items to see if any cross-loading occurs and if a factor does not load on its construct (Diamantopoulos and Siguaw 2006). In this study, all the factors loaded highly on their respective construct and no cross-loading was found among items. In addition, the correlation coefficients of the constructs can be examined before further analysis is undertaken (Diamantopoulos and Winklhofer 2001). The correlation matrix (Table 5.8) shows that all correlation coefficients for the multi-item scales are positive and significant ($p < 0.01$).

Table 5.1: Items Dropped during EFA

Construct	Item	Reason for exclusion
Formalisation	Formalisation 4 – the employees are constantly being checked on for rule violations	Low Loading
	Formalisation 5 – people feel as though they are constantly being watched to see that they obey all the rules	Low Loading
Willingness to Cannibalise	Willingness to Cannibalise 4 – we find it difficult to change established procedures to cater to the needs of a new product	Low Loading
	Willingness to Cannibalise 5 – we tend to oppose new technologies that cause our manufacturing facilities to become obsolete	Low Loading
Top Managerial Risk-Taking Propensity	Top Managerial Risk-Taking Propensity 4 – top managers like to implement plans only if they are very certain that they will work	Low Loading

5.1.2 Item-To-Total Correlation Analysis

In order to proceed with the CFA, the corrected item-total correlation was calculated for each construct. Item-total correlation analysis involves the calculation of the correlation of each item in a scale using the total sum of all items (Howard and Forehand 1962). It is expected that each item's corrected item-to-total value should be above .5 (Bearden and Netemeyer 1999; Zaichkowsky 1985). Table 5.2 shows the corrected item-total correlations. All the items for each construct show acceptable item-total correlation values excluding 'adaptive marketing capability 1' which has a corrected item-total correlation of ≈.45 that is borderline with regard to the acceptable minimum value of .5.

Table 5.2: Corrected Item-Total Correlation

Items	**Corrected Item-Total Correlation**
Disruptive Business Model	
Disruptive Business Model 1	.745
Disruptive Business Model 2	.614
Disruptive Business Model 3	.828
Disruptive Business Model 4	.702
Disruptive Business Model 5	.772
Formalisation	
Formalisation 1	.672
Formalisation 2	.764
Formalisation 3	.716
Willingness to Cannibalise	
Willingness to Cannibalise 1	.647
Willingness to Cannibalise 2	.686
Willingness to Cannibalise 3	.557
Top Managerial Risk-Taking Propensity	
Top Managerial Risk-Taking Propensity 1	.735
Top Managerial Risk-Taking Propensity 2	.716
Top Managerial Risk-Taking Propensity 3	.597
Management Commitment to Innovation[a]	
Management Commitment to Innovation 1	.795
Management Commitment to Innovation 2	.810
Management Commitment to Innovation 3	.742
Management Commitment to Innovation 4	.827
Management Commitment to Innovation 5	.840
Management Commitment to Innovation 6	.810
Management Commitment to Innovation 7	.847

Items	Item-Total Correlation
Big Data Analytics Capability	
Big Data Analytics Capability 1	.823
Big Data Analytics Capability 2	.814
Big Data Analytics Capability 3	.797
Big Data Analytics Capability 4	.831
Big Data Analytics Capability 5	.792
Big Data Analytics Capability 6	.835
Big Data Analytics Capability 7	.771
Big Data Analytics Capability 8	.825
Big Data Analytics Capability 9	.777
Big Data Analytics Capability 10	.629
Big Data Analytics Capability 11	.726
Big Data Analytics Capability 12	.710
Adaptive Marketing Capability	
Adaptive Marketing Capability 1	.445
Adaptive Marketing Capability 2	.720
Adaptive Marketing Capability 3	.716
Adaptive Marketing Capability 4	.630
Adaptive Marketing Capability 5	.764
Adaptive Marketing Capability 6	.770
Adaptive Marketing Capability 7	.727
Adaptive Marketing Capability 8	.727
Adaptive Marketing Capability 9	.759
Adaptive Marketing Capability 10	.751
Adaptive Marketing Capability 11	.749
Adaptive Marketing Capability 12	.701
Adaptive Marketing Capability 13	.767
Adaptive Marketing Capability 14	.802
Adaptive Marketing Capability 15	.772
Market Performance	
Market Performance 1	.787
Market Performance 2	.804
Market Performance 3	.817
Market Performance 4	.786
Market Performance 5	.658
New Product Performance	
New Product Performance 1	.817
New Product Performance 2	.819
New Product Performance 3	.850
New Product Performance 4	.821
New Product Performance 5	.849
New Product Performance 6	.836

Items	Item-Total Correlation
Anticipated Financial Performance	
Anticipated Financial Performance 1	.809
Anticipated Financial Performance 2	.831
Anticipated Financial Performance 3	.871
Anticipated Financial Performance 4	.841

[a] Logarithmically transformed

5.1.3 Confirmatory Factor Analysis

CFA is used when the researcher has an idea of the links or relationships between the measured and unmeasured variables being examined and as such, has some knowledge on the nature of the latent variable structure (Byrne 2001). CFA further helps in purifying the scales used in the study in addition to establishing the validity and reliability of the scales (Cadogan et al. 2006). In line with conventional practices to maintain acceptable observation to estimated parameter ratios of at least five observations per estimated parameter (Bentler and Chou 1987), the CFA was conducted by grouping variables that were theoretically linked to ensure good model fit (Baker and Sinkula 1999; Tabachnick, Fidell, and Ullman 2007).

The first model contained the antecedents of disruptive business model: formalisation, willingness to cannibalise, top managerial risk-taking propensity, and management commitment to innovation. The second model contained items for the central construct of this study: disruptive business model. The third model contained the organisational capabilities: big data analytics capability and adaptive marketing capability and the fourth model contained the performance outcomes: market performance, new product performance, and anticipated financial performance. Thus, all the constructs in this study were subjected to CFA using EQS 6.1 (Byrne 2013).

The Elliptical Reweighted Least Squared (ERLS) method in EQS was used for the CFA as this method provides objective estimates for both normal and non-normal data (Sharma, Durvasula, and Dillon 1989; Stump and Heide 1996). The Elliptical iteration was set at 500 and the first item for each construct was fixed to set the scale. Following academic conventions, various goodness-of-fit statistics were used to assess the confirmatory factor analysis models including: Root mean square error of approximation (RMSEA) which indicates the "average amount of misfit for a model per degree of freedom" (Bagozzi and Yi 2012, p. 28); Non-normed fit index/Tucker and Lewis index (NNFI/TLI) that provides an indication of how complex a model is, Comparative fit index (CFI) which compares the hypothesised model with the independence model; and Standardised root mean square residual (SRMR) which computes the square root of the average squared residuals (Bagozzi and Yi 2012; Byrne 2001). Table 5.3 provides the recommended thresholds for the goodness-of-fit statistics discussed.

Table 5.3: Goodness-of-fit Indices and their Thresholds

Goodness-of-fit index	**Recommended threshold**
Non-Normed Fit Index (NNFI)	≥0.95
Comparative Fit Index (CFI)	≥0.95
Root Mean Square Error of Approximation (RMSEA)	≤0.06
Standard Root Mean Squared Residual (SRMR)	≤0.08
Normed Chi-square (χ^2/DF)	<3

Adapted from Hu and Bentler (1999), Byrne (2001), Bagozzi and Yi (2012).

5.1.3.1 CFA Model One: Antecedents to Disruptive Business Model

The first CFA model which was conducted focused on the antecedents of disruptive business model: formalisation, willingness to cannibalise, top managerial risk-taking propensity, and management commitment to innovation. The items of each construct were set to load on their respective unobserved construct and the first item was fixed to 1.0. Specifically, formalisation (F1) had factor loadings between 0.738 (formalisation 1) and 0.862 (formalisation 2); willingness to cannibalise (F2) had factor loadings between 0.671 (willingness to cannibalise 3) and 0.805 (willingness to cannibalise 2); top managerial risk-taking propensity (F3) had factor loadings between 0.678 (top managerial risk-taking propensity 3) and 0.841 (top managerial risk-taking propensity 1); and management commitment to innovation (F4) had factor loadings between 0.761 (management commitment to innovation 3) and 0.881 (management commitment to innovation 7). Therefore, all items met the required threshold of at least 0.5 factor loading on their respective latent constructs. Hence, there was no need to delete any items.

Furthermore, all t-statistic indicators were high and significant ($t \geq 10.158$). The model fit indices were also assessed to examine how well the model fit the data. The CFA model provided the following goodness-of-fit statistics: $\chi^2 = 253.588$; df = 98; χ^2/df = 2.59; p = .00; NNFI = 0.966; CFI = 0.972; RMSEA = 0.067; SRMR = 0.049. All the fit indices meet the recommended thresholds indicated in Table 5.3. Due to the satisfactory standardised loadings, t-values, significance levels, and goodness-of-fit statistics of all the items indicated in Table 5.4, it can be concluded that CFA measurement model one for the antecedents of disruptive business model adequately fits and describes the data.

Table 5.4: Measurement Model One – Antecedents to Disruptive Business Model

Items/Construct	**Standardised Loadings (t-values)**
Formalisation (F1)	
Formalisation 1	.738[a]
Formalisation 2	.862 (12.518)
Formalisation 3	.824 (12.366)
Willingness to Cannibalise (F2)	
Willingness to cannibalise 1	.770[a]
Willingness to cannibalise 2	.805 (11.761)
Willingness to cannibalise 3	.671 (10.158)
Top Managerial Risk-Taking Propensity (F3)	
Top managerial risk-taking propensity 1	.841[a]
Top managerial risk-taking propensity 2	.840 (14.051)
Top managerial risk-taking propensity 3	.678 (11.364)

Items/Construct	Standardised Loadings (t-values)
Management Commitment to Innovation (F4)	
Management commitment to innovation 1	.815[a]
Management commitment to innovation 2	.823 (15.867)
Management commitment to innovation 3	.761 (14.206)
Management commitment to innovation 4	.859 (16.916)
Management commitment to innovation 5	.877 (17.477)
Management commitment to innovation 6	.848 (16.611)
Management commitment to innovation 7	.881 (17.604)
Goodness-of-fit Statistics	
χ^2 = 253.588; df = 98; χ^2/df = 2.59; p = .00; NNFI = .966; CFI = .972; RMSEA = .067; SRMR = .049	

[a]Item fixed to set the scale

5.1.3.2 CFA Model Two: Disruptive Business Model

The second CFA model focused on disruptive business model as the central construct of this study. Disruptive business model had factor loadings between 0.647 (disruptive business model 2) and 0.902 (disruptive business model 3). All items met the required threshold of at least 0.5 factor loading on their respective latent constructs, hence, there was no need to delete any items.

Furthermore, all t-values were high and significant (t ≥ 810.880). The model fit indices were also assessed to examine how well the model fit the data. The CFA model provided the following goodness-of-fit statistics: χ^2 = 4.796; df = 5; χ2 /df = .9592; p = .00; NNFI = 0.99; CFI = 0.99; RMSEA = .0; SRMR = 0.013. All the fit indices meet the recommended thresholds indicated in Table 5.3. Due to the satisfactory standardised loadings, t-values, significance levels, and goodness-of-fit statistics of all the items, it can be concluded that CFA measurement model two for disruptive business model adequately fits and describes the data.

Table 5.5: Measurement Model Two – Disruptive Business Model

Items/Construct	Standardised Loadings (t-values)
Disruptive Business Model	
Disruptive business model 1	.802[a]
Disruptive business model 2	.647 (10.880)
Disruptive business model 3	.902 (16.396)
Disruptive business model 4	.746 (12.950)
Disruptive business model 5	.835 (14.984)
Goodness-of-fit Statistics	
χ^2 = 4.796; df = 5; χ^2/df = .9592; p = .00; NNFI = .99; CFI = .99; RMSEA = .0; SRMR =.013	

[a]Item fixed to set the scale

5.1.3.3 CFA Model Three: Organisational Capabilities

The third CFA model focused on the two moderators of the disruptive business model–performance relationship: big data analytics capability and adaptive marketing capability. Big data analytics capability consists of three sub-dimensions namely big data volume, big data variety, and big data velocity. Similarly, adaptive marketing capability consists of three sub-dimensions namely: vigilant market learning, adaptive market experimentation, and open marketing capability. The items of each construct were set to load on their respective unobserved construct and the first item was fixed to 1.0.

For big data analytics capability, big data volume (F1) had factor loadings between 0.888 (big data volume 4) and 0.906 (big data volume 3); big data variety (F2) had factor loadings between 0.838 (big data variety 3) and 0.901 (big data variety 2); and big data velocity (F3) had factor loadings between 0.736 (big data velocity 2) and 0.919 (big data velocity 3).

For adaptive marketing capability, vigilant market learning (F4) had factor loadings between 0.511 (vigilant market learning 1) and 0.815 (vigilant market learning 5); adaptive market experimentation (F5) had factor loadings between 0.770 (adaptive market experimentation 6) and 0.820 (adaptive market experimentation 5); and open marketing capability (F6) had factor loadings between 0.766 (open marketing capability 1) and 0.895

(open marketing capability 3). Therefore, all items met the required threshold of at least 0.5 factor loading on their respective latent constructs, hence, there was no need to delete any items.

Furthermore, all t-values were high and significant ($t \geq 8.347$). The model fit indices were also assessed to examine how well the model fit the data. The CFA model provided the following goodness-of-fit statistics: $\chi^2 = 592.099$; df = 309; χ^2/df = 1.92; p = .00; NNFI = 0.986; CFI = 0.988; RMSEA = 0.051; SRMR = 0.042. All the fit indices meet the recommended thresholds indicated in Table 5.3. Due to the satisfactory standardised loadings, t-values, significance levels, and goodness-of-fit statistics of all the items indicated in Table 5.6, it can be concluded that CFA measurement model three for organisational capabilities adequately fits and describes the data.

Table 5.6: Measurement Model Three – Organisational Capabilities

Items/Construct	**Standardised Loadings (t-values)**
Big Data Analytics Capability	
Big Data Volume (F1)	
Big data volume 1	.899a
Big data volume 2	.896 (22.215)
Big data volume 3	.906 (22.850)
Big data volume 4	.888 (21.754)
Big Data Variety (F2)	
Big data variety 1	.853a
Big data variety 2	.901 (19.753)
Big data variety 3	.838 (17.320)
Big data variety 4	.886 (19.137)
Big Data Velocity (F3)	
Big data velocity 1	.870a
Big data velocity 2	.736 (14.299)
Big data velocity 3	.919 (21.295)
Big data velocity 4	.904 (20.622)

Items/Construct	Standardised Loadings (t-values)
Adaptive Marketing Capability	
Vigilant Market Learning (F4)	
Vigilant market learning 1	.511a
Vigilant market learning 2	.781 (8.189)
Vigilant market learning 3	.776 (8.166)
Vigilant market learning 4	.685 (7.673)
Vigilant market learning 5	.815 (8.347)
Adaptive Market Experimentation (F5)	
Adaptive market experimentation 1	.803a
Adaptive market experimentation 2	.783 (14.150)
Adaptive market experimentation 3	.781 (14.092)
Adaptive market experimentation 4	.817 (14.999)
Adaptive market experimentation 5	.820 (15.076)
Adaptive market experimentation 6	.770 (13.835)
Open Marketing Capability (F6)	
Open marketing capability 1	.766a
Open marketing capability 2	.834 (14.316)
Open marketing capability 3	.895 (15.585)
Open marketing capability 4	.855 (14.752)
Goodness-of-fit Statistics	
χ^2 = 592.099; df = 309; χ^2/df = 1.92; p = .00; NNFI = .986; CFI = .988; RMSEA = .051; SRMR = 0.042.	

[a]Item fixed to set the scale

5.1.3.4 CFA Model Four: Performance Outcomes

The fourth CFA model focused on performance outcomes of disruptive business model: market performance, new product performance, and anticipated financial performance. The items of each construct were set to load on their respective unobserved construct and the first item was fixed to 1.0. Specifically, market performance (F1) had factor loadings between 0.723 (market performance 5) and 0.855 (market performance 2); new product performance (F2) had factor loadings between 0.843 (new product performance 2) and 0.877 (new product performance 5); and anticipated financial performance (F3) had factor loadings between 0.847 (anticipated financial performance 1) and 0.914 (anticipated financial performance 3). All items met the required threshold of at least 0.5 factor loading on their respective latent constructs, hence, there was no need to delete any items.

Furthermore, all t-values were high and significant ($t \geq 12.407$). The model fit indices were also assessed to examine how well the model fit the data. The CFA model provided the following goodness-of-fit statistics: $\chi^2 = 153.005$; df = 87; χ^2/df = 1.76; p = .00; NNFI = 0.992; CFI = 0.994; RMSEA = 0.046; SRMR = 0.032. All the fit indices meet the recommended thresholds indicated in Table 5.3. Due to the satisfactory standardised loadings, t-values, significance levels, and goodness-of-fit statistics of all the items indicated in Table 5.7, it can be concluded that CFA measurement model four for the performance outcomes of disruptive business model adequately fits and describes the data.

Table 5.7: Measurement Model Four – Performance Outcomes

Items/Construct	Standardised Loadings (t-values)
Market Performance (F1)	
Market performance 1	.821[a]
Market performance 2	.855 (15.768)
Market performance 3	.850 (15.642)
Market performance 4	.846 (15.526)
Market performance 5	.723 (12.407)
New Product Performance (F2)	
New product performance 1	.853[a]
New product performance 2	.843 (16.800)
New product performance 3	.868 (17.711)
New product performance 4	.850 (17.044)
New product performance 5	.877 (18.029)
New product performance 6	.873 (17.898)
Anticipated Financial Performance (F3)	
Anticipated financial performance 1	.847[a]
Anticipated financial performance 2	.879 (17.631)
Anticipated financial performance 3	.914 (18.921)
Anticipated financial performance 4	.877 (17.557)
Goodness-of-fit-Statistics	
$\chi^2 = 153.005$; df = 87; χ^2/df = 1.76; p = .00; NNFI = .992; CFI = .994; RMSEA = .046; SRMR = 0.032	

[a]Item fixed to set the scale

5.2 Correlation Matrix and Model Fit

The items relating to each latent variable were averaged in order to form composite measures. A correlation analysis was then conducted in SPSS and this is provided in Table 5.8. The EQS 6.1 package was used to examine the model fit statistics based on the retained items from the exploratory and confirmatory factor analyses. As such, all the constructs examined in this study were inputted into a single model to examine the model fit statistics. The analysis revealed a good structural model fit as reflected in the normed chi-square (χ^2/DF = 2.42) and the results of the comparative and absolute fit indices (χ^2 = 2399.145; df = 990; NNFI = 0.978; CFI = 0.982; RMSEA = 0.063; SRMR = 0.091).

Table 5.8: Correlation Matrix

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Formalisation	1.00													
2	Management Commitment to Innovation[a]	.21**	1.00												
3	Top Managerial Risk-Taking Propensity	.32**	.42**	1.00											
4	Willingness to Cannibalise	.28**	.48**	.58**	1.00										
5	Disruptive Business Model	.28**	.43**	.59**	.53**	1.00									
6	Adaptive Marketing Capability	.24**	.52**	.53**	.56**	.55**	1.00								
7	Big Data Analytics Capability	.14**	.38**	.40**	.39**	.47**	.67**	1.00							
8	New Product Performance	.26**	.41**	.35**	.31**	.41**	.57**	.35**	1.00						
9	Market Performance	.23**	.38**	.34**	.34**	.46**	.59**	.38**	.84**	1.00					
10	Anticipated Financial Performance	.18**	.38**	.31**	.31**	.39**	.50**	.33**	.80**	.76**	1.00				
11	Firm Size[a]	-.17**	.02	-.00	.03	.11*	.09	.18**	.11*	.18**	.14**	1.00			
12	Firm Age[a]	-.22	-.22**	-.20**	-.22**	-.13**	-.11*	-.03	-.06	-.00	-.07	.54	1.00		
13	Industry (B2B/B2C)	-.02	-.05	.02	.04	.02	.01	-.07	.01	.01	.06	.10	.04	1.00	
14	Industry (Manufacturing/Services)	.08	.04	.06	.04	.09	.10*	.02	.07	.04	.02	-.12*	-.04	.13**	1.00

n = 360; *p<0.05; **p<0.01

[a] Logarithmically transformed

5.3 Assessment of Construct Validity and Reliability

Reliability is defined as the "accuracy or precision of a measuring instrument and is a necessary condition for validity" (Hinkin 1998, p. 112). Establishing the reliability of a construct is crucial to ensure that the survey instrument accurately measures the construct under examination. Convergent validity shows the degree to which the constructs correlate with other scales measuring similar constructs while discriminant validity shows the degree to which the constructs do not correlate with dissimilar constructs (Hinkin 1998). The reliability of the scales used was computed by calculating the squared correlation, Cronbach alpha, Composite Reliability (CR), and Average Variance Extracted (AVE) for each construct. Specifically, the CR and Cronbach Alpha were used to assess convergent validity while AVE and the squared correlation are used to assess discriminant validity.

The Cronbach alpha provides insights into the extent to which items of a reflective scale are internally consistent (Josiassen et al. 2013) and it should be at least 0.7 to show the reliability of a scale (Cronbach 1951; Hair et al. 2013). A large Cronbach alpha for a construct shows that it adequately captures the sampling domain (Churchill Jr 1979). All constructs in the model exhibited high reliability scores ranging from 0.78 to 0.95. The composite reliability for all constructs ranged from 0.97 to 0.99 indicating high levels of reliability for each scale (Fornell and Larcker 1981). The Cronbach alpha and CR figures indicate that one can assume that the measures indicate convergent validity.

The AVE measures the "amount of variance that is captured by the construct in relation to the amount of variance due to measurement error" (Fornell and Larcker 1981, p. 45). Thus, if the AVE for a construct is less than 0.50, it implies that the construct captures a higher variance due to measurement error than the variance captured by the construct and this is not ideal to establish validity of the indicators and construct (Fornell and Larcker 1981). The AVE figures for each construct ranged from 0.86 to 0.96 which is well above the recommended threshold of 0.50. Additionally, the recommendation is that the squared correlations should not be greater than the AVEs (Fornell and Larcker 1981). All the squared correlations for all constructs were all lower than their corresponding AVEs and this is shown in Table 5.9. Therefore, the results show that all constructs have passed the test for discriminant validity.

Thus, the Cronbach alpha and composite reliability figures indicate convergent validity for all constructs while the AVEs and the comparison between the squared correlations and AVEs indicate discriminant validity of each construct. The squared correlations, Cronbach alpha, CR, and AVE values are provided in Table 5.9.

Table 5.9: Squared Correlation Matrix

		1	2	3	4	5	6	7	8	9	10
1	Formalisation	1									
2	Management Commitment to Innovation[a]	.04	1								
3	Top Managerial Risk-Taking Propensity	.10	.17	1							
4	Willingness to Cannibalise	.07	.23	.33	1						
5	Disruptive Business Model	.07	.18	.34	.28	1					
6	Adaptive Marketing Capability	.05	.27	.28	.31	.30	1				
7	Big Data Analytics Capability	.01	.14	.16	.15	.22	.44	1			
8	New Product Performance	.06	.16	.12	.09	.16	.32	.12	1		
9	Market Performance	.05	.14	.11	.11	.21	.34	.14	.70	1	
10	Anticipated Financial Performance	.03	.14	.09	.09	.15	.25	.10	.64	.57	1
	Cronbach alpha	.84	.95	.82	.78	.89	.94	.95	.94	.90	.93
	Composite reliability (CR)	.97	.99	.97	.97	.98	.99	.99	.99	.98	.98
	Average variance extracted (AVE)	.92	.94	.93	.93	.93	.86	.96	.93	.91	.94

n = 360

[a] Logarithmically transformed

5.4 Common Method Bias

Various steps were undertaken to ascertain that common method bias did not pose a problem and negatively impact the study. This included both procedural and *post-hoc* remedies proposed by Podsakoff et al. (2003). A procedural remedy which was undertaken was the use of different response formats for the scales of predictor and criterion variables, as such, different common-scale anchors were used (Lindell and Whitney 2001; Podsakoff et al. 2003). Also, all respondents were assured of anonymity in written form via the cover letter provided and on the first page of the online questionnaire (Podsakoff et al. 2003). Additionally, the independent and dependent variables in the questionnaire were mixed to ensure that respondents could not easily guess the relationships under examination (Podsakoff et al. 2003).

Following Lindell and Whitney's (2001) marker variable technique, a marker variable was included in the questionnaire. A marker variable can be described as a variable that has no theoretical links to any of the constructs examined in a study (Lindell and Whitney 2001). The marker variable used in this study was ‘negative affectivity’ and the scale was measured with three items: (1) minor setbacks tend to irritate me too much; (2) often, I get irritated at little annoyances; and (3) there are days when I am “on-edge” all the time (Menguc, Auh, and Yannopoulos 2014). Furthermore, it showed good reliability (mean = 3.9, standard deviation [SD] = 1.53, Cronbach alpha = .833). Finally, the questionnaire asked respondents to answer questions retrospectively with a focus on actual behaviours and not belief systems (Golden 1992).

Furthermore, Harman’s single factor test was performed on all the constructs in the questionnaire (Harman 1967). This involved EFA where all the constructs were loaded on a single factor with no rotation and the number of factors to be extracted was fixed to 1. All the constructs accounted for 62% of the total variance while the first factor explained only 38% of the variance. The variance explained by the first factor (38%) is below the recommended threshold of 50% suggesting that there is no single general factor in the dataset and common method bias is not a concern (Karimi and Walter 2016). Also, the variances extracted by the latent factor is 62% which is above the recommended cutoff of 50% (Hair et al. 1998). Therefore, the analysis showed that there was no single factor in the factor structure.

Additionally, the common latent factor method was used to further ascertain the impact of common method bias on the dataset. CFA was conducted where all the constructs were modelled to a common latent factor and all the regression weights were fixed. As such, all the paths were constrained and made to be equal and the common latent factor was constrained to be equal to one (Eichhorn 2014). To ascertain if common method bias is an issue in the dataset, the common variance is calculated as the square of the common factor (regression coefficient) of each path. The results showed that the regression coefficient for all the regression equations was 0.36 and this value was squared to indicate common variance of 13%. This suggests that common method bias is not a major concern in this study as the common variance of 13% is well below the recommended threshold of 50% (Eichhorn 2014).

Finally, the marker variable included in the questionnaire (negative affectivity) was modelled in addition to the common latent factor. A similar approach to the common latent factor method was undertaken as all the paths were constrained and made to be equal. The results also showed that the regression coefficient for all the equations was 0.363 and this value was squared to indicate a common variance of 13%. As such, the common variance value of 13% is well below the recommended threshold of 50% (Eichhorn 2014). Therefore, the results from all the analyses conducted show that common method bias does not pose a serious threat to the findings derived from this study.

5.5 Seemingly Unrelated Regression

In order to test the hypotheses of this study, the Seemingly Unrelated Regression (SUR) method was used in STATA 15.1. SUR is an econometric modelling technique introduced by Zellner (1962) and studies that utlise SUR have contributed extensively to theory development. This is because the SUR method estimates multiple equations when there is a possibility that one or more pairs of constructs can have correlated error terms in the equations (Fiebig 2001). Hence, SUR allows a system where variables can be independent in one equation and dependent in another within the same system (Autry and Golicic 2010). Even though the equations might initially appear unrelated, the equations estimated are actually related due to the correlation in the error terms (Devaraj, Hollingworth, and Schroeder 2004). Thus, the technique has been termed 'seemingly unrelated regression'.

The SUR technique was ideal for this study because this study aims to simultaneously examine the relationships among the independent, control, moderating, and dependent variables (Zellner 1962) presented in the conceptual model (Figure 3.1). Furthermore, the SUR method facilitates the estimation of several equations and takes correlated errors of regression equations into consideration which helps to produce more reliable estimates (Elberse 2010; Griffis et al. 2012; Zellner 1962). Therefore, SUR provides more precise estimates of the standard error for each parameter estimate (Green 1993).

As such, the SUR method is superior to others, such as path modelling as it enables the simultaneous testing of several equations and accounts for the likelihood that variables in the model are correlated (Autry and Golicic 2010; Devaraj, Hollingworth, and Schroeder 2004). The SUR technique provides a Breush-Pagan test of independence that indicates if the error terms in the regression equations are significantly correlated. Hence, if there is a likelihood that the error terms might be significantly correlated, using the SUR helps to mitigate this concern (Greene 2003; Katsikeas, Leonidou, and Zeriti 2016).

Therefore, SUR “accounts for contemporaneous cross-equation error correlations” (Griffis et al. 2012, p. 289) which makes it ideal for this research as several equations are being tested. In addition, the correlation matrix provided in Table 5.8 shows significant correlation among several of the performance indicators. Thus, estimating the equations using SUR can help to capture these correlations (Autry and Golicic 2010; Devaraj, Hollingworth, and Schroeder 2004).

To ensure effectiveness of the analysis, the models tested included at least one regressor that was used in one equation but not the other in order to avoid obtaining the same results as ordinary least squares (Elberse 2010). Therefore, the variable ‘anticipated financial performance’ is included in one of the equations and not in the others. Other variables that are different across equations include the mean-centered variable for adaptive marketing capability and big data analytics capability; interaction term for disruptive business model and adaptive marketing capability; and the interaction term for disruptive business model and big data analytics capability. Additionally, the Breusch-Pagan test for independent equations was performed in order to confirm that the disturbance of the covariance matrix was not diagonal (Elberse 2010), and the results show that the error terms between the regression equations are significantly correlated.

5.6 Hypotheses Test Results

The results are based on four regression models. Model *one* contains the effects of the control links on disruptive business model, new product performance, and market performance. Model *two* shows the effects of the control links on disruptive business model, new product performance, and market performance in addition to the effect of the moderators on new product performance and market performance.

Model *three* includes the effects of the control links on disruptive business model, new product performance, and market performance; the effect of the moderators on new product performance and market performance; the effects of the antecedents on disruptive business model; the effect of disruptive business model on new product performance and market performance; and the effects of new product performance and market performance on anticipated financial performance.

Model *four* reports the effects of the control links on disruptive business model, new product performance, and market performance; the effect of the moderators on new product performance and market performance; the effects of the antecedents on disruptive business model; the effect of disruptive business model on new product performance and market performance; and the effects of new product performance and market performance on anticipated financial performance. It also includes the effects of the interaction term of big data analytics capability and disruptive business model on new product performance and market performance on one hand and the effects of the interaction term of adaptive marketing capability and disruptive business model on new product performance and market performance on the other hand.

Three regression equations were estimated for models *one* and *two* with disruptive business model, new product performance, and market performance as the dependent variables. In models *three* and *four*, four regression equations were estimated with disruptive business model, new product performance, market performance, and anticipated financial performance as the dependent variables. For estimation purposes, firm size, firm age, and management commitment to innovation were logarithmically transformed and all relevant variables were mean-centered before producing interaction terms (Aiken, West, and Reno 1991).

The SUR method was considered appropriate for this study as the Breusch-Pagan test for the full model (model *four*) indicated that the error terms were significantly correlated (χ^2= 209.063; 6 DF, p<0.001) justifying the use of SUR as this method is specially designed to handle situations like this (Greene 2003; Katsikeas, Leonidou, and Zeriti 2016; Zellner 1962). The results also show that the full model (model *four*) has substantial explanatory power, as the R^2 was 0.45 for disruptive business model, 0.35 for new product performance, 0.40 for market performance and 0.66 for anticipated financial performance. All the equations estimated for each model are written as follows;

Model 1

$$(1)\ \mathbf{DIS\_BM} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_2}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_3}\mathbf{MANUFAC} + \boldsymbol{\beta_4}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(2)\ \mathbf{NP\_PER} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_2}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_3}\mathbf{MANUFAC} + \boldsymbol{\beta_4}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(3)\ \mathbf{MKT\_PER} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_2}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_3}\mathbf{MANUFAC} + \boldsymbol{\beta_4}\mathbf{B2B} + \boldsymbol{\mu_t}$$

Model 2

$$(1)\mathbf{DIS\_BM} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_2}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_3}\mathbf{MANUFAC} + \boldsymbol{\beta_4}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(2)\mathbf{NP\_PER} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{BDA\_MEAN} + \boldsymbol{\beta_2}\mathbf{AMC\_MEAN} + \boldsymbol{\beta_3}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_4}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_5}\mathbf{MANUFAC} + \boldsymbol{\beta_6}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(3)\mathbf{MKT\_PER} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{BDA\_MEAN} + \boldsymbol{\beta_2}\mathbf{AMC\_MEAN} + \boldsymbol{\beta_3}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_4}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_5}\mathbf{MANUFAC} + \boldsymbol{\beta_6}\mathbf{B2B} + \boldsymbol{\mu_t}$$

Model 3

$$(1)\mathbf{DIS\_BM} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_2}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_3}\mathbf{MANUFAC} + \boldsymbol{\beta_4}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(2)\mathbf{NP\_PER} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{BDA\_MEAN} + \boldsymbol{\beta_2}\mathbf{AMC\_MEAN} + \boldsymbol{\beta_3}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_4}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_5}\,\mathbf{MANUFAC} + \boldsymbol{\beta_6}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(3)\mathbf{MKT\_PER} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{BDA\_MEAN} + \boldsymbol{\beta_2}\mathbf{AMC\_MEAN} + \boldsymbol{\beta_3}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_4}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_5}\,\mathbf{MANUFAC} + \boldsymbol{\beta_6}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(4)\mathbf{AFP} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{NP\_PER} + \boldsymbol{\beta_2}\mathbf{MKT\_PER} + \boldsymbol{\mu_t}$$

Model 4

$$(1)\mathbf{DIS\_BM} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{FORMAL} + \boldsymbol{\beta_2}\mathbf{CANIB} + \boldsymbol{\beta_3}\mathbf{RSK_{AVE}} + \boldsymbol{\beta_4}\mathbf{LG\_MCI} + \boldsymbol{\beta_5}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_6}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_7}\mathbf{MANUFAC} + \boldsymbol{\beta_8}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(2)\mathbf{NP\_PER} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{DIS\_BM} + \boldsymbol{\beta_2}\mathbf{BDA\_MEAN} + \boldsymbol{\beta_3}\mathbf{DBM\_BDA} + \boldsymbol{\beta_4}\mathbf{AMC\_MEAN} + \boldsymbol{\beta_5}\mathbf{DBM\_AMC} + \boldsymbol{\beta_6}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_7}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_8}\,\mathbf{MANUFAC} + \boldsymbol{\beta_9}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(3)\mathbf{MKT\_PER} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{DIS\_BM} + \boldsymbol{\beta_2}\mathbf{BDA\_MEAN} + \boldsymbol{\beta_3}\mathbf{DBM\_BDA} + \boldsymbol{\beta_4}\mathbf{AMC\_MEAN} + \boldsymbol{\beta_5}\mathbf{DBM\_AMC} + \boldsymbol{\beta_6}\mathbf{LN\_EMPLO} + \boldsymbol{\beta_7}\mathbf{LN\_YRSOP} + \boldsymbol{\beta_8}\,\mathbf{MANUFAC} + \boldsymbol{\beta_9}\mathbf{B2B} + \boldsymbol{\mu_t}$$

$$(4)\mathbf{AFP} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\mathbf{NP\_PER} + \boldsymbol{\beta_2}\mathbf{MKT\_PER} + \boldsymbol{\mu_t}$$

Where: disruptive business model (DIS_BM); firm size (LN_EMPLO); firm age (LN_YRSOP); manufacturing (MANUFAC); business-to-business (B2B); new product performance (NP_PER), market performance (MKT_PER), anticipated market performance (AFP); big data analytics capability (BDA_MEAN); adaptive marketing capability

(AMC_MEAN); interactive term of disruptive business model and adaptive marketing capability (DBM_AMC); interactive term of disruptive business model and big data analytics capability (DBM_BDA). $\boldsymbol{\mu_t}$ is the error term calculated as the value of the dependent variable if all the independent variables = 0 and $\boldsymbol{\beta_0}$ is the constant term in the equations.

5.6.1 Model One

In model one (Table 5.10), the analysis shows that firm size (b = 0.37, $p < 0.001$) and industry classifications into manufacturing/services (b = 0.34, $p < 0.05$) are positively related to disruptive business model. On the other hand, firm age (b = -0.86, $p < 0.001$) is negatively related to the development of a disruptive business model and the industry classification into B2B versus B2C has no significant relationship on the development of a disruptive business model (b = 0.85, $p > .10$).

Similar results are obtained for new product performance as the analysis indicates that firm size (b = 0.22, $p < 0.001$) and industry classifications into manufacturing/services (b = 0.21, $p < 0.10$) are positively related to new product performance. Firm age (b = -0.43, $p < 0.01$) is negatively related to new product performance and industry classification into B2B/B2C has no significant relationship with new product performance (b = 0.03, $p > .10$).

Firm size (b = 0.28, $p < 0.001$) shows a positive relationship with market performance while firm age (b = -0.36, $p < 0.05$) shows a negative relationship with market performance. However, both industry classifications based on manufacturing/services (b = 0.17, $p > .10$) and B2B/B2C (b = 0.07, $p > .10$) were not significantly related to market performance.

Therefore, firm size appears to have positive relationships with disruptive business model, new product performance, and market performance. On the other hand, firm age is negatively related to disruptive business model, new product performance, and market performance. The industry of operation based on manufacturing or services also shows a positive relationship with disruptive business model and new product performance but not with market performance. However, industry of operation based on B2B or B2C classifications is not significantly related with disruptive business model, new product performance, and market performance.

Table 5.10: Results of SUR estimation – Model One

		Disruptive Business Model		New product Performance		Market Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		4.44 (17.57) ****	0.25	4.80 (23.75) ****	0.20	4.45 (21.59)****	0.20
Main Effects							
Formalisation	1						
Willingness to Cannibalise	2						
Top Managerial Risk-Taking Propensity	3						
Management Commitment to Innovation	4						
Disruptive Business Model	5/6						
Big Data Analytics Capability							
Adaptive Marketing Capability							
New product Performance							
Market Performance							
Interaction Effects							
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$						
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$						
Control Links							
Firm Size		0.37 (4.77)****	0.07	0.22 (3.66)****	0.06	0.28 (4.51)****	0.06
Firm Age		-0.86 (-4.79)****	0.18	-0.43 (-3.03)***	0.14	-0.36 (-2.48) **	0.14
Manufacturing/Services		0.34 (2.22)**	0.15	0.21 (1.71)*	0.12	0.17 (1.35)	0.12
B2B/B2C		0.85 (0.55)	0.15	0.03 (0.26)	0.12	0.07 (0.58)	0.12
χ^2		33.36****		16.90***		21.29****	
R^2		0.08		0.04		0.05	

n = 360; $^{*}p< 0.10$; $^{**}p<0.05$; $^{***}p<0.01$; $^{****}p<0.001$

Breusch-Pagan test of independence: χ^2 = 374.302; p = 0.0000

5.6.2 Model Two

In model two, the direct effects of the moderators – big data analytics capability and adaptive marketing capability – on new product performance and market performance were examined in addition to control links on disruptive business model, new product performance, and market performance. The results show that big data analytics capability has an insignificant relationship with both new product performance (b = -0.07, $p > .10$) and market performance (b = -0.06, $p > .10$). However, adaptive marketing capability has a positive and significant relationship with both new product performance (b = 0.59, $p < 0.001$) and market performance (b = 0.61, $p < 0.001$).

Model two (Table 5.11) shows that there are substantial R^2 changes for new product performance and market performance from the R^2 values in model one (Table 5.10). Thus, model two has a higher explanatory power for new product performance and market performance than model one.

Table 5.11: Results of SUR estimation – Model Two

		Disruptive Business Model		New product Performance		Market Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		4.44 (17.57)****	0.25	4.78 (28.25)****	0.16	4.44 (26.36) ****	0.16
Main Effects							
Formalisation	1						
Willingness to Cannibalise	2						
Top Managerial Risk-Taking Propensity	3						
Management Commitment to Innovation	4						
Disruptive Business Model	5/6						
Big Data Analytics Capability				-0.07 (-1.33)	0.05	-0.06 (-1.23)	0.05
Adaptive Marketing Capability				0.59 (9.38)****	0.06	0.61 (9.86)****	0.06
New product Performance							
Market Performance							
Interaction Effects							
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$						
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$						
Control Links							
Firm Size		0.37 (4.77)****	0.07	0.11 (2.20)**	0.05	0.16 (3.19)****	0.05
Firm Age		-0.86 (-4.79)****	0.18	-0.16 (-1.30)	0.12	-0.07 (-0.60)	0.12
Manufacturing/Services		0.34 (2.22)**	0.15	0.06 (0.63)	0.10	0.01 (0.17)	0.10
B2B/B2C		0.08 (0.55)	0.15	0.01 (0.11)	0.10	0.05 (0.52)	0.10
χ^2		33.36****		153.24****		177.93****	
R^2		0.08		0.32		0.36	

n = 360; $^{*}p< 0.10$; $^{**}p<0.05$; $^{***}p<0.01$; $^{****}p<0.001$

Breusch-Pagan test of independence: χ^2 = 226.183; p = 0.0000

5.6.3 Model Three

In model three, the direct effects of formalisation, willingness to cannibalise, top managerial risk-taking propensity, and management commitment to innovation on disruptive business models were examined. In addition, the direct effects of disruptive business model, big data analytics capability, and adaptive marketing capability on new product performance and market performance were examined. Finally, the effects of new product performance and market performance on anticipated financial performance were examined.

The results show that formalisation (b = 0.08, $p < 0.05$), willingness to cannibalise (b = 0.22, $p < 0.001$), top managerial risk-taking propensity (b = 0.39, $p < 0.001$), and management commitment to innovation (b = 0.56, $p < 0.001$) are positively associated with disruptive business model. Also, disruptive business model is positively related to both new product performance (b = 0.13, $p < 0.001$) and market performance (b = 0.15, $p < 0.001$). Similar to the results found in model two, big data analytics capability has an insignificant relationship with both new product performance (b = -0.07, $p > .10$) and market performance (b = -0.07, $p > .10$) while adaptive marketing capability has a positive relationship with both new product performance (b = 0.56, $p < 0.001$) and market performance (b = 0.59, $p < 0.001$).

The findings indicate that both new product performance (b = 0.54, $p < 0.001$) and market performance (b = 0.30, $p < 0.001$) are positively related to anticipated financial performance. Furthermore, model three (Table 5.12) shows an increase in the explanatory power compared to model two (Table 5.11) and this is reflected in the increase in R^2 for disruptive business model, new product performance, and market performance.

Table 5.12: Results of SUR estimation – Model Three

		Disruptive Business Model		New product Performance		Market Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		0.06 (0.17)	0.35	4.18 (16.71)****	0.25	3.73 (15.15)****	0.24
Main Effects							
Formalisation	1	0.08 (2.01)**	0.04				
Willingness to Cannibalise	2	0.22 (3.90)****	0.05				
Top Managerial Risk-Taking Propensity	3	0.39 (7.43)****	0.05				
Management Commitment to Innovation	4	0.56 (3.35)****	0.16				
Disruptive Business Model	5/6			0.13 (3.31)****	0.04	0.15 (3.89)****	0.04
Big Data Analytics Capability				-0.07 (-1.44)	0.05	-0.07 (-1.38)	0.05
Adaptive Marketing Capability				0.56 (8.39)****	0.06	0.59 (8.88)****	0.06
Interaction Effects							
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$						
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$						
Control Links							
Firm Size		0.20 (3.29)****	0.06	0.07 (1.47)	0.05	0.12 (2.33)**	0.05
Firm Age		-0.13 (-0.91)	0.14	-0.06 (-0.55)	0.12	0.03 (0.30)	0.12
Manufacturing/Services		0.19 (1.60)	0.12	0.02 (0.23)	0.10	-0.03 (-0.31)	0.10
B2B/B2C		0.08 (0.68)	0.12	0.00 (0.05)	0.10	0.04 (0.45)	0.10
χ^2		297.21****		197.23****		239.61****	
R^2		0.45		0.34		0.39	

n = 360; *p< 0.10; **p<0.05; ***p<0.01; ****p<0.001

Breusch-Pagan test of independence: χ^2 = 208.946; p = 0.0000

5.6.4 Model Four

In model four, the interaction effect of disruptive business model and big data analytics capability on new product performance and market performance was examined. Similarly, the interaction effect of disruptive business model and adaptive marketing capability on new product performance and market performance was examined. This is in addition to the direct effects of formalisation, willingness to cannibalise, top managerial risk-taking propensity, and management commitment to innovation on disruptive business model; the direct effects of disruptive business model, big data analytics capability, and adaptive marketing capability on new product performance and market performance; and the direct effects of new product performance and market performance on anticipated financial performance.

The results in Table 5.13 show that the interaction term of disruptive business model and big data analytics capability is positively related to new product performance (b = 0.08, $p < 0.001$) but not significantly related to market performance (b = 0.05, $p > .10$). On the other hand, the interaction term of disruptive business model and adaptive marketing capability is negatively related to new product performance (b = -0.10, $p < 0.05$) and market performance (b = -0.07, $p < 0.10$).

The findings also indicate that formalisation (b = 0.08, $p < 0.05$), willingness to cannibalise (b = 0.22, $p < 0.001$), top managerial risk-taking propensity (b = 0.39, $p < 0.001$), and management commitment to innovation (b = 0.57, $p < 0.001$) are positively related to the disruptive business model. Additionally, disruptive business model has a positive relationship with both new product performance (b = 0.14, $p < 0.001$) and market performance (b = 0.16, $p < 0.001$).

Regarding the direct effects of the moderators on performance, big data analytics capability has an insignificant relationship with new product performance (b = -0.00, $p > .10$)

and market performance (*b* = -0.02, $p > .10$) while adaptive marketing capability has positive and significant relationships with both new product performance (*b* = 0.48, $p < 0.001$) and market performance (*b* = 0.53, $p < 0.001$). The results also indicate that new product performance (*b* = 0.55, $p < 0.001$) and market performance (*b* = 0.30, $p < 0.001$) are positively related to anticipated financial performance.

Regarding the control links, firm size has a positive relationship with disruptive business model (*b* = 0.20, $p < 0.001$) and market performance (*b* = 0.11, $p < 0.05$). However, its relationship with new product performance is not significant (*b* = 0.07, $p > .10$). Firm age is not significantly related to disruptive business model (*b* = -0.13, $p > .10$), new product performance (*b* = -0.05, $p > .10$) and market performance (*b* = 0.04, $p > .10$). The nature of the firm regarding manufacturing/services is also not significantly related to disruptive business model (*b* = 0.19, $p > .10$), new product performance (*b* = 0.00, $p > .10$), and market performance (*b* = -0.04, $p > .10$). In addition, industry classification based on B2B/B2C firms is insignificantly related to disruptive business model (*b* = 0.08, $p > .10$), new product performance (*b* = 0.00, $p > .10$) and market performance (*b* = 0.04, $p > .10$).

Compared to the previous three models, model four (Table 5.13) has the highest explanatory power for new product performance and market performance reflected in the increase in R^2 values. However, the explanatory power in model four (Table 5.13) for estimating disruptive business model and anticipated financial performance remains the same as that of model three (Table 5.12).

Figure 5.2 shows the moderating effect of big data analytics capability on the disruptive business model–new product performance relationship while Figure 5.3 shows the moderating effect of big data analytics capability on the disruptive business model–market performance relationship. The figures indicate that combining high levels of big data analytics capability and disruptive business model results in high new product and market performance. This is evident in the findings provided in Model four (Table 5.13). As such, the interaction term of big data analytics capability and disruptive business model is positively related to new product performance (b = 0.08, $p < 0.05$) and market performance (b = 0.05, $p > .10$).

On the other hand, Figure 5.4 shows the moderating effect of adaptive marketing capability on the disruptive business model–new product performance relationship and Figure 5.5 shows the moderating effect of adaptive marketing capability on the disruptive business model–market performance relationship. The figures indicate that high levels of adaptive marketing capability are directly related to high performance. However, combining high levels of adaptive marketing capability and disruptive business model will negatively impact new product and market performance. As such, the two lines in Figure 5.4 and Figure 5.5 do not converge and this indicates the negative relationship of adaptive marketing capability and disruptive business model on new product and market performance.

In addition, the findings show that the interaction term of adaptive marketing capability and disruptive business model is negatively related to both new product (b = -0.10, $p < 0.05$) and market performance(b = -0.00, $p < 0.10$). This is buttressed by the statistical findings in Table 5.13 that show that adaptive marketing capability is positively related to new product performance (b = 0.48, $p < 0.001$) and market performance (b = 0.53, $p < 0.001$).

Table 5.13: Results of SUR estimation – Model Four

		Disruptive Business Model		New product Performance		Market Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		0.05 (0.16)	0.35	4.17 (16.80)****	0.24	3.72 (15.11)****	0.24
Main Effects							
Formalisation	1	0.08 (2.02)**	0.04				
Willingness to Cannibalise	2	0.22 (3.89)****	0.05				
Top Managerial Risk-Taking Propensity	3	0.39 (7.43)****	0.05				
Management Commitment to Innovation	4	0.57 (3.38)****	0.16				
Disruptive Business Model	5/6			0.14 (3.44)****	0.04	0.16 (4.08)****	0.04
Big Data Analytics Capability				-0.00 (-0.01)	0.06	-0.02 (-0.43)	0.06
Adaptive Marketing Capability				0.48 (6.71)****	0.07	0.53 (7.42)****	0.07
Interaction Effects							
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$			0.08 (2.42)**	0.03	0.05 (1.48)	0.03
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$			-0.10 (-2.53)**	0.04	-0.07 (-1.94)*	0.04
Control Links							
Firm Size		0.20 (3.29)****	0.06	0.07 (1.34)	0.05	0.11 (2.25)**	0.05
Firm Age		-0.13 (-0.90)	0.14	-0.05 (-0.45)	0.12	0.04 (0.39)	0.12
Manufacturing/Services		0.19 (1.60)	0.12	0.00 (0.05)	.010	-0.04 (-0.44)	0.10
B2B/B2C		0.08 (0.68)	0.12	0.00 (0.00)	0.10	0.04 (0.42)	0.10
χ^2		297.41****		209.03****		247.00****	
R^2		0.45		0.35		0.40	

n = 360; $^{*}p< 0.10$; $^{**}p<0.05$; $^{***}p<0.01$; $^{****}p<0.001$

Breusch-Pagan test of independence: χ^2 = 208.313; p = 0.000

Figure 5.2: Moderating Effect of Big Data Analytics Capability on the Disruptive Business Model–New Product Performance Relationship

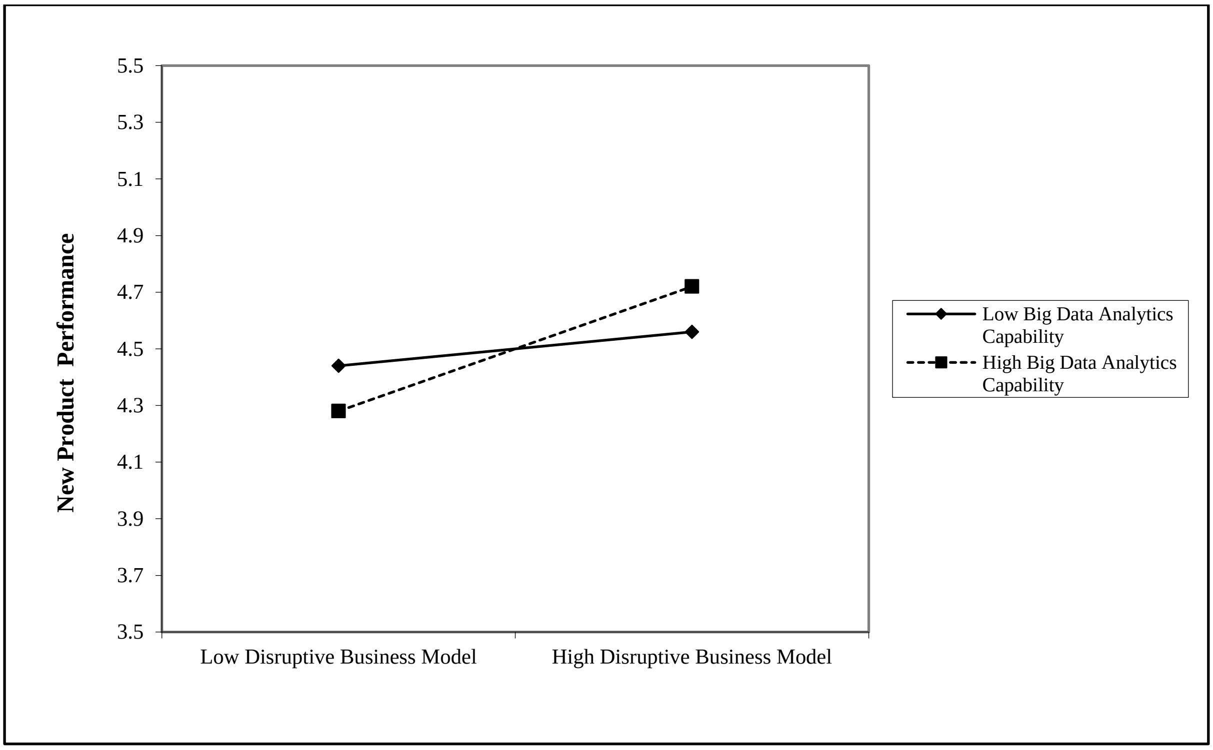


Figure 5.3: Moderating Effect of Big Data Analytics Capability on the Disruptive Business Model–Market Performance Relationship

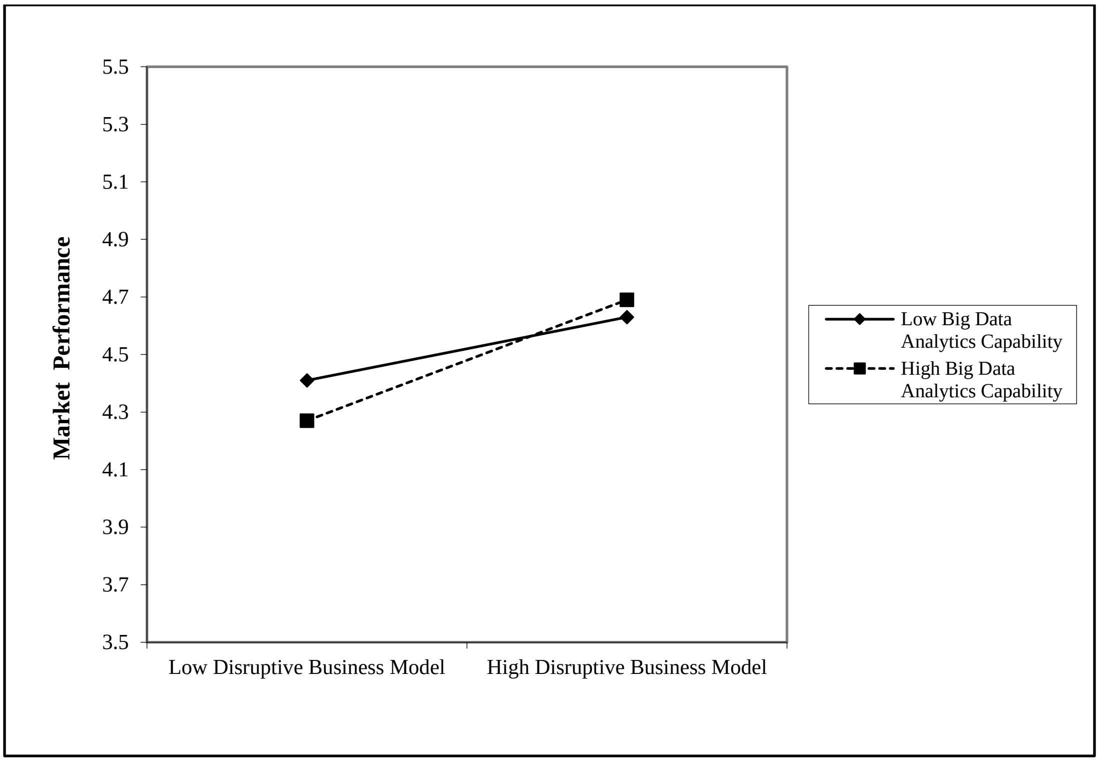


Figure 5.4: Moderating Effect of Adaptive Marketing Capability on the Disruptive Business Model–New Product Performance Relationship

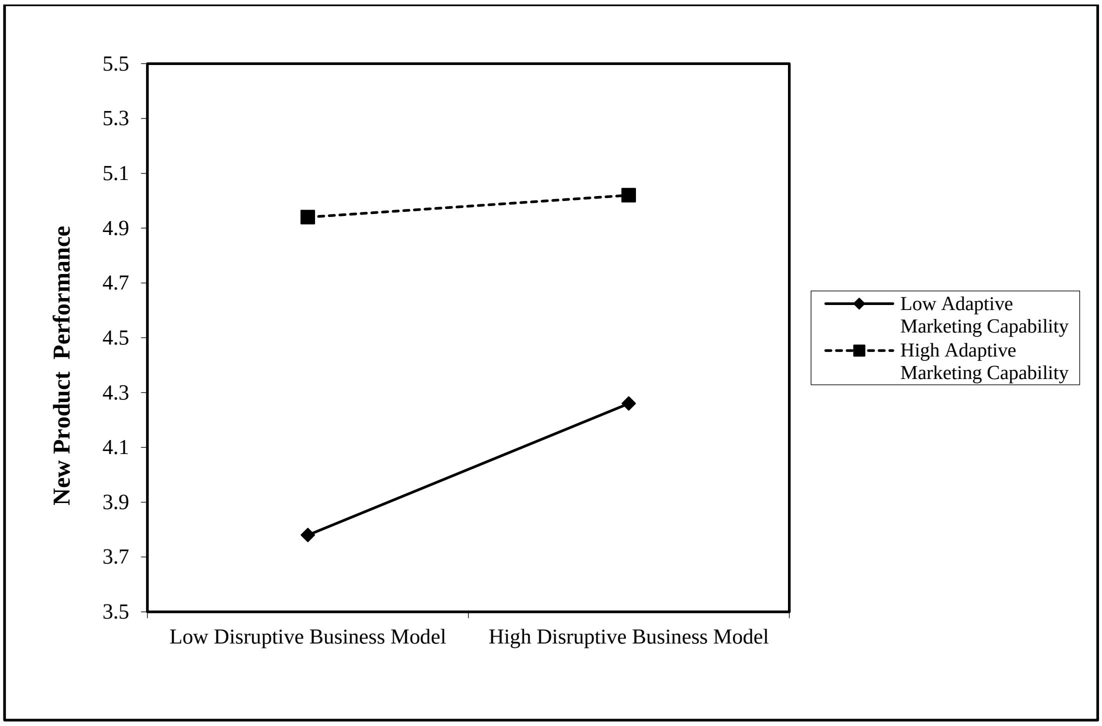
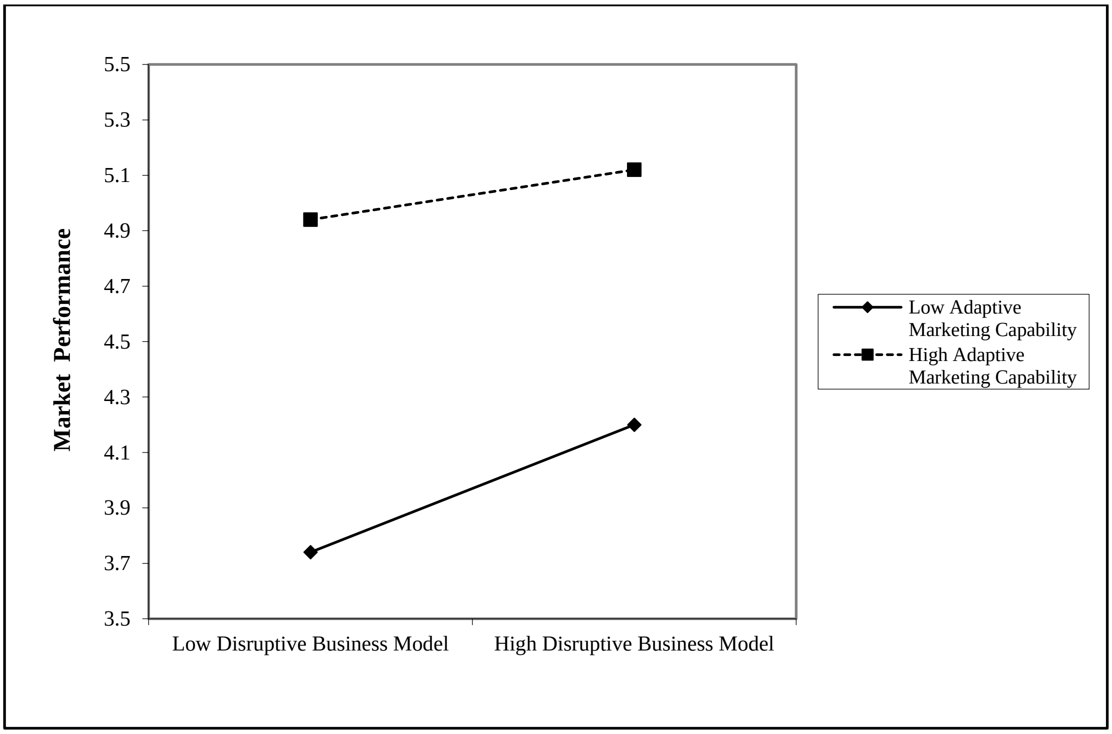


Figure 5.5: Moderating Effect of Adaptive Marketing Capability on the Disruptive Business Model–Market Performance Relationship



5.7 Robustness Checks and Additional Analyses

In this study, various checks and analyses were undertaken to examine the conceptual model under different assumptions. The findings from the slope test for interaction plots are presented and the moderation effects are examined in more detail using SPSS Process. In addition, moderated mediation effects were examined (using SPSS process and the bootstrap standard error in STATA). Finally, the data was classified based on industry and firm size in order to show the intricate relationships between constructs in the conceptual model in different industrial settings and firm contexts.

5.7.1 Slope Test for Interaction Plots

The interaction effects and plots represented in Figures 5.2, 5.3, 5.4, and 5.5 were further examined using the slope test to find out if the slopes were statistically different from one another for each dependent variable (new product performance and market performance). The *first* step involved the creation of high and low levels of the moderator variables (big data analytics capability and adaptive marketing capability) at 1 SD above the mean and 1 SD below the mean. In addition, the high level (1 SD above the mean) of both moderator variables was multiplied with the mean-centered focal variable in this study (disruptive business model).

The *second* step involved estimating the regression equations in order to calculate the slope analysis. The effects of mean-centered disruptive business model, high level of big data analytics capability, and the interaction term of high big data analytics capability and mean-centered disruptive business model on new product performance and market performance were estimated. Thereafter, the effects of mean-centered disruptive business model, low level of big data analytics capability, and the interaction term of low big data analytics capability and mean-centered disruptive business model on new product performance and market performance were estimated.

A similar process was then adopted for the second moderator variable (adaptive marketing capability). The effects of mean-centered disruptive business model, high level of adaptive marketing capability, and the interaction term of high adaptive marketing capability and mean-centered disruptive business model on new product performance and market performance were estimated. Thereafter, the effects of mean-centered disruptive business model, low level of adaptive marketing capability, and the interaction term of low adaptive marketing capability and mean-centered disruptive business model on new product performance and market performance were estimated.

For new product performance as the dependent variable, the results show that disruptive business model is significant at both high levels of big data analytics capability ($b = 0.289$, $p < 0.001$) and low levels of big data analytics capability ($b = 0.188$, $p < 0.001$). In addition, disruptive business model is significant at both high levels of adaptive marketing capability ($b = 0.094$, $p < 0.05$) and low levels of adaptive marketing capability ($b = 0.151$, $p < 0.01$).

For market performance as the dependent variable, the results show that disruptive business model is significant at both high levels of big data analytics capability ($b = 0.311$, $p < 0.001$) and low levels of big data analytics capability ($b = 0.251$, $p < 0.001$). In addition, disruptive business model is significant at both high levels of adaptive marketing capability ($b = 0.129$, $p < 0.01$) and low levels of adaptive marketing capability ($b = 0.193$, $p < 0.001$).

The *third* step involved calculating and finding out if the slopes are statistically different from one another using the estimates presented in the preceding paragraphs and the Daniel Soper calculator was used for this estimation. The slopes for disruptive business model at high and low levels of big data analytics capability were compared for both new product performance and market performance. The results show that the slopes are not statistically different for new product performance ($t = 1.31$; df = 716; $p > 0.10$) and market performance ($t = 0.78$; df = 716; $p > 0.10$). Furthermore, the slopes for disruptive business model at high and low levels of adaptive marketing capability were compared for both new product performance and market performance. The results show that the slopes are not statistically different for new product performance (t = 0.79; df = 716; p > 0.10) and market performance (t = 0.90; df = 716; p > 0.10).

5.7.2 Moderating Effects

To further explore the moderating effects of big data analytics capability and adaptive marketing capability on the disruptive business model– performance relationship, the structural paths were examined at ±1 standard deviation from the independent (disruptive business model) and moderator (big data analytics capability and adaptive marketing capability) variables. To achieve this, both the independent and moderator variables were mean-centered. In the *first* model, disruptive business model, adaptive marketing capability, and big data analytics capability were imputed.

In the *second* model, the interaction term of mean-centered disruptive business model and mean-centered adaptive marketing capability was included in addition to the interaction term of mean-centered disruptive business model and mean-centered big data analytics capability. In the *third* model, the squared term of disruptive business model was included. The *fourth* model included the interaction term of squared disruptive business model and mean-centered adaptive marketing capability on one hand; and the interaction term of squared disruptive business model and mean-centered big data analytics capability on the other hand.

The results from Model 4 in Table 5.14 show that the insignificant moderating effect of big data analytics capability on the disruptive business model–market performance relationship becomes significant (b = 0.11, p < 0.05). Furthermore, the results also indicate that the R^2 for Model 4 (0.41) is 1% higher than the R^2 for Model 3 (0.40). However, the results for the moderating effect of adaptive marketing capability remains the same and hypotheses 8a and 8b remain unsupported.

Furthermore, the moderating effects of big data analytics capability and adaptive marketing capability were examined in Process for SPSS version 3.5. using Model 2. The first double moderation test had new product performance as the dependent variable. The results show that big data analytics capability has a significant and positive moderating effect on the disruptive business model–new product performance relationship ($b = 0.08$, $p < 0.05$; LLCI = 0.0164, ULCI = 0.1602). On the other hand, adaptive marketing capability has a significant and negative influence on the disruptive business model–new product performance relationship ($b = -0.102$, $p < 0.05$; LLCI = -0.1836, ULCI = -0.0205).

The second double moderation test was conducted with market performance as the dependent variable. The results show that the moderating effect of big data analytics capability on the disruptive business model–market performance relationship is insignificant ($b = 0.05$, $p > .10$; LLCI = -0.0169, ULCI = 0.1269). However, the moderating effect of adaptive marketing capability on the disruptive business model–market performance relationship is negative and significant ($b = -0.0768$, $p < 0.10$; LLCI = -0.1584, ULCI = 0.0048).

Figure 5.6 provides a graphical representation of the effects of big data analytics capability and adaptive marketing capability on the disruptive business model–new product performance relationship while Figure 5.7 shows the effects of big data analytics capability and adaptive marketing capability on the disruptive business model–market performance relationship.

Table 5.14: Additional Analysis – Market Performance as Dependent Variable

	Model 1		Model 2		Model 3		Model 4	
	Market performance		Market performance		Market Performance		Market performance	
Independent Variable	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant	3.75 (15.22)****	0.24	3.75 (15.24)****	0.24	3.83 (12.96)****	0.29	4.18 (13.28)****	0.31
Main Effects								
Disruptive Business Model (DBM)	0.15 (3.78)****	0.04	0.16 (3.88)****	0.04	0.14 (2.93)****	0.04	0.07 (1.48)	0.05
Big Data Analytics Capability (BDA)	-0.07 (-1.38)	0.05	-0.02 (-0.47)	0.06	-0.02 (-0.35)	0.06	-0.05 (-0.81)	0.07
Adaptive Marketing Capability (AMC)	0.59 (8.92)****	0.06	0.54 (7.50)****	0.07	0.55 (7.36)****	0.07	0.49 (5.41)****	0.09
Interaction Effects								
DBM x BDA			0.05 (1.43)	0.03	0.05 (1.51)	0.06	0.11 (2.11)**	0.05
DBM x AMC			-0.07 (-1.89)*	0.04	-0.06 (-1.61)	0.04	-0.06 (-1.12)	0.05
DBM x DBM					-0.01 (-0.51)	0.02	-0.03 (-1.39)	0.02
DBM Squared x BDA							0.03 (1.19)	0.02
DBM Squared x AMC							0.01 (0.57)	0.02
Control Links								
Firm Size	0.12 (2.29)**	0.05	0.11 (2.23)**	0.05	0.11 (2.20)**	0.05	0.10 (2.00)**	0.05
Firm Age	0.04 (0.35)	0.12	0.05 (0.43)	0.12	0.05 (0.44)	0.12	0.03 (0.03)	0.12
Manufacturing/Services	-0.02 (-0.26)	0.10	-0.03 (-0.37)	0.10	-0.03(-0.35)	0.10	-0.06 (-0.60)	0.10
B2B/B2C	0.03 (0.39)	0.10	0.03 (0.35)	0.10	0.03 (0.36)	0.10	0.04 (0.54)	0.10
χ^2	237.53****		243.47****		243.90****		258.76****	
R^2	0.39		0.40		0.40		0.41	
Breusch-Pagan test of independence (χ^2)	207.80****		206.63****		206.52****		203.624****	

n = 360; *p< 0.10; **p<0.05; ***p<0.01; ****p<0.001

Table 5.15: Additional Analysis – New Product Performance as Dependent Variable

	Model 1		Model 2		Model 3		Model 4	
	New product performance		New product performance		New Product Performance		New product performance	
Independent Variable	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant	4.27 (17.08)****	0.25	4.28 (17.23)****	0.24	4.40 (14.72)****	0.29	4.76 (15.02)****	0.31
Main Effects								
Disruptive Business Model (DBM)	0.11 (2.79)***	0.04	0.11 (2.83)***	0.04	0.09 (1.96)**	0.05	0.02 (0.54)	0.05
Big Data Analytics Capability (BDA)	-0.07 (-1.44)	0.05	-0.00 (-0.04)	0.06	0.00 (0.10)	0.06	-0.05 (-0.82)	0.07
Adaptive Marketing Capability (AMC)	0.57 (8.54)****	0.06	0.50 (6.90)****	0.07	0.51 (6.84)****	0.07	0.50 (5.45)****	0.09
Interaction Effects								
DBM x BDA			0.08 (2.35)**	0.03	0.09 (2.45)***	0.03	0.18 (3.33)****	0.05
DBM x AMC			-0.1 (-2.45)***	0.04	-0.09 (-2.08)***	0.04	-0.11 (-2.03)**	0.05
DBM x DBM					-0.01 (0.70)	0.02	-0.04 (-1.57)	0.02
DBM Squared x BDA							0.05 (2.00)**	0.02
DBM Squared x AMC							-0.00 (-0.26)	0.02
Control Links								
Firm Size	0.08 (1.52)	0.05	0.07 (1.40)	0.05	0.07 (1.36)	0.05	0.06 (1.18)	0.05
Firm Age	-0.07 (-0.06)	0.12	-0.06 (-0.50)	0.12	-0.06 (-0.49)	0.12	-0.08 (-0.68)	0.12
Manufacturing/Services	0.03 (0.31)	0.10	0.015 (0.15)	0.10	0.018 (0.18)	0.10	-0.00 (-0.10)	010
B2B/B2C	0.00 (0.01)	0.10	-0.00 (-0.05)	0.10	-0.00 (-0.04)	0.10	-0.00 (-0.01)	0.10
χ^2	191.04****		201.15****		201.91****		217.53****	
R^2	0.346		0.358		0.359		0.37	
Breusch-Pagan test of independence (χ^2)	207.80****		206.63****		206.52****		203.624****	

n = 360; *p< 0.10; **p<0.05; ***p<0.01; ****p<0.001

Figure 5.6: Double Moderating Effect of Big Data Analytics Capability and Adaptive Marketing Capability on the Disruptive Business Model–New Product Performance Relationship

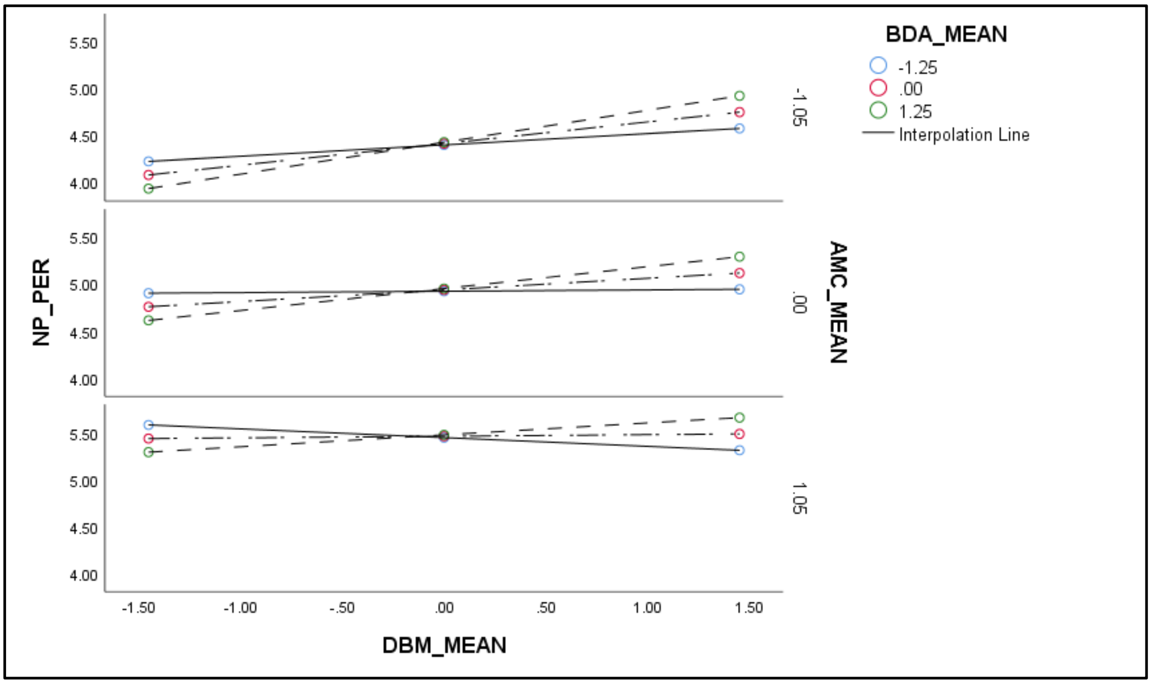
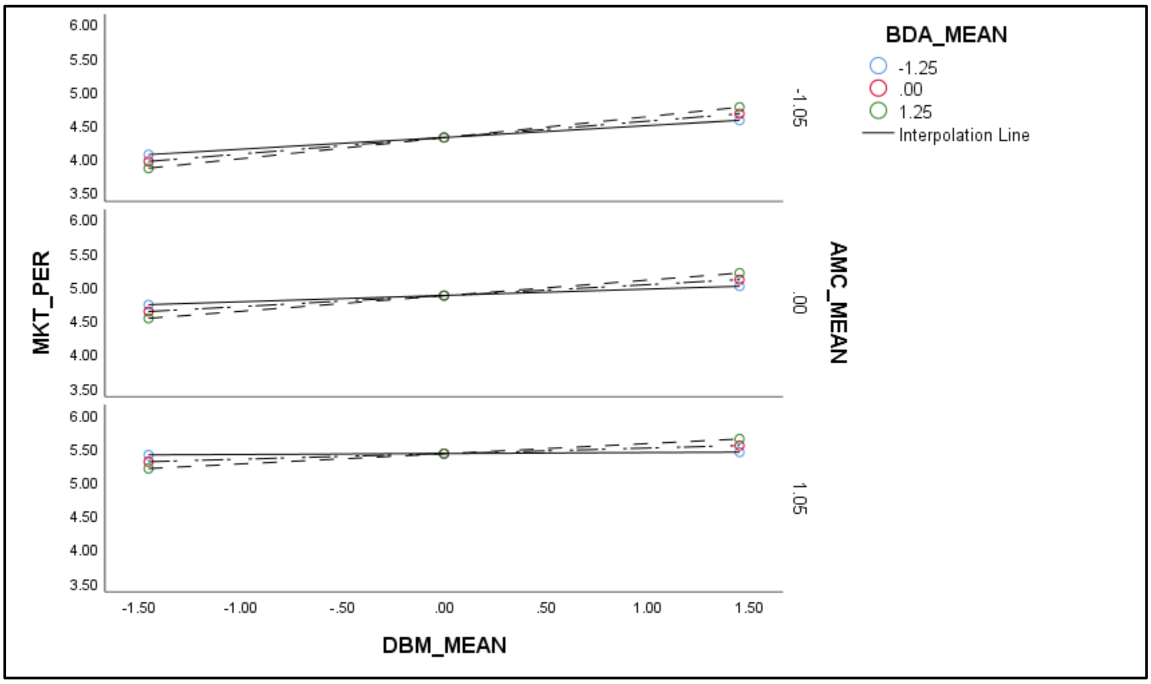


Figure 5.7: Double Moderating Effect of Big Data Analytics Capability and Adaptive Marketing Capability on the Disruptive Business Model–Market Performance Relationship

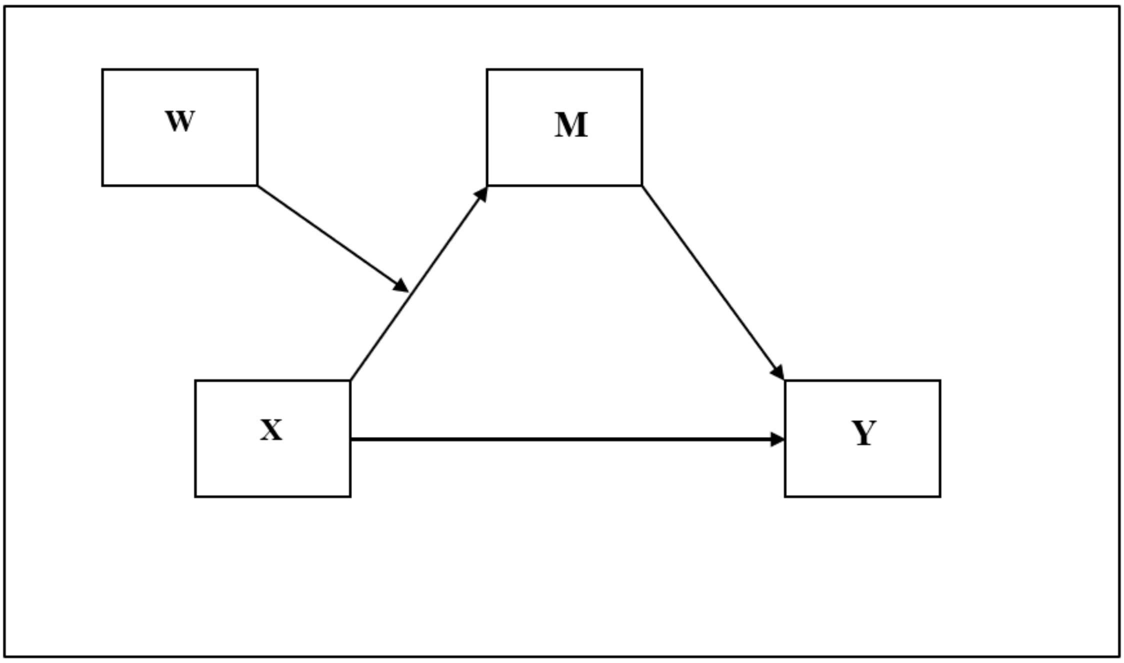


5.7.3 Moderated Mediation Effects

5.7.3.1 Moderated Mediation using Process

Process version 3.5 was used to further examine the possibility of moderated mediation for both adaptive marketing capability and big data analytics capability on the disruptive business model–performance relationship. Four moderated mediation models were estimated using Model 7 in Process with the format shown in Figure 5.8.

Figure 5.8: Conceptual Model for Moderated Mediation

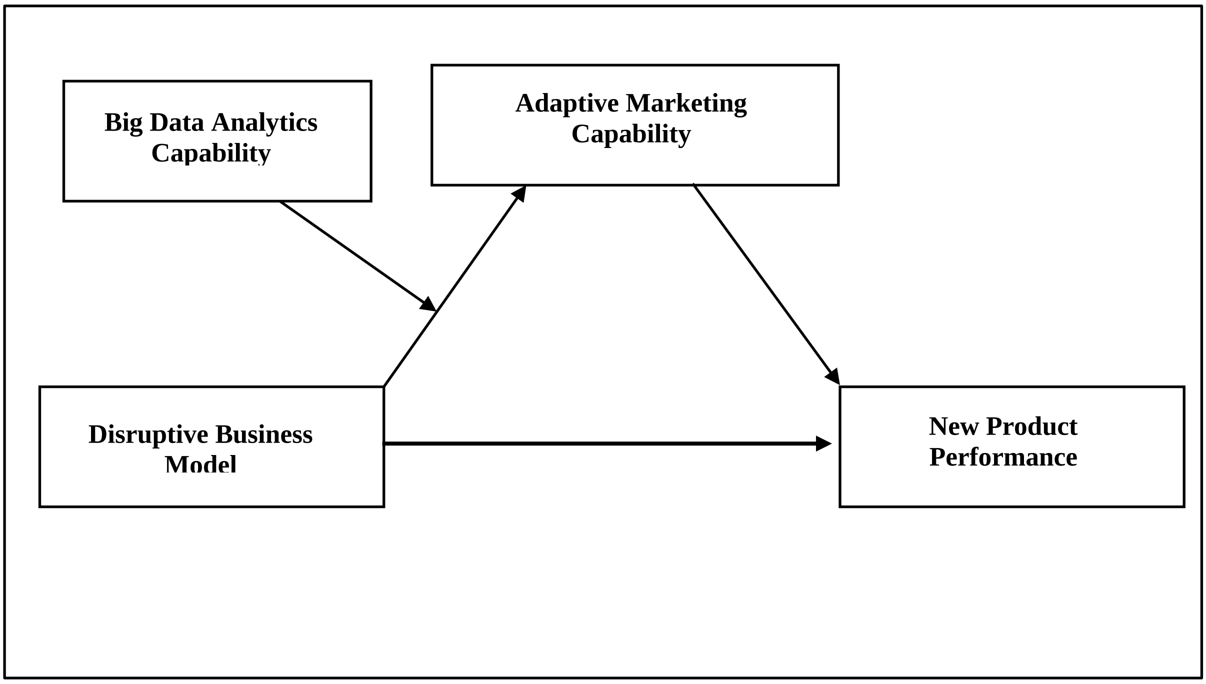


The first model (Figure 5.9) examined adaptive marketing capability as the mediator (M), big data analytics capability as the moderator (W), and new product performance as the dependent variable (Y). The results show that big data analytics capability has a positive and significant moderating influence on the disruptive business model–adaptive marketing capability relationship (b = 0.0342, $p < 0.10$; LLCI = -0.0032, ULCI = 0.0717). Disruptive business model is positively and significantly related to new product performance (b = 0.11, p

< 0.01; LLCI = 0.0354, ULCI = 0.1952) and adaptive marketing capability is positively and significantly related to new product performance (*b* = 0.52, p < 0.001; LLCI = 0.4184, ULCI = 0.6396).

The results also indicate that adaptive marketing capability mediates the effect of disruptive business model on new product performance when big data analytics capability is low (-1 SD), at the mean, and high (+1 SD). The coefficient of the conditional indirect effect of disruptive business model at -1 SD was 0.0902 (LLCI = 0.0260 and ULCI = 0.1589), at mean was 0.1128 (LLCI = 0.0672 and ULCI = 0.151), and at +1 SD of big data analytics was 0.1354 (LLCI = 0.0835 and ULCI = 0.1958). Thus, the mediation effect was significant when big data analytics was low, at its mean, and high. Regarding the moderated mediation, the confidence interval contained zero (LLCI = -0.0095 and ULCI = 0.0500). Therefore, no moderated mediation effect is present.

Figure 5.9: Moderated Mediation - Model One



The second model (Figure 5.10) examined adaptive marketing capability as the mediator (M), big data analytics capability as the moderator (W), and market performance as the dependent variable (Y). The results show that big data analytics capability has a positive and significant moderating effect on the disruptive business model–adaptive marketing capability relationship (b = 0.0342, $p < 0.10$; LLCI = -0.0032 and ULCI = 0.0717) and disruptive business model is significantly and positively related to market performance (b = 0.1530, $p < 0.001$; LLCI = 0735 and ULCI = 0.2324).

The coefficient of the conditional indirect effect of disruptive business model at -1 SD was 0.930 (LLCI = 0.0241 and ULCI = 0.1669), at mean was 0.1163 (LLCI = 0.0679 and ULCI = 0.1733), and at +1 SD of big data analytics capability was 0.1396 (LLCI = 0.0880 and ULCI = 0.2047). The moderated mediation results showed that the confidence interval contained zero (LLCI = -0.0106 and ULCI = 0.0517) indicating no moderated mediation effect. Figure 5.11 depicts the conditional effect of disruptive business model at values of big data analytics capability.

Figure 5.10: Moderated Mediation - Model Two

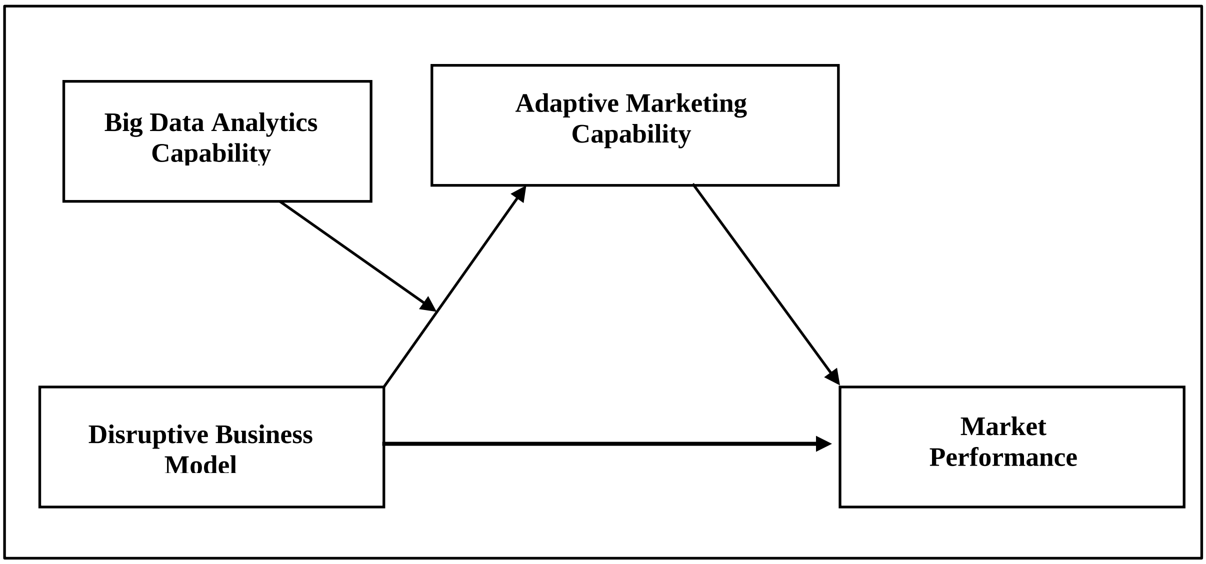
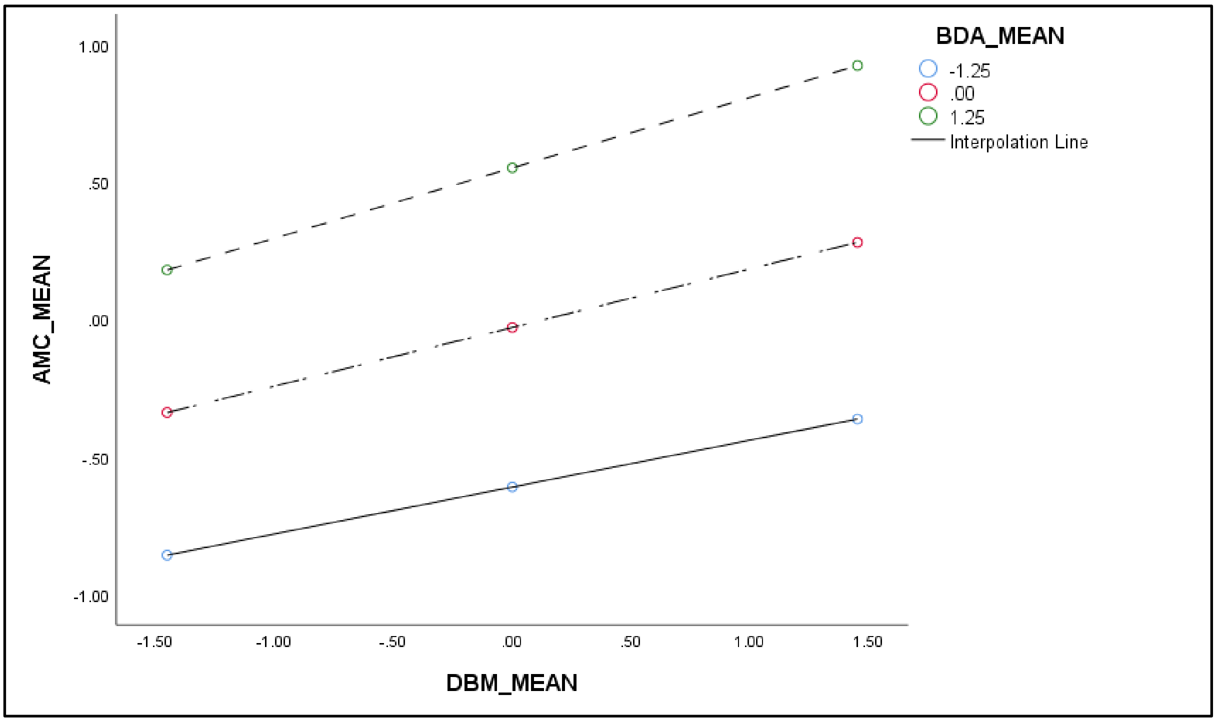
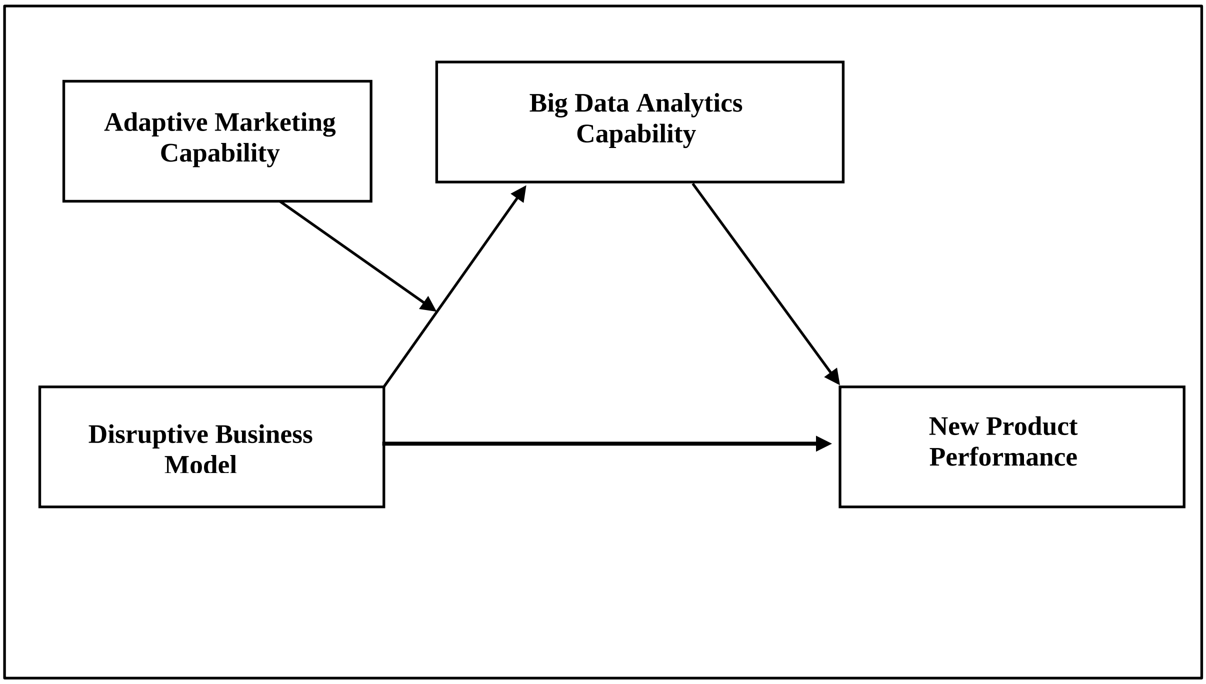


Figure 5.11: Conditional Effect of Disruptive Business Model at Values of Big Data Analytics Capability



The third model (Figure 5.12) examined big data analytics capability as the mediator (M), adaptive marketing capability as the moderator (W), and new product performance as the dependent variable (Y). The results indicate that adaptive marketing capability has a positive and significant moderating effect on the disruptive business model–big data analytics capability relationship (*b* = 0.0021, p < 0.10; LLCI = -0.0520, ULCI = 0.0562). The coefficient of the conditional indirect effect of disruptive business model at -1 SD was 0.0220 (LLCI = -0.0049 and ULCI = 0.0521), at mean was 0.0224 (LLCI = 0.0039 and ULCI = 0.0443), and at +1 SD of adaptive marketing capability was 0.0228 (LLCI = 0.0056 and ULCI = 0.044). The test for moderated mediation was not supported as the confidence interval contained zero (LLCI = -0.0120 and ULCI = 0.0139).

Figure 5.12: Moderated Mediation - Model Three



The fourth model (Figure 5.13) examined big data analytics capability as the mediator (M), adaptive marketing capability as the moderator (W), and market performance as the dependent variable (Y). The moderating effect of adaptive marketing capability on the disruptive business model–big data analytics capability relationship was insignificant (b = 0.0021, $p > 0.10$; LLCI = -0.0520 and ULCI = 0.0562). The coefficient of the conditional indirect effect of disruptive business model at -1 SD was 0.0242 (LLCI = -0.0041and ULCI = 0.0575), at the mean was 0.0246 (LLCI = 0.0048 and ULCI = 0.0484), and at +1 SD of adaptive marketing capability was 0.0251 (LLCI = 0.0068 and ULCI = 0.0478). The test for moderated mediation was not supported as the confidence interval contained zero (LLCI = -0.0135 and ULCI = 0.0146). Figure 5.14 shows the conditional effect of disruptive business model at values of adaptive marketing capability.

Figure 5.13: Moderated Mediation - Model Four

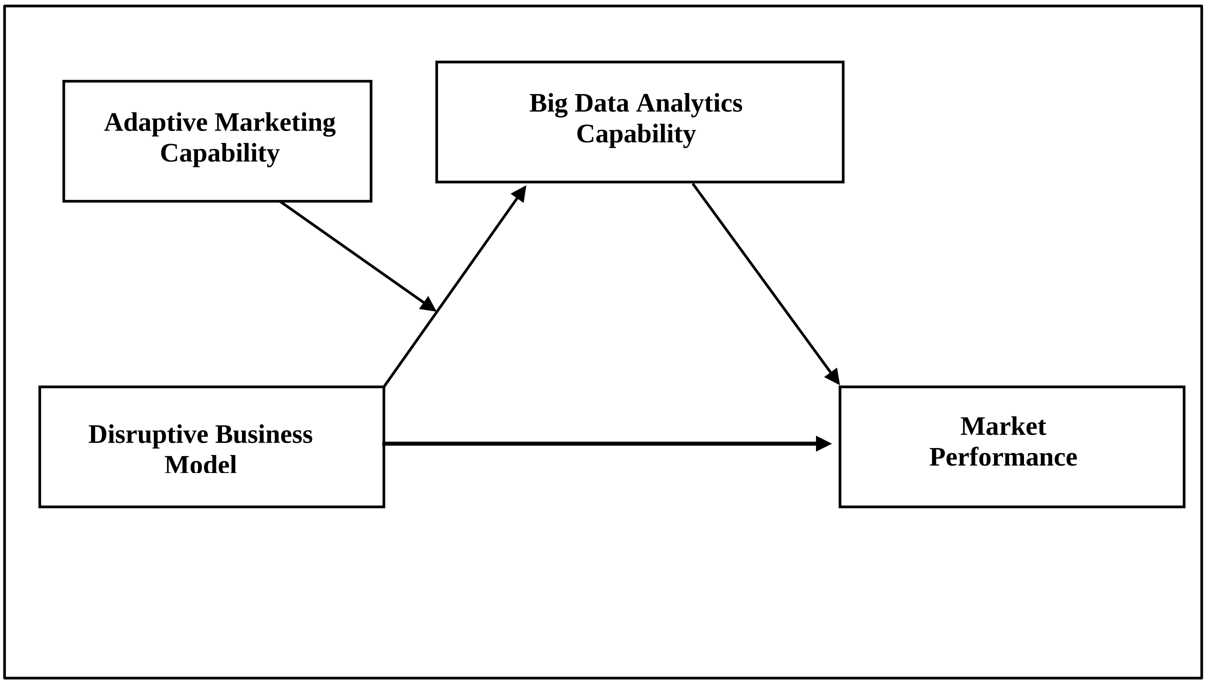
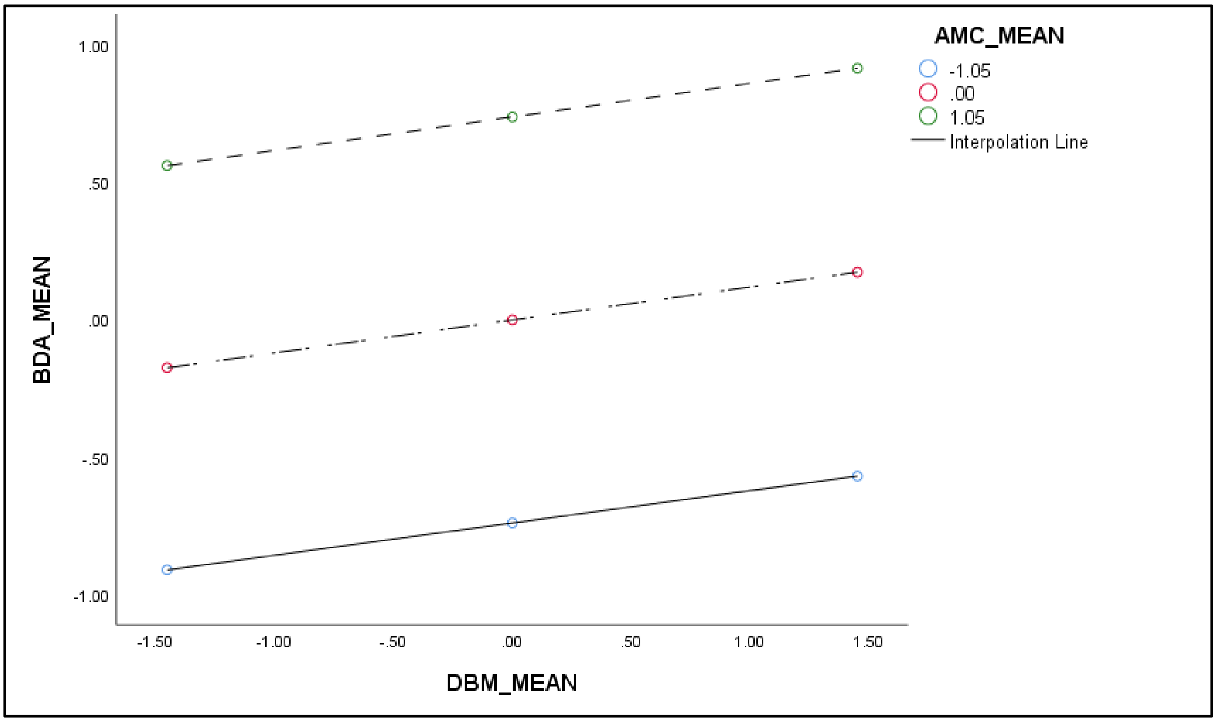


Figure 5.14: Conditional Effect of Disruptive Business Model at Values of Adaptive Marketing Capability



5.7.3.2 Moderated Mediation using Stata

To further assess the moderated mediation effects with both outcome variables in a single model, a structural equation model was estimated in Stata that used the maximum likelihood and bootstrap standard errors (BSE) methods. The results show that there is no significant moderated mediation effect of adaptive marketing capability (mediator) and big data analytics capability (moderator) on the relationship between disruptive business model and new product performance ($b = 0.19$, $p > 0.10$, BSE = 0.01); and on the relationship between disruptive business model and market performance ($b = 0.01$, $p > 0.10$, BSE = 0.01). The R-squared value for these equations was 0.56.

Similarly, the findings show that there is no significant moderated mediation effect of big data analytics capability (mediator) and adaptive marketing capability (moderator) on the relationship between disruptive business model and new product performance ($b = -0.00$, $p > 0.10$, BSE = 0.01); and on the relationship between disruptive business model and market performance ($b = -0.00$, $p > 0.10$, BSE = 0.00). The R-squared value for these equations was 0.68.

In sum, the results of the moderated mediation analysis using both Process and Stata reveal no moderated mediation effect on the disruptive business model–performance relationship. n

In sum

5.7.4 Industry Effects

The data was split into manufacturing firms, service firms, and manufacturing & services firms to further examine the hypotheses developed in this study based on industry differences. For manufacturing firms (Table 5.16), only top managerial risk-taking propensity ($b = 0.45$, $p < 0.001$) and management commitment to innovation ($b = 0.86$, $p < 0.001$) had positive and significant relationships with disruptive business model. Also, disruptive business model is positively related to both new product ($b = 0.18$, $p < 0.001$) and market performance

($b = 0.19$, $p < 0.001$). In addition, new product performance ($b = 0.60$, $p < 0.001$) and market performance ($b = 0.20$, $p < 0.51$) are positively related to anticipated market performance.

Regarding, the interaction effects, big data analytics capability has a positive moderating influence on the disruptive business model–new product performance relationship ($b = 0.19$, $p < 0.05$) and on the disruptive business model–market performance relationship ($b = 0.15$, $p < 0.05$). However, adaptive marketing capability has a negative moderating influence on the disruptive business model–new product performance relationship ($b = -0.21$, $p < 0.05$) and on the disruptive business model–market performance relationship ($b = -0.18$, $p < 0.05$).

In service firms (Table 5.17), only willingness to cannibalise ($b = 0.27$, $p < 0.001$) and top managerial risk-taking propensity ($b = 0.40$, $p < 0.001$) were positively and significantly related to disruptive business model. The results also show that disruptive business model is positively related to new product performance ($b = 0.16$, $p < 0.01$) and market performance ($b = 0.19$ $p < 0.01$). Also, new product performance ($b = 0.58$, $p < 0.001$) and market performance ($b = 0.28$, $p < 0.001$) are positively related to anticipated financial performance. However, neither big data analytics capability nor adaptive marketing capability have significant moderating effects on the disruptive business model–performance relationship.

For firms that combine both manufacturing and services in their business operations (Table 5.18), the results indicate that only top managerial risk-taking propensity is positively related to disruptive business model ($b = 0.32$, $p < 0.05$). Surprisingly, disruptive business model is negatively related to market performance ($b = -0.21$, $p < 0.05$) and does not have a significant relationship with new product performance ($b = -0.23$, $p > 0.10$). Also, new product performance is not significantly related to anticipated financial performance ($b = 0.22$, $p > 0.10$) while market performance is positively related to anticipated financial performance ($b = 0.77$, $p < 0.001$).

Regarding the interaction effects, as expected, big data analytics capability has a positive moderating effect on the disruptive business model–new product performance relationship ($b = 0.35$, $p < 0.001$) and on the disruptive business model–market performance relationship ($b = 0.22$, $p < 0.01$). However, adaptive marketing capability has a negative moderating effect on the disruptive business model–new product performance relationship ($b = -0.20$, $p < 0.10$) and no significant effect on the disruptive business model–market performance relationship ($b = -0.10$, $p > 0.10$).

Table 5.16: Industry Effects - Manufacturing Firms

		Disruptive Business Model		New product Performance		Market Performance		Anticipated Financial Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		0.09 (0.16)	0.58	3.90 (10.64) ****	0.36	3.37 (8.92) ****	0.37	0.99 (3.84) ****	0.25
Main Effects									
Formalisation	1	0.08 (1.26)	0.06						
Willingness to Cannibalise	2	0.04 (0.35)	0.11						
Top Managerial Risk-Taking Propensity	3	0.45 (4.40) ****	0.10						
Management Commitment to Innovation	4	0.86 (3.16) ****	0.27						
Disruptive Business Model	5/6			0.18 (2.73) ****	0.06	0.19 (2.78) ***	0.06		
Big Data Analytics Capability				-0.11 (-1.07)	0.10	-0.12 (-1.10)	0.11		
Adaptive Marketing Capability				0.51 (4.44) ****	0.11	0.57 (4.76) ****	0.12		
New product Performance								0.60 (6.57) ****	0.09
Market Performance								0.20 (2.42) **	0.08
Interaction Effects									
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$			0.19 (2.51) **	0.07	0.15 (1.92) **	0.07		
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$			-0.21 (-2.56) **	0.08	-0.18 (-2.08) **	0.08		
Control Links									
Firm Size		0.31 (2.87) ****	0.11	0.01 (0.20)	0.08	0.13 (1.44)	0.09		
Firm Age		-0.21 (-0.85)	0.24	0.12 (0.63)	0.19	0.14 (0.70)	0.20		
B2B/B2C		0.15 (0.82)	0.19	-0.00 (-0.05)	0.15	0.09 (0.56)	0.16		
χ^2		113.46****		61.71****		78.28****		256.52****	
R^2		0.458		0.312		0.378		0.660	

n = 130; *p< 0.10; **p<0.05; ***p<0.01; ****p<0.001

Breusch-Pagan test of independence: χ^2 = 79.154; p = 0.000

Table 5.17: Industry Effects - Service Firms

		Disruptive Business Model		New product Performance		Market Performance		Anticipated Financial Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		0.28 (0.53)	0.53	3.97 (9.59) ****	0.41	3.54 (8.71) ****	0.40	0.78 (3.52) ****	0.22
Main Effects									
Formalisation	1	0.09 (1.61)	0.06						
Willingness to Cannibalise	2	0.27 (3.38) ****	0.08						
Top Managerial Risk-Taking Propensity	3	0.40 (5.47) ****	0.07						
Management Commitment to Innovation	4	0.35 (1.40)	0.24						
Disruptive Business Model	5/6			0.16 (2.58) ***	0.06	0.19 (3.02) ***	0.06		
Big Data Analytics Capability				0.01 (0.13)	0.08	-0.02 (-0.23)	0.08		
Adaptive Marketing Capability				0.50 (4.25) ****	0.11	0.56 (4.86) ****	0.11		
New product Performance								0.58 (7.26) ****	0.08
Market Performance								0.28 (3.63) ****	0.07
Interaction Effects									
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$			0.03 (0.81)	0.04	0.01 (0.36)	0.04		
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$			-0.07 (-1.26)	0.06	-0.04 (-0.75)	0.05		
Control Links									
Firm Size		0.16 (2.02) **	0.08	0.07 (1.04)	0.07	0.10 (1.39)	0.07		
Firm Age		-0.24 (-1.15)	0.21	-0.19 (-0.10)	0.19	0.09 (0.52)	0.18		
B2B/B2C		-0.11 (-0.64)	0.18	-0.03 (-0.21)	0.16	-0.08 (-0.54)	0.16		
χ^2		128.94****		105.02****		124.00****		349.30****	
R^2		0.425		0.358		0.403		0.655	

n = 175; *p< 0.10; **p<0.05; ***p<0.01; ****p<0.001

Breusch-Pagan test of independence: χ^2 = 96.023; p = 0.000

Table 5.18: Industry Effects - Manufacturing and Service Firms

		Disruptive Business Model		New product Performance		Market Performance		Anticipated Financial Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		0.51 (0.47)	1.09	6.54 (10.71)	0.61	6.42 (13.26) ****	0.48	0.11 (0.23)	0.50
Main Effects									
Formalisation	1	0.09 (1.03)	0.08						
Willingness to Cannibalise	2	0.17 (1.34)	0.13						
Top Managerial Risk-Taking Propensity	3	0.32 (2.46) **	0.13						
Management Commitment to Innovation	4	0.65 (1.40)	0.46						
Disruptive Business Model	5/6			-0.23 (-2.21)	0.10	-0.21 (-2.55) **	0.08		
Big Data Analytics Capability				0.09 (0.76)	0.12	0.06 (0.63)	0.10		
Adaptive Marketing Capability				0.61 (4.05) ****	0.15	0.53 (4.42) ****	0.12		
New product Performance								0.22 (1.42)	0.15
Market Performance								0.77 (3.98) ****	0.19
Interaction Effects									
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$			0.35 (3.50) ****	0.10	0.22 (2.81) ***	0.08		
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$			-0.20 (-1.78) *	0.11	-0.10 (-1.20)	0.09		
Control Links									
Firm Size		0.12 (0.70)	0.17	0.11 (1.03)	0.11	0.11 (1.26)	0.09		
Firm Age		0.15 (0.38)	0.39	-0.64 (-2.70)	0.23	-0.51 (-2.72) ***	0.18		
B2B/B2C		0.09 (0.31)	0.31	0.21 (1.05)	0.20	0.30 (1.86) *	0.16		
χ^2		33.05****		66.67****		69.37****		132.41****	
R^2		0.369		0.532		0.543		0.659	

n = 55; $^{*}p< 0.10$; $^{**}p<0.05$; $^{***}p<0.01$; $^{****}p<0.001$

Breusch-Pagan test of independence: χ^2 = 38.370; p = 0.000

5.7.5 Size Effects

The data was split into small, medium, and large organisations using the number of employees in the firm. Small organisations are those who have 1–99 employees, medium-sized organisations have 100–499 employees, while large organisations have over 500 employees (Brooksbank 1991). Thus, 89 firms are classified as small, 74 firms as medium, and 197 firms as large.

For small organisations (Table 5.19), the results show that formalisation is not significantly related to disruptive business model ($b = 0.05$, $p > .10$). However, cannibalisation ($b = 0.44$, $p < 0.001$), top managerial risk-taking propensity ($b = 0.21$, $p < 0.10$), and management commitment to innovation ($b = 1.00$, $p < 0.001$) are positively and significantly related to disruptive business model. Also, disruptive business model is positively related to new product ($b = 0.14$, $p < 0.01$) and market performance ($b = 0.24$, $p < 0.001$). However, the moderating effects of both big data analytics capability and adaptive marketing capability are not significant.

For medium-sized organisations (Table 5.20), the findings show that willingness to cannibalise ($b = 0.32$, $p < 0.01$) and top managerial risk taking propensity ($b = 0.35$, $p < 0.001$) are positively and significantly related to disruptive business model. However, formalisation ($b = 0.07$, $p > .10$) and management commitment to innovation ($b = -0.22$, $p > .10$) are not significantly related to disruptive business model. Big data analytics capability has a positive moderating effect on the disruptive business model–new product performance relationship ($b = 0.22$, $p < 0.01$) but not on the disruptive business model–market performance relationship ($b = 0.11$, $p > .10$). However, adaptive marketing capability has a significant negative moderating influence on the disruptive business model–new product performance relationship ($b = -0.32$, $p < 0.001$) but a non-significant effect on the disruptive business model–market performance relationship ($b = -0.16$, $p > .10$). Importantly, disruptive business models do not have a significant relationship with either new product performance (b = 0.00, $p > .10$) or market performance (b = 0.08, $p > .10$).

For large organisations (Table 5.21), formalisation is positively related to disruptive business model (b = 0.08, $p < 0.10$), however, this is borderline significant at 10% significance level. Regarding the moderating effects of big data analytics and adaptive marketing capabilities, the results show that big data analytics capability has a positive moderating influence on the disruptive business model–new product performance relationship (b = 0.15, $p < 0.001$) but not on the disruptive business model–market performance relationship (b = -0.06, $p > .10$). Adaptive marketing capability has a negative moderating effect on the disruptive business model–new product performance relationship (b = -0.11, $p < 0.05$) and on the disruptive business model–market performance relationship (b = -0.06, $p > .10$). Furthermore, disruptive business model is positively and significantly related to new product performance (b = 0.16, $p < 0.001$) and market performance (b = 0.14, $p < 0.01$).

Table 5.19: Size Effects - Small Firms

		Disruptive Business Model		New product Performance		Market Performance		Anticipated Financial Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		-0.63 (-0.84)	0.76	4.29 (8.29) ****	0.51	3.66 (7.01) ****	0.52	0.84 (3.46) ****	0.24
Main Effects									
Formalisation	1	0.05 (0.60)	0.09						
Willingness to Cannibalise	2	0.44 (3.17) ***	0.14						
Top Managerial Risk-Taking Propensity	3	0.21 (1.72) *	0.12						
Management Commitment to Innovation	4	1.00 (2.99) ***	0.33						
Disruptive Business Model	5/6			0.14 (1.66) *	0.08	0.24 (2.72) ***	0.08		
Big Data Analytics Capability				-0.25 (-1.51)	0.16	0.00 (0.03)	0.16		
Adaptive Marketing Capability				0.73 (3.22) ****	0.22	0.54 (2.39)	0.22		
New product Performance								0.49 (4.87) ****	0.10
Market Performance								0.34 (3.58) ****	0.09
Interaction Effects									
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$			-0.03 (-0.45)	0.07	0.06 (0.81)	0.08		
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$			0.02 (0.25)	0.10	-0.07 (-0.68)	0.10		
Control Links									
Firm Age		0.12 (0.44)	0.28	-0.21 (-0.81)	0.26	-0.01 (-0.05)	0.26		
Manufacturing/Services		-0.05 (-0.20)	0.25	0.07 (0.33)	0.23	-0.23 (-1.02)	0.23		
B2B/B2C		0.13 (0.55)	0.25	-0.09 (-0.41)	0.232	-0.10 (-0.45)	0.23		
χ^2		74.11****		45.32****		55.97****		258.46****	
R^2		0.452		0.316		0.371		0.745	

n = 89; *p< 0.10; **p<0.05; ***p<0.01; ****p<0.001

Breusch-Pagan test of independence: χ^2 = 61.332; p = 0.000

Table 5.20: Size Effects - Medium-sized Firms

		Disruptive Business Model		New product Performance		Market Performance		Anticipated Financial Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		1.22 (1.10)	1.11	4.73 (9.87) ****	0.48	4.04 (8.11) ****	0.49	0.57 (1.38)	0.41
Main Effects									
Formalisation	1	0.07 (0.83)	0.09						
Willingness to Cannibalise	2	0.32 (2.57) ***	0.12						
Top Managerial Risk-Taking Propensity	3	0.35 (3.04)	0.11						
Management Commitment to Innovation	4	-0.22 (-0.48)	0.46						
Disruptive Business Model	5/6			0.00 (0.01)	0.07	0.08 (1.04)	0.07		
Big Data Analytics Capability				-0.17 (-1.84) *	0.09	-0.12 (-1.24)	0.10		
Adaptive Marketing Capability				0.59 (4.51) ****	0.13	0.58 (4.24) ****	0.13		
New product Performance								0.83 (6.78) ****	0.12
Market Performance								0.07 (0.62)	0.12
Interaction Effects									
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$			0.22 (2.51) **	0.09	0.11 (1.25)	0.09		
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$			-0.32 (-3.46) ****	0.09	-0.16 (-1.63)	0.09		
Control Links									
Firm Age		0.08 (0.19)	0.43	0.01 (0.07)	0.27	0.23 (0.84)	0.28		
Manufacturing/Services		0.31 (1.09)	0.29	0.20 (1.10)	0.18	0.34 (1.79) *	0.19		
B2B/B2C		-0.06 (-0.23)	0.27	0.41 (2.35)	0.17	0.46 (2.58) ***	0.18		
χ^2		32.26****		55.57****		48.70****		138.46****	
R^2		0.272		0.414		0.375		0.600	

n = 74; $^{*}p< 0.10$; $^{**}p<0.05$; $^{***}p<0.01$; $^{****}p<0.001$

Breusch-Pagan test of independence: χ^2 = 38.556; p = 0.000

Table 5.21: Size Effects - Large Firms

		Disruptive Business Model		New product Performance		Market Performance		Anticipated Financial Performance	
Independent Variable	**H**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**	**Coefficient (t-value)**	**Standard Error**
Constant		0.94 (2.07) **	0.45	4.29 (11.07) ****	0.38	4.19 (11.09) ****	0.37	1.13 (4.91) ****	0.23
Main Effects									
Formalisation	1	0.08 (1.85) *	0.04						
Willingness to Cannibalise	2	0.13 (1.93) *	0.06						
Top Managerial Risk-Taking Propensity	3	0.46 (7.18) ****	0.06						
Management Commitment to Innovation	4	0.57 (2.77) ***	0.20						
Disruptive Business Model	5/6			0.16 (2.69) ***	0.06	0.14 (2.48) **	0.05		
Big Data Analytics Capability				0.13 (1.69) *	0.08	-0.01 (-0.16)	0.07		
Adaptive Marketing Capability				0.38 (4.29) ****	0.08	0.53 (6.14) ****	0.08		
New product Performance								0.49 (6.31) ****	0.07
Market Performance								0.30 (3.82) ****	0.07
Interaction Effects									
Disruptive Business Model x Big Data Analytics Capability	$7_a/7_b$			0.15 (2.76) ***	0.05	0.06 (1.24)	0.05		
Disruptive Business Model x Adaptive Marketing Capability	$8_a/8_b$			-0.11 (-2.22) **	0.05	-0.06 (-1.23)	0.05		
Control Links									
Firm Age		-0.22 (-1.41)	0.15	0.00 (0.00)	0.13	0.09 (0.73)	0.13		
Manufacturing/Services		0.29 (1.98) **	0.15	-0.15 (-1.20)	0.13	-0.11 (-0.88)	0.12		
B2B/B2C		0.02 (2.07) **	0.15	-0.12 (-0.90)	0.13	-0.13 (-1.04)	0.13		
χ^2		220.56****		154.46****		152.17****		324.54****	
R^2		0.521		0.415		0.437		0.624	

n = 197; *p< 0.10; **p<0.05; ***p<0.01; ****p<0.001

Breusch-Pagan test of independence: χ^2 = 107.763; p = 0.000

5.8 Summary

This chapter presents the scale development, measurement assessment, correlation matrix, model fit, construct validity, construct reliability, common method bias, results of the hypotheses testing, robustness checks, and additional analyses. The conceptual model of this study and all the hypotheses were tested for significance using SUR. The results show a good model fit and all hypotheses except H_1, H_{8a}, and H_{8b} were found to be in the right direction.

Table 5.22 provides a summary of the results from the hypotheses tests while Table 5.23 provides a summary of the robustness checks and some additional analyses conducted. In addition, Table 5.24 provides a summary of the industry effects and a summary of the size effects is provided in Table 5.25. The next and final chapter of this thesis discusses the findings from the in-depth interviews conducted, results of each hypothesis in line with past research findings and theoretical underpinnings of the study, the theoretical contributions and implications of the study, the limitations of the study, future research directions, and ends with the conclusion of the study.

Table 5.22: Summary of Main Findings

Hypothesis		Findings
H_1:	Formalisation is negatively related to disruptive business model	Not supported
H_2:	Willingness to cannibalise is positively related to disruptive business model	Supported
H_3:	Top managerial risk-taking propensity is positively related to disruptive business model	Supported
H_4:	Management commitment to innovation is positively related to disruptive business model	Supported
H_5:	Disruptive business model is positively related to new product performance	Supported
H_6:	Disruptive business model is positively related to market performance	Supported
H_{7a}:	Big data analytics capability strengthens the positive relationship between disruptive business model and new product performance	Supported
H_{7b}:	Big data analytics capability strengthens the positive relationship between disruptive business model and market performance	Supported
H_{8a}:	Adaptive marketing capability strengthens the positive relationship between disruptive business model and new product performance	Not Supported
H_{8b}:	Adaptive marketing capability strengthens the positive relationship between disruptive business model and market performance	Not supported

Table 5.23: Summary of Robustness Checks and Additional Analyses

Slope Test for Interaction Plots	**Findings**
Slope for disruptive business model at high and low levels of big data analytics capability for new product and market performance	Not statistically different
Slope for disruptive business model at high and low levels of adaptive marketing capability for new product and market performance	Not statistically different
Moderating Effects (±1SD and SPSS Process)	
Big data analytics capability strengthens the positive relationship between disruptive business model and new product performance	Supported
Big data analytics capability strengthens the positive relationship between disruptive business model and market performance	Supported
Adaptive marketing capability strengthens the positive relationship between disruptive business model and new product performance	Not Supported
Adaptive marketing capability strengthens the positive relationship between disruptive business model and market performance	Not supported
Moderated Mediation (SPSS Process and STATA)	
Big data analytics capability as the moderator and adaptive marketing capability as the mediator with new product performance and market performance	No moderated mediation
Adaptive marketing capability as the moderator and big data analytics capability as the mediator with new product and market performance	No moderated mediation

Table 5.24: Summary of Industry Effects

Hypothesis		**Manufacturing**	**Services**	**Manufacturing & Services**
H_1:	Formalisation is negatively related to disruptive business model	Not supported	Not supported	Not supported
H_2:	Willingness to cannibalise is positively related to disruptive business model	Not Supported	Supported	Not supported
H_3:	Top managerial risk-taking propensity is positively related to disruptive business model	Supported	Supported	Supported
H_4:	Management commitment to innovation is positively related to disruptive business model	Supported	Not supported	Not supported
H_5:	Disruptive business model is positively related to new product performance	Supported	Supported	Not supported
H_6:	Disruptive business model is positively related to market performance	Supported	Supported	Not supported
H_{7a}:	Big data analytics capability strengthens the positive relationship between disruptive business model and new product performance	Supported	Not supported	Supported
H_{7b}:	Big data analytics capability strengthens the positive relationship between disruptive business model and market performance	Supported	Not supported	Supported
H_{8a}:	Adaptive marketing capability strengthens the positive relationship between disruptive business model and new product performance	Not supported	Not supported	Not supported
H_{8b}:	Adaptive marketing capability strengthens the positive relationship between disruptive business model and market performance	Not supported	Not supported	Not supported

Table 5.25: Summary of Size Effects

Hypothesis		Small	Medium	Large
H_1:	Formalisation is negatively related to disruptive business model	Not Supported	Not Supported	Not Supported
H_2:	Willingness to cannibalise is positively related to disruptive business model	Supported	Supported	Supported
H_3:	Top managerial risk-taking propensity is positively related to disruptive business model	Supported	Not Supported	Supported
H_4:	Management commitment to innovation is positively related to disruptive business model	Supported	Not Supported	Supported
H_5:	Disruptive business model is positively related to new product performance	Supported	Not Supported	Supported
H_6:	Disruptive business model is positively related to market performance	Supported	Not Supported	Supported
H_{7a}:	Big data analytics capability strengthens the positive relationship between disruptive business model and new product performance	Not Supported	Supported	Supported
H_{7b}:	Big data analytics capability strengthens the positive relationship between disruptive business model and market performance	Not Supported	Not Supported	Not Supported
H_{8a}:	Adaptive marketing capability strengthens the positive relationship between disruptive business model and new product performance	Not Supported	Not Supported	Not Supported
H_{8b}:	Adaptive marketing capability strengthens the positive relationship between disruptive business model and market performance	Not Supported	Not Supported	Not Supported

CHAPTER 6

DISCUSSION, CONTRIBUTIONS, LIMITATIONS, DIRECTION FOR FUTURE RESEARCH, AND CONCLUSIONS

6.0 Introduction

This chapter presents the discussion of interview and survey findings, key theoretical contributions, and the implications of the findings to business organisations, managers, and policy making. Thereafter, the limitations of the study are identified and various avenues for future research are discussed. The chapter ends with the conclusion of the study.

6.1 Discussion of Findings

The theoretical underpinning of the empirical model will be discussed and the findings on the drivers of disruptive business model will be examined. The performance consequences of adopting a disruptive business model are presented followed by a discussion on the moderating effects of adaptive marketing capability and big data analytics capability on the disruptive business model–performance relationship.

6.1.1 Paradigmatic Theoretical Findings

The RBV opines that organisations have distinct and heterogeneous resources at their disposal that are rare, valuable, non-substitutable, and immobile across organisations operating within the same industry or market (Barney 1991). The survey findings buttress this by showing that organisations that possess big data analytics capabilities can understand customer needs and utilise this knowledge in developing and implementing successful business models that have positive relationships with new product and market performance.

In addition, the findings show that disruptive business models can be viewed as organisational capabilities that are rare, valuable, heterogenous, and immobile. As such, organisations can utilise a disruptive business model as a strategic resource that provides unique competitive advantages against other firms operating in the same industry or market. In addition, a disruptive business model is a unique capability that can be harnessed to cater to consumer needs. This corroborates the tenets of the RBV that unique resources and capabilities cannot be easily exchanged among firms and they provide firms with sustainable competitive advantages.

In addition, the survey findings show that internal organisational characteristics have positive influences on the development of disruptive business models. Specifically, formalisation, management commitment to innovation, top managerial risk-taking propensity, and willingness to cannibalise existing assets and resources are positively associated with the development of a disruptive business model. These organisational idiosyncratic resources and capabilities facilitate the firm's ability to introduce disruptive business models.

Furthermore, the analyses show that big data analytics capability has a positive influence on the performance outcomes of disruptive business models. Big data analytics capability can be viewed as a differentiating capability possessed by organisations that introduce disruptive business models. Big data analytics capability consists of big data volume, big data velocity, and big data variety (McAfee et al. 2012). The ability of organisations to access different sources and types of consumer data and analyse the data quickly, effectively, and efficiently is a potent factor in ensuring the success of disruptive business models. As such, organisations that possess high levels of big data analytics capability are in a better position to maximise the performance benefits and outcomes of disruptive business models. Therefore, in-depth knowledge on consumer trends plays a significant role in ensuring that the introduction of a disruptive business model leads to increased new product and market performance.

Contrary to expectations, the results show that the combination of adaptive marketing capability and disruptive business models is negatively associated with new product and market performance. This is counterintuitive as it is expected that organisational alliances and collaborations, market experimentation, and vigilant market learning will enhance the performance effects of disruptive business models. A plausible reason for this might be an over-reliance of organisations on existing customer needs and over-dependence on monitoring environmental signals which can be misleading. Open marketing capability which involves establishing alliances and collaborations might also bring bureaucracies and long decision-making processes which might be negatively associated with the fast response rates of organisations to changing consumer needs and the ever-dynamic business environment.

Thus, the findings of this study corroborate the RBV by showing that knowledge is indeed one of the crucial strategic resources that a firm can have at its disposal to ensure positive performance outcomes. The findings of the in-depth interviews are discussed in the next section.

6.1.2 Nature and Drivers of Disruptive Business Model

In order to identify the nature and drivers of disruptive business models among others, interviews were conducted with 23 organisations in the United Kingdom. The interview findings show that managers view disruptive business models as a way of changing existing business and industry operations. Jane, the CEO of a Marketing Services firm mentioned that "*a disruptive business model or a disruptive approach is one which first makes you question everything you do. It is an earthquake where everything falls into little pieces, but you could re-assemble them back better*". Gary, a Managing Director in the Pharmaceutical Industry viewed disruption as "*when you upset the market because you have a more competitive way*".

Furthermore, Henry described disruptive business models as "*when you change the way you work, the way you manage the workforce, you change what you offer the market or how you engage the market. Or you could create a new market with new consumers. You can take what you have and present it in a different way.* Thus, managers viewed disruptive business models as a way of changing what is offered to consumers, targeting a new market segment, and creating a new value offering to consumers.

Regarding the antecedents of disruptive business models, the interviews findings show that there are five major external factors that influence the development of disruptive business models. Hence, technological advancements, political uncertainty and government regulations, competitive pressures, the press and media, and consumer dynamism are the major external factors that drive the development of disruptive business models in various industries.

First, technological advancements such as the rise of the internet, automation, and mobile technologies facilitate the development of disruptive business models. This was echoed by various managers during the in-depth interviews. For instance, Jeffery, a CEO in Marketing services industry, noted that "*Google has changed things phenomenally… I mean, mobile is probably the biggest change since 2011*." In addition, Henry, explained that automation had a significant impact on the organisational processes, value propositions, market, competitors, and consumers. This is also corroborated by the Head of automotive (organisation E) who noted in the company report that "*while the opportunities (with technology) are great, technology led companies including Google, Waymo, and Uber are disrupting and reshaping the market and driving traditional manufacturers to invest heavily in a bid to stay ahead of the innovation curve*".

Similarly, Alex noted that technological advancements facilitated the change from a traditional business model to a disruptive business model. Thus, his organisation was able to change from a license fee business model to a subscription-based business model to facilitate business operations, provide increased value to consumers, and enhance organisational performance. Furthermore, Alfred noted that his organisation introduced a platform for moving vehicles from one geographical location to the other. However, this business model was changed and the disruptive business model utilised technological advancements. Specifically, Alfred noted that the disruptive business model is "*essentially about aggregating demand for transport with supplier transport. What we would call in terms of what its does? In a way, it's very kind of uber-like in terms of bringing supply and demand together and essentially charging a fee. But it's been disruptive because its replaced that traditional model of how transportation is sourced. In terms of other things we have done, is it disruptive, well, it is, where we have introduced an online wholesale business to business vehicle platform. Effectively what that has done is disrupt the traditional ways of disposing vehicles. So that has been very disruptive*."

Second, political uncertainty and government regulations can greatly affect organisational processes and the development of disruptive business models. A major reason is the need for organisations to conform to institutional and industry-wide regulations. Importantly, the political uncertainty around Brexit has affected various industries and is arguably one of the greatest disruptions to organisations operating in the UK. Frederick emphasised the negative impact which Brexit would have on his organisation's business operations. He noted that "*the political climate has a negative impact on our business because 50% of our work is non-EU and US. Many of the companies we conduct business with do not have branches in Europe. These companies are worried about using UK as a platform because of Brexit. So, we try to mitigate the risk*".

The internal documents of organisation E buttress this by stating that "*as with great periods of disruption, there comes opportunities and challenges. New players in the manufacturing, technology and innovation spaces are putting pressure on the traditional* *automotive industry and the uncertainty around Brexit is affecting the industry at large*". Some managers also emphasised the significance of the Financial Reporting Council (e.g., Charles, a Director of a Management Consulting Firm) and the General Data Protection Regulation in respect to their impact on internal organisational processes (e.g., Alex, a CEO of Business software and IT firm).

The General Data Protection Regulation (GDPR) was implemented in May 2018, with the aim of protecting personal data of individuals within the EU and European Economic Area. Thus, many organisations that possessed consumer data needed to obtain explicit consent from consumers to keep their data. The sugar tax levy imposed on manufacturers of sugary drinks in the UK, as part of an anti-obesity policy, is another example. In response to this regulatory requirement, Derek, a marketing manager in FMCG firm spoke about an organisational strategy of gradually reducing the sugar in his firm's dairy products as a precautionary measure in the event that the sugar tax takes effect in the dairy industry.

Third, competitive pressures can result in the development of disruptive business models, as the introduction of a new product, service, or business model by a competitor can change industry dynamics, consumer expectations, and organisational processes. The threat of disruption by competitors can propel organisations to develop and introduce new products, services, and business models. Many organisations believe that a competitor (big or small) can introduce new products, services, or business models that can potentially disrupt their existing operations. This was emphasised by managers whose organisations were smaller players in the organisational field (e.g., Charles, A Director in a Management Consulting firm, and Jeffery, a CEO of a Marketing Services firm).

Fourth, some managers emphasised the role of the press and media in creating certain awareness, leading to the need to develop disruptive business models. A notable example is the UK 'Blue Planet 2' series, which depicted the dangers of plastic and its negative impact on the ocean and the animals that live and feed in the ocean. This series was aired on BBC One to 37.6 million people and more than 62% of the UK population (BBC Pulse Survey 2018). This has forced high street UK retailers to introduce regulations on the amount of plastic allowed on supermarket shelves by manufacturing organisations (Derek). An example is Sainsbury's which has become the first UK supermarket to launch a trial plastic-free supermarket where consumers are to bring in their containers to purchase groceries, wine, pasta, rice, fruits, vegetables, and bakery items (Horton 2019).

Fifth, the dynamic nature of consumer needs and trends can necessitate the need to create disruptive business models to replace established organisational business models. To meet changing consumer needs and emerging consumer trends, existing organisational business models might need modification or replacement. Some managers (e.g., Alex and Jeremy) noted that some consumers make specific demands, have a clear idea of the products and services they need and want, and make conscious shifts towards sustainable and authentic brands.

This implies that organisations need to have access to information on consumer needs and wants, have the capacity to analyse data on consumer preferences, and ensure that they provide products and services that reflect consumer needs and wants. Given the dynamic nature of consumer needs, organisation N emphasised in its internal documents the need to "*continuously analyse consumer needs and expectations*" to regularly provide innovative products to the market. The next sections discuss the drivers of disruptive business models based on the survey findings and hypotheses testing.

6.1.2.1 Formalisation

One of the unexpected findings regarding the drivers of disruptive business models is the presence of a positive relationship between formalisation and disruptive business model.

This implies that managers perceive the need to ensure a level of adherence to rules and regulations within their organisations and this facilitates the development of disruptive business models. This is rather surprising as the hypothesis was backed by strong theoretical arguments and supported by previous empirical findings (i.e., Hamel 1998, 2001; Le Roy and Yami 2007).

It was expected that formalisation will limit the ability of organisations to develop and implement disruptive business models due its focus on rigid rules, regulations, and processes. Specifically, Le Roy and Yami (2007) argue that disruptive strategies thrive in environments and organisational cultures that are informal in nature; encourage creativity and the continuous questioning of set rules, processes, and practices; and allow free flow of information and dialogues between different hierarchical levels within organisations. Their findings imply that organisations with highly formalised structures will most likely introduce incremental business models and not disruptive business models.

Moreover, Karimi and Walter (2016) find that autonomy has a positive relationship with disruptive business model. In the same vein, Markides and Oyon (2010) argue that autonomy is crucial when developing disruptive business models. This is because employees are empowered and encouraged to present and implement new ideas successfully when they have autonomy in decision making and organisational processes (Lumpkin, Cogliser, and Schneider 2009). Thus, the existence of a positive relationship between formalisation and disruptive business model contradicts extant literature and past research findings.

However, the positive relationship between formalisation and disruptive business model can be attributed to some factors. Firstly, it is possible that in formalised organisational structures, a creative and innovative approach can still be encouraged even though this might be guided by set rules, processes, and procedures. An organisation can simultaneously create a structured and enabling innovative environment that facilitates the development of disruptive business models. Thus, formalisation is not necessarily a negative factor that needs to be avoided by organisations.

Secondly, the lack of set rules, processes, and procedures can result in disorganisation and the inability to decide on which disruptive business model to develop. Disruptive business models are risky by nature, as such, they need to be embarked upon with careful consideration and meticulous strategic planning. Therefore, formalisation might not necessarily inhibit the development of a disruptive business model and it can play a facilitating role by encouraging decisions based on established organisational parameters.

6.1.2.2 Willingness to Cannibalise

Regarding the hypothesised relationship between willingness to cannibalise and disruptive business model, the findings point to a significant positive link. This conforms with past research findings that show a positive association between willingness to cannibalise and innovation (Tellis, Prabhu, and Chandy 2009). Innovative organisations are very likely to introduce disruptive business models which might involve the cannibalisation of existing assets, resources, know-how, sales, profits, and business models.

As such, managers understand that developing a disruptive business model can not only influence customers, competitors and other industry stakeholders but can also influence internal resources, assets, knowledge, business models, and profitability. In a bid to ensure the success of disruptive business models, the results show that managers are willing to cannibalise and forfeit sales of existing products; support new innovations that can negatively affect the sales of existing products; replace existing technology with new technology; change established organisational processes; and encourage technologies that might make existing manufacturing facilities go obsolete. This finding is similar to that of Habtay (2012) who argues that disruptive business models lead to the obsolescence of current business models.

Disruptive business models create ground-breaking phenomenal changes in the way value is created and delivered to customers. This in turn influences consumer demand, competitor activities, and existing business models. Developing and introducing a disruptive business model can therefore mean a complete overhaul of existing organisational practices, norms, and processes. This can also affect current manufacturing processes and organisational capabilities on one hand and current sales, profits, and investments on the other hand. Furthermore, the products, services, and business models currently implemented by organisations can become obsolete as a result of the introduction of a disruptive business model.

Thus, organisational willingness to sacrifice existing sales, profits, and even inventions provides the platform for the development of next generation innovations (Tellis, Prabhu, and Chandy 2009) such as disruptive business models. As such, managers understand that developing a disruptive business model can erode prior manufacturing investments, technological know-how, and previous innovations introduced. This is especially due to high levels of uncertainty that surround the successful introduction of disruptive business models (Dattée, Alexy, and Autio 2018; Snihur, Thomas, and Burgelman 2018).

Therefore, the positive relationship between willingness to cannibalise and disruptive business model corroborates past research findings. As such, organisations that develop and introduce disruptive business models are aware that it can lead to the cannibalisation of sales, profits, and market share of existing products, services, and business models (Van Heerde, Srinivasan, and Dekimpe 2010; Velu and Stiles 2013). In sum, willingness to cannibalise is an essential characteristic of organisations that develop and implement disruptive business models.

6.1.2.3 Top Managerial Risk-Taking Propensity

The development and implementation of disruptive business models can be a risky decision especially because there is no concrete assurance of success. The findings show that top managerial risk-taking propensity is positively associated with the development of disruptive business models. This implies that managers understand that disruptive business model development and commercialisation involves financial risks and innovative marketing strategies that have a possibility of failing (Tellis, Prabhu, and Chandy 2009). As such, managers believe that high financial risks are likely to produce higher rewards for the organisation and this is central to the creation and implementation of disruptive business models. Thus, managers who view failure as normal are likely to encourage new ideas, innovative suggestions, and implement these to satisfy consumer needs (Kohli and Jaworski 1990).

This finding is in line with previous research (Tellis, Prabhu, and Chandy 2009) that highlights the importance of a corporate culture that encourages risk-taking in order to exploit business opportunities. This shows that managers are willing to take financial risks in order to exploit business opportunities related to developing disruptive business models and thus incorporate this into their organisational culture. Furthermore, the willingness to undertake financial risks reflects the audacious actions that need to be taken when developing disruptive business models that involve high levels of uncertainty. This is summed up by Rauch et al. (2009, p. 763) who argue that managerial risk-taking propensity involves “taking bold actions by venturing into the unknown, borrowing heavily, and/or committing significant resources to ventures in uncertain environments." As such, it is crucial to take investment decisions and commitments in uncertain environmental conditions (Rauch et al. 2009) especially when developing and introducing a disruptive business model.

Also, Karimi and Walter (2016) find that risk-taking behavior has a positive relationship with disruptive business models. Hence, organisations that are not risk-averse can identify and adopt a new business model in order to satisfy customer needs. For instance, Amazon and Salesforce introduced disruptive business models and took major risks by changing their existing business models to disruptive business models (DaSilva et al. 2013).

To successfully develop disruptive business models, managers need to exhibit a willingness to undertake risks and view failure of some innovative activities as normal and inevitable. If managers are risk-averse, it can have a negative ripple effect on the ability of the organisation to develop disruptive business models. Additionally, risk-averse management styles can deter employees from discussing innovative ideas and emerging trends (Jaworski and Kohli 1993). Specifically, Pérez-Luño, Wiklund and Cabrera (2011) find that risk-taking managers developed more innovations than their risk-averse counterparts who like to 'play-it-safe' by introducing innovations that are sure to succeed.

In sum, the finding that managerial risk-taking propensity has a positive relationship with disruptive business model is in line with extant literature and past research findings on the development of innovative practices and processes (Gilman 1995; Kuczmarski 1996; Tellis, Prabhu, and Chandy 2009). It also reflects the proactive, forward-looking, long-term focus of organisations on sales, profits, and sustainable competitive advantages.

6.1.2.4 Management Commitment to Innovation

As expected, the results show that management commitment to innovation has a positive and statistically significant relationship with disruptive business model. This is in line with past research (e.g., Doz and Kosonen 2010) that argues that for organisations to successfully introduce new business models, the top management team needs to ensure that financial investments are made towards research and development, new product development, marketing of new products, and advertising of new products. Hence, it can be said that when managers increasingly perceive the importance of creating and implementing disruptive business models, they invest in innovative activities, technological advancements, conduct ground-breaking research, and use this information to create new markets.

This finding indicates that decision making within organisations and the level of financial investment into innovative activities is based on the perceived importance and success of disruptive business models. This is because managers will only develop and implement disruptive business models if there is a likelihood that the investments made will yield positive performance outcomes for the organisation. As such, the level of investments put in place by managers is positively related to the extent to which disruptive business models will be successfully developed.

Furthermore, management commitment to innovation reflects the proactive nature of managers to identify business opportunities and engage in innovative activities to exploit such opportunities (Heavey, Simsek, and Fox 2015). This is crucial because disruptive business models are based on organisational proactive strategies that are implemented to address latent consumer needs. Thus, it involves making strategic projections about consumer demand, needs, wants, trends, and behaviour which then influences commitment to innovative activities by organisations. It also enables organisations develop important capabilities to further exploit business opportunities (Cohen and Levinthal 1994).

This managerial attribute helps organisations to “allocate resources and champion activities that lead to the development of new products, technologies, and processes consistent with marketplace opportunities” (Hitt, Hoskisson, and Ireland 1990, pp. 29–30). Furthermore, the ability of organisations to engage in innovative activities by introducing new products, services, and processes is positively related to disruptive business model development (Karimi and Walter 2016). This is crucial as disruptive business models can involve the combination of new products, services, and processes.

As such, the finding that management commitment to innovation is positively related to disruptive business models is in line with past research and extant literature. Therefore, management commitment to innovation facilitates resource allocation towards innovative activities which is fundamental to ensuring the successful development and implementation of disruptive business models.

6.1.3 Performance Consequences of Disruptive Business Model

As previously established, extant literature shows different performance outcomes of implementing disruptive business models ranging from customer satisfaction (Velu and Stiles 2013), to business model performance (Karimi and Walter 2016) and increased profits, growth, and market share (Yovanof and Hazapis 2008). In this study, performance was examined as an outcome of disruptive business models and was categorised into new product performance and market performance. The relationships between new product performance and anticipated financial performance, and between market performance and anticipated financial performance were examined even though these links are not hypothesised in the conceptual model. The findings from the analysis reveal that disruptive business model is positively related to new product and market performance. Furthermore, the results show that both new product performance and market performance have a positive relationship with anticipated financial performance. These findings are discussed in more detail below.

6.1.3.1 New Product Performance

The findings of this study indicate that the development and implementation of disruptive business models has a positive and significant relationship with new product performance. This implies that adopting disruptive business models leads to increased sales and profitability from new products. Thus, compared to competitors, organisations that introduce disruptive business models get increased return-on-investment, profits, sales, and market share from new products.

Disruptive business models aim at providing products and services to consumers using un-conventional methods. As such, introducing a disruptive business model incorporates disruptive technologies, products, and services and is positively associated with new product performance. New product performance is the ability of organisations to successfully generate new product ideas and introduce new products into the market (Gatignon and Xuereb 1997; Im and Workman Jr 2004; Montoya-Weiss and Calantone 1994).

Furthermore, disruptive business models can facilitate the successful launch of products resulting in product advantages and launch proficiency (Langerak, Hultink, and Robben 2004). Managers understand the importance of disruptive business models in achieving new product performance as it has a positive relationship with sales, profitability, and sustained competitive advantages. Similarly, Habtay (2012) find that disruptive business models resulted in new product success and retention of profitable markets. Thus, introducing disruptive business models facilitates new product success and helps to achieve increased market share.

Firms that introduce disruptive business models are usually pioneers of the business model and this can have a direct impact on other organisations operating within the same industry. Thus, disruptive business models can change the dynamics, institutional norms, accepted behaviour, and practices within an industry (Sabatier, Craig-Kennard, and Mangematin 2012). This implies that introducing disruptive business models leads to increased profits from the sales of new product which in turn increases the market share from new products. Therefore, developing and implementing disruptive business models has a positive relationship with sales, profits, and market share from new products.

6.1.3.2 Market Performance

As the results indicate, a positive significant link between disruptive business model and market performance was established. In this study, market performance refers to the ability of an organisation to experience increased market share, growth in market share, growth in sales volume, and product development (Sarkar, Echambadi, and Harrison 2001). Specifically, the analysis revealed that disruptive business models that offer new combinations of products, services, and information directly influence the ability of the firm to achieve market performance outcomes such as increased market share, sales volume, and product development.

Additionally, organisations that continually introduce disruptive business models are usually the pioneers of the business model. This implies that competitors imitate the disruptive business model which gives the pioneering firm first-mover advantages that can lead to dominance in an industry and increased market share. This also resonates with the interview findings as managers generally agreed that the introduction of disruptive business models has a negative effect on competitors operating in the same industry.

Thus, compared to competitors, firms that introduce disruptive business models have higher market share, sales volume, and product development. This finding is in line with extant literature that shows a positive relationship between disruptive business model and market performance (Habtay 2012; Yovanof and Hazapis 2008). Therefore, the findings show that the market share and sales volume of organisations that introduce disruptive business models increases and is higher than competing organisations who do not introduce disruptive business models.

6.1.4 The Moderating Role of Big Data Analytics Capability

The first moderating effect examined in this study is the influence of big data analytics capability on the disruptive business model–performance relationship. This study hypothesised that big data analytics capability will strengthen the positive relationship between disruptive business model and new product performance on one hand and strengthen the relationship between disruptive business model and market performance on the other hand. As hypothesised, the findings show that the combination of big data analytics capability and disruptive business models has a positive and significant relationship with new product performance and market performance.

This implies that managers understand the importance of possessing large amounts of consumer data, analysing this data, and sharing to relevant departments within the organisation (Pisano, Pironti, and Rieple 2015). Big data analytics capability works hand-in-hand with disruptive business models to ensure positive new product and market performance for organisations. Big data analytics capability consists of big data volume, big data velocity, and big data variety (McAfee et al. 2012). Big data volume is the ability of an organisation to analyse large amounts of consumer data (Johnson, Friend, and Lee 2017) which helps in making strategic decisions such as the development and implementation of disruptive business models. Disruptive business models involve the right combination of products, services, and information targeted at consumers and doing this successfully involves a thorough understanding of consumer behaviour which is facilitated by the ability to analyse large amounts of consumer data.

Big data velocity refers to the ability of organisations to speedily analyse consumer data as soon as it is received (Johnson, Friend, and Lee 2017). The timing of data analysis is crucial to the development and implementation of disruptive business models. This is because organisations who introduce disruptive business models are usually the pioneers of such business models in their industries. Thus, the ability of an organisation to be lightning fast in exploring consumer data will help in providing necessary insights into the 'how' of developing and introducing disruptive business models.

Big data variety refers to the capability of organisations to have access to multitude of sources for consumer data, consumer databases, and different types of consumer data (Johnson, Friend, and Lee 2017). This is a crucial capability as organisations can gain immense knowledge from various sources about past, present, and future consumer trends which facilitates the success of disruptive business models.

Therefore, the findings show that big data analytics capability strengthens the positive relationship between disruptive business and performance (new product performance and market performance). As such, compared to competitors, firms can achieve higher product development, sales from new products, profits from new products, and return-on investment from new products by combining disruptive business model with big data analytics capability. Similarly, firms can outwit competitors by increasing their market share, sales growth, and market development through the combination of big data analytics capability and disruptive business model. In sum, the insights gotten from big data analytics provide organisations with the platform to successfully commercialise disruptive business models and achieve higher performance outcomes compared to competitors.

6.1.5 The Moderating Role of Adaptive Marketing Capability

Adaptive marketing capability involves the ability of an organisation to form partnerships and alliances in order to provide superior offerings to consumers, engage in market experimentation of new ideas, and engage in vigilant market learning (Guo et al. 2018). Hence, adaptive marketing capability consists of open marketing capability, adaptive market experimentation, and vigilant market learning. It can also be described as the ability of an organisation to "identify and capitalise on emerging market opportunities" (Polat and Akgün 2017, p. 1139).

Thus, firms possess adaptive marketing capability when they can effectively "reconfigure resources and coordinate processes promptly and effectively to meet rapid environmental changes" (Zhou and Li 2010, p. 225). In sum, adaptive marketing capability refers to firms' ability to "proactively sense and act on market signals, continuously learn from market experiments, and integrate and coordinate social network resources to adapt to market changes and predict industry trends" (Guo et al. 2018, p. 3).

In this study, it was expected that adaptive marketing capability will strengthen the positive relationship between disruptive business model and performance. This is because organisations that possess the ability to actively collaborate with other organisations are more likely to develop superior capabilities and know-how (Gassmann and Reepmeyer 2005) which can positively influence the performance outcomes of disruptive business models (Sabatier, Craig-Kennard, and Mangematin 2012).

Additionally, continuous market experimentation can pave the way and enable organisations understand consumer needs in order to ensure that products, services, and business models introduced are well suited to these needs (DaSilva et al. 2013; Sosna, Trevinyo-Rodríguez, and Velamuri 2010). Vigilant market learning is another crucial capability that involves active and continuous observation of the marketing environment and learning from competitor activities, environmental occurrences, and consumer trends (Guo et al. 2018).

In line with previous research, this study hypothesised that adaptive marketing capability will strengthen the positive relationship between disruptive business model and performance. Surprisingly, the findings reveal that the combination of adaptive marketing capability and disruptive business model is negatively related to new product performance and market performance. This shocking finding can be caused by a variety of factors.

Ancona and Caldwell (1992) find a negative relationship between prolonged environmental scanning/scouting activity and innovation efficiency and performance. There is therefore a possibility that increased environmental scanning activities can have a negative influence on innovations and by extension disruptive business models. In addition, Stubbart (1982) provides a word of caution of having high expectations from environmental scanning. Thus, it is plausible that organisations that constantly adapt internal processes to suit consumer needs and demands might have a limited and myopic focus on current customer needs and not on latent (future) needs.

Also, adaptive marketing capability involves collaborations to develop innovative strategies and tactics and this can have its down sides as decision making can take longer periods because of approval levels and opportunistic behavior of partners (Villena, Revilla, and Choi 2011). This in turn can have a negative relationship with the timing and introduction of disruptive business models. Furthermore, learning from channel partners, market leaders, and peer companies can provide a one-sided view of future changes to consumer needs and preferences.

Additionally, past research shows that long-term relational exchanges can result in homogeneity in organisational thinking processes, group think, and isomorphism which reduces creativity, independent thinking, and the ability to take optimal decisions (Autry and Griffis 2008; Bendoly et al. 2010). Furthermore, information-sharing between partners in a collaborative relationship can result in stress and confusion between important information and unimportant information leading to less effective decision-making processes (Grover, Lim, and Ayyagari 2006).

Therefore, firms might not always combine the right type of monitoring process of alliance partners with levels of information exchange and this mis-match can be negatively linked to performance (Musarra, Robson, and Katsikeas 2016). Also, too much interaction with other firms can reduce a firm’s ability to conduct activities critical to facilitating positive performance outcomes (McFadyen and Cannella Jr 2004). As such, heavy reliance on other organisations, collaborations, alliances, and partnerships to develop disruptive business models is negatively associated with organisational new product and market performance.

Also, market signals detected by organisations can be temporal as some consumer trends fade away as quickly as they come and this can be reflected in environmental dynamism. Meeran *et al.* (2017) argue that consumer preferences vary over time and assuming static preferences can lead to inaccurate market share forecasts. Hence, heavy dependence on market signals, past consumer data, and past market experiments to develop disruptive business models can negatively affect new product performance and market performance. This is in line with Zhou and Li (2010) who argue that in dynamic environments, an overriding focus on specific resources can result in reduced flexibility in decision making.

In sum, organisational forecasts of future consumer demand based on present and past trends can be misleading especially when developing disruptive business models. Additionally, heavy reliance on collaborations, alliances, partnerships, and even market experiments can provide the wrong signals to organisations about market occurrences and consumer preferences. This is buttressed by our findings that indicate a negative and significant moderating influence of adaptive marketing capability on both the disruptive business model–new product performance relationship and the disruptive business model–market performance relationship.

6.1.6 Additional Analysis

The additional analysis conducted based on industry type point to various implications for organisations. The findings indicate that for manufacturing firms, top managerial risk-taking propensity, and management commitment to innovation are important for developing disruptive business models. For service firms, willingness to cannibalise and top managerial risk-taking propensity are positively related to the development of disruptive business models. However, only top managerial risk-taking propensity is positively and significantly related to disruptive business models for firms that engage in both manufacturing and services. These findings indicate that top managerial risk-taking propensity is crucial irrespective of industry affiliations. Therefore, the need for managers to take risky decisions in uncertain environmental conditions and outcomes is fundamental to the successful development of disruptive business models.

Furthermore, the additional analysis conducted based on organisational size show that in small firms, willingness to cannibalise, top managerial risk-taking propensity, and management commitment to innovation are positively and significantly related to disruptive business models. For medium-sized firms, only willingness to cannibalise had a positive and significant relationship with disruptive business models. In large firms however, formalisation, willingness to cannibalise, top managerial risk-taking propensity, and management commitment to innovation are positively associated with disruptive business models. Thus, willingness to cannibalise shows a constant positive relationship with disruptive business model irrespective of organisational size. Policy makers can use the insights from this study in advocating policies that offer recommendations on best practice when developing and implementing disruptive business models.

6.2 Theoretical Contributions, Contributions of the Study, and Implications

The importance of disruptive business models has been discussed extensively in the existing literature especially due to the increased pressures faced by organisations to ensure organisational survival, competitive advantages, and positive performance outcomes. As a result of this, organisations now view the introduction of disruptive business models as a strategic tool that can be maximised to achieve increased market share, sales, and profitability. Similarly, the debates on disruptive business models have received increased attention in academic circles. As a result, academics have begun examining disruptive business models and various attempts have been made to gain in-depth knowledge and understanding on their nature, drivers, outcomes, and contingency effects.

Extant literature has examined some drivers of disruptive business models such as disruptive technologies, willingness to cannibalise, autonomy, and risk-taking behaviour

(Karimi and Walter 2016; Osiyevskyy and Dewald 2015; Velu and Stiles 2013). Another stream of research has examined the outcomes of introducing disruptive business models, specifically, financial, new product, consumer, and market performance outcomes (e.g., Gilbert and Bower, 2002; Danneels, 2004). However, many of studies on disruptive business models are atheoretical (Osiyevskyy and Dewald 2015) and an accepted operational measure is yet to be utilised to empirically examine disruptive business models (Habtay 2012).

Due to these limitations in past literature, this thesis makes a significant contribution by developing an integrated model that incorporates the drivers of disruptive business models, its outcomes, and contingency factors based on the RBV and Disruptive Innovation theory. Furthermore, a novel operational measure of disruptive business models was used in this study. The first phase of the research included in-depth interviews conducted with 23 top level managers in various industries across the UK and the second phase of the research was a survey of 360 managers in both manufacturing and service industries in the UK.

As such, this study links disruptive business models to the RBV and Disruptive Innovation theory and provides an explanation on why organisations create and implement disruptive business models. This research extends the RBV to the disruptive innovation and disruptive business model literature by conceptualising disruptive business model as an organisational capability that can be utilised to achieve sustainable competitive advantages in various industries of operation. Thus, this study views disruptive business models as a unique, valuable, rare, heterogenous, and immobile capability at the disposal of an organisation. The ability of an organisation to successfully develop and commercialise a disruptive business model is non-substitutable and cannot be easily exchanged among firms. Thus, this provides firms with competitive advantages, increased new product performance, increased market performance, and the possibility for future financial benefits.

One of the major contributions of this study is the adoption of a novel operational measurement for disruptive business models as this can advance future research on disruptive business models in various industrial settings and contexts. In addition, this study proposes that organisational capabilities moderate the relationship between disruptive business model and performance. This is in line with the RBV that argues that organisations possess rare, valuable, non-substitutable resources, assets, and capabilities that are heterogenous in nature and provide sustainable competitive advantages (Barney 1991; Grant 1996).

6.3 Limitations and Future Research Directions

As any study, this research has some limitations. However, these limitations can serve as possible avenues for future research. *First*, this is a cross-sectional study and one major limitation is the inability to make causal inferences. As such, longitudinal data, in spite of its limitations can help to increase confidence in findings (Rindfleisch et al. 2008).

Second, cross-sectional data is subject to concerns about common method bias due to sourcing for information (e.g., through surveys) from a single respondent at a single point in time. In order to mitigate this, various steps were taken to reduce this possibility such as using a marker variable and conducting statistical analysis to ensure that common method bias did not pose a serious threat to the validity of the findings. Nevertheless, this research can be advanced by conducting a longitudinal study with multiple organisational informants that examines the effect of disruptive business models on performance over time. This will help to comprehensively resolve the methodological issues with this research and test the antecedents, consequences, and contingency effects of disruptive business models.

Third, this research was conducted in the UK, a developed economy that boasts of highly competitive industries that pave the way for innovative practices within organisations.

The UK is among the top ten competitive countries in the world and the fourth most competitive economy in Europe (Schwab 2018). As such the findings of this study might be unique to this national context and other similar settings (e.g., United States, European Union). Efforts were made to include as many industries as possible, however this was not exhaustive. Thus, the findings of this study need to be applied with caution to other contexts, countries, and settings.

Future research can examine the conceptual model of this study in emerging and developing economies in order to make comparisons on the impact of disruptive business models on performance in both developed and developing economies (Corsi and Di Minin 2014). This is especially important as disruption can exacerbate the divide between developed and developing nations especially when it involves disruptive technologies such as ICT convergence (Yovanof and Hazapis 2008). Examining developing and emerging economies is crucial as their competitive landscape and growth opportunities differ from developed economies (Story, Boso, and Cadogan 2015) and they can sometimes outgrow developed economies (Luo and Tung 2007).

Fourth, single key informants were used in this study to gather data. Even though extensive efforts were implemented into identifying and scrutinising the appropriate key informants such as the key informant competency test, this limitation cannot be overlooked. Thus, future research can examine the effect of having multiple key informants in each organisation on the findings gotten regarding the relationship between disruptive business model and performance. Also, having multiple informants can help to reduce the possibilities of common method variance and enable studies make causal inferences (Jap and Anderson 2004; Podsakoff et al. 2003).

Fifth, this study examined subjective managerial perceptions of performance outcomes as opposed to objective performance information. Having access to objective data will be ideal to investigating the relationship between disruptive business model and performance, however, access to this data was not a valid possibility for this study. Furthermore, access to different forms of data can facilitate triangulation to ensure validity of research findings (Rindfleisch et al. 2008).

Sixth, although the choice of factors that drive a disruptive business model was appropriate for this study because they are within the control of the organisation, it might be useful to empirically examine external factors that can be related to a disruptive business model. Hence, it will be interesting for future research to extend the conceptual model by collecting data on external factors that can be related to the development of a disruptive business model. Some interesting external factors unearthed in the in-depth interviews conducted that can be examined include competitive intensity (Jaworski and Kohli 1993), technological turbulence (Jaworski and Kohli 1993), market turbulence (Guo et al. 2018), and regulatory forces (Katsikeas, Samiee, and Theodosiou 2006). These factors can significantly influence organisational operations to conform to industry changes, standards, and regulations (Alvesson and Spicer 2019).

Seventh, examining the potential quadratic effects of disruptive business model on performance can be a fruitful area for future research. It would also be useful to include additional control variables to the conceptual model examined in this study to mitigate omitted variable bias and account for other factors that can influence the development and success of disruptive business models. Some controls that can be included include annual sales, percentage of profits from new products, percentage of sales from new products, and R&D spending as a percentage of sales.

Eighth, this study examines two capabilities as moderators of the disruptive business model–performance relationship. Future research can investigate into other organisational and marketing capabilities to find out which capabilities have a positive/negative impact on the disruptive business model–performance relationship. Also, future research can further investigate into the reasons for the negative moderating influence of adaptive marketing capability on the disruptive business model–performance relationship.

Finally, given the recent Covid-19 Pandemic it will be incredibly useful to explore whether firms with disruptive business models are better in handling global crises such as this than their counterparts. Analysis of performance data before and after the crisis can help shed light into this very important issue. Furthermore, many organisations had to make drastic and significant changes to their working patterns, working schedule, and ways of delivering value to consumers and these might have necessitated the development of disruptive business models. The importance of disruptive business models that meet consumer needs is more relevant than ever before considering the changes organisations were forced to make to ensure continued value creation, provision, and delivery to consumers.

It will therefore be interesting to evaluate how organisations responded to the pandemic, the disruptive business models that were birthed as a result of the pandemic, and their success rates during and after the pandemic. Thus, future research can evaluate the viability of disruptive business models developed as a result of the COVID-19 crisis to provide a roadmap about how organisations can successfully remain competitive and successful in the face of global disruption. Furthermore, the relationship between disruptive business model and performance can also be compared with the relationship between circular business models (that are environmentally sustainable) and performance (Oghazi and Mostaghel 2018).

6.4 Conclusion

This study examines the antecedents and performance outcomes of disruptive business models on one hand and the contingency effects of organisational capabilities on the disruptive business model–performance relationship on the other hand. The interview findings show that the major external drivers of disruptive business models are technological advancements, political uncertainty and government regulations, competitive pressures, the press and media, and consumer dynamism. In addition, the survey findings show that there are four main drivers of disruptive business models which include formalisation, management commitment to innovation, top managerial risk-taking propensity, and willingness to cannibalise. Organisations need to ensure that a level of formalisation exists within the organisations, the top management team is willing to take financial risks, resources are allocated to innovative activities, and there is a willingness to cannibalise existing resources, capabilities, assets, infrastructural facilities, sales, and profits.

Furthermore, finding show that disruptive business model is positively related to new product performance and market performance. In addition, new product performance and market performance are positively related to anticipated financial performance. Therefore, implementing and developing disruptive business models is beneficial to organisations regardless of the industry of operation or the kind of consumer base served.

The results also indicate that adaptive marketing capability inhibits the successful implementation of disruptive business models while big data analytics capability facilitates the successful implementation of disruptive business models. The implications of these findings for researchers and theory, organisations, managers, and policy making were discussed, the limitations of this study were highlighted, and future research directions of the study were proposed.

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