ORGANIZATIONAL AMBIDEXTERITY AND GREEN INNOVATION: THE MODERATING EFFECT OF BIG DATA ANALYTICS CAPABILITY IN THE CONTEXT OF CHINA

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ABSTRACT

With pressure from consumer preference, societal expectation and regulatory policies, firms are increasingly integrating green business practices to achieve financial success. Although green innovation (GI) is regarded as an essential strategic element in helping firms to address environmental challenges, there is a lack of research on whether ambidexterity can be adopted to improve two key GI practices, namely green product innovation (GPDI) and green process innovation (GPCI). Meanwhile, with the rapid development of disruptive innovation, technologies like big data analytics have been widely adopted into product innovation, yet the impact of big data analytics capability (BDAC) as a dynamic capability of environment management remains unclear. Drawing on theories such as Resource Based Theory, Knowledge Based View, and Information Processing View, this study developed a theoretical model of GI success that aims to investigate the direct impact of ambidexterity and the moderator role of BDAC on GI. The model also investigates the overall impact of GI on firm's financial, environmental and social performance. The model was tested with survey data collected from 375 Chinese firms. Surprisingly, the empirical results suggest that ambidexterity does not improve GI. In particular, the findings indicate that ambidexterity is negatively associated with GPDI and that there is no association between ambidexterity and GPCI. Regarding to the moderator roles of each type of BDAC in the relationship between ambidexterity and GI, Big data analytics infrastructure (BDAI) and big data analytics personnel (BDAP) have a positive and significant influence on the relationship between ambidexterity and two types of GI. This indicates that the development of BDAI and BDAP has the potential to lessen the negative relationship between ambidexterity and GPDI and to have a positive influence on the relationship between ambidexterity and GPCI. The findings also demonstrate that big data analytics management (BDAM) has no impact on the relationship between ambidexterity and two different GI categories. Additionally, existing literature doesn't adequately examine under what conditions GI can be achieved from a holistic perspective. In order to fill this gap, this study also employs a fuzzy-set qualitative comparative analysis to examine how exploitation and exploration interact with BDAC to produce higher levels of GI. Different configurations are presented for both small and medium enterprises, and large firms, indicating that the same configuration of ambidexterity and BDAC practices lead to high levels of GPDI and GPCI. Outcomes highlight the inter-relationships between ambidexterity and BDAC practices and provide suggestions that firms regarding orchestrating resources in achieving GI.

Keywords: ambidexterity, green product innovation, big data analytics capability, triple bottom line, empirical research

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LIST OF ABBREVIATIONS

AVE – Average Variance Extract

BDA – Big data analytics

BDAC – Big Data Analytics Capability

BDAI – Big Data Analytics Infrastructure Capability

BDAM – Big Data Analytics Management Capability

BDAP – Big Data Analytics Personnel Capability

CFA – Confirmatory Factor Analysis

EFA – Exploratory Factor Analysis

EP – Environmental Performance

FP – Financial Performance

FsQCA – Fuzzy-set qualitative comparative analysis

GI – Green Innovation

GPCI – Green Process Innovation

GPDI – Green Product Innovation

IPV – Information processing view

KBV – Knowledge-based view

PDAM – Product Development and Management Association

RBT – Resource-based theory

SMEs – Small and Medium Sized Enterprise

SEM – Structural Equation Modelling

SP – Social Performance

UNFCCC – United Nations Framework Convention on Climate Change

CHAPTER 1 INTRODUCTION

1.1 BACKGROUND

In recent decades, environmental management concerns have received a lot of attention from both academics and practitioners. One major driver of environmental development is compliance with the environmental laws and regulations. In response to pressures from the national and international authorities and organisations, it is becoming increasingly necessary for firms to implement relevant policies and integrate greenness into the entire product lifecycle when making the decisions relating to product and process (Chiou et al., 2011). For instance, the 2015 United Nations Framework Convention on Climate Change (UNFCCC) resulted in the Paris Agreement, which serves as a blueprint for future legislation and environmental protection activities whilst having a considerable impact on firm behaviour.

Besides, due to the serious environmental harm caused by industrial manufacturing operations, there is a greater customer consciousness of environmental protection which has resulted in considerable changes in stakeholders' preferences, vis a vis the tendency to purchase green products. In other words, firms are under intense pressures to minimise the environmental impact of their processes and products from a variety of stakeholders, such as governments and customers. However, stakeholders often have conflicting motivations, purposes, and emphases when it comes to sustainability issues, adding to uncertainty for firms (Dangelico et al., 2013). Taking the car manufacturing industry as an example, the United States Office of Energy Efficiency and Renewable Energy announced dramatic sales growth for both hybrid and plug-in electric vehicles about 4 years after their market launch (Liu and De Giovanni, 2019). As a result of the dual pressure, a rising number of firms created various strategies to reduce their environmental effect while also contributing to environmental protection. In this context, green management has become a common business strategy for reducing environmental pressure and increasing competitiveness through the development of green capacities (Dangelico et al., 2017; Ottman et al., 2006).

In China, development has been disturbed by environmental deterioration for years. Since China joined the WTO from December 2001, the emission of carbon dioxide has increased dramatically, and the production of carbon dioxide equivalent greenhouse gases have exceeded the threshold that can potentially cause serious climate change (Tang et al., 2018). Besides, the amount of good quality underwater quality is decreasing from 39% to 37% from 2012 to 2016, and excessive emission of polluted water has caused the amount of drinkable water to decrease (D. Zhang et al., 2019). With the environmental problems brought by economic development, innovation should be encouraged to respond to globalisation and environmental challenges. However, With the increasing awareness of environmental protection, the Chinese government has also made environmental protection one of its key policies. As one of the signatories of UNFCCC, China has formally agreed to reduce carbon dioxide emissions per unit of GDP by 65 percent (compared to 2005 levels) by 2030 (Zhang et al., 2021). Furthermore, the Ministry of Ecology and Environment was promoted by the Chinese State Environmental Protection Administration in July 2018, with the goal of improving environmental quality and building a beautiful China through the formulation and implementation of national ecological and environmental legislation related to water and air quality, solid waste management, nature protection, and nuclear/radiation safety in collaboration with other government departments (Q. Zhang et al., 2019). Therefore, the study of how to improve environmental management in the Chinese context is of high value and practicality (Tang et al., 2018; Zhang et al., 2021).

As an important part of green management, green innovation (GI) has been applied to deal with the pressures of environmental regulation and consumer preference (Chiou et al., 2011; Tang et al., 2018; Zhang and Walton, 2017). GI is understood as improvements in product design and manufacturing processes that save energy, reduce pollution, minimise waste, and reduce a firm's overall negative impact on the environment. Thus, it provides value to both businesses and customers, while also dramatically reducing negative environmental consequences (OECD, 2009; Tang et al., 2018). GI practices are important for firms since the market has high expectations with respect to environmental concerns and regulation places significant constraints on a firm's overall performance (Sun et al., 2020). In contrast to conservative innovations, GI provides new solutions to satisfy customers' current and future needs regarding environmental protection, and also to obtain a sustainable competitive advantage (Pujari et al., 2003). Therefore, there is a call for firms to constantly invest in GI with the purpose to reduce emissions, save energy in production, cut down waste, manage pollution, take advantage of recycled products, and more generally enhance environmental performance (Liu and De Giovanni, 2019).

Existing research has argued that GI is necessarily more complex and therefore difficult to achieve. From an external perspective, green markets received more regulatory interventions, especially from the development of renewable energy. Besides, regulations change quickly and unpredictably, also leading to higher uncertainty in the market. These uncertainties increase entrepreneurial risk and keeps some firms away from making GI investments. Besides, the green market is still at an early stage of development and most likely to focus on different functions compared to mature markets; in general, young market are usually more volatile (Wicki and Hansen, 2019). From the firm perspective, GI is more directional and expected to have a strong environmental impact, which could lead to less emphasis to the functionality of the product (Hansen et al., 2019). Moreover, developing GI is complicated since there are usually several paths to be walked down before one GI is effectively realised, which means that a few separate innovations are embedded to create one successful GI. As a result of these factors, only few firms are able to effectively develop GI.

The increasing attention on GI means that much is discussed about the field's antecedents, practices, and success factors (Chen et al., 2006; Kawai et al., 2018; Kraus et al., 2020). Nevertheless, research reports that manufacturing firms still have difficulties making products or processes greener (Peters and Buijs, 2021). In this study, ambidexterity, which refers to the simultaneous employment of exploitative and explorative activities, is examined with regards to its antecedent role in promoting GI. The reason this paper examines ambidexterity is that prior research suggests that it is very difficult for organisations to survive or succeed without engaging in both exploitation and exploration (Peter and Buijs, 2021; Gomes et al., 2020; Wei et al., 2014b; O'Reilly and Tushman, 2008). In fact, some researchers have provided empirical evidence in support of ambidextrous organisation being more capable of excelling in innovation, that is, exploring new opportunities for radical innovation and exploiting existing products for incremental innovation (Andriopoulos and Lewis, 2009). More specifically, exploitative activities centre on meeting the requirements of existing customers and markets, by developing existing knowledge and skills, improving on established designs, products, and services, and increasing the efficiency of existing distribution channels; while exploratory innovation seeks new resources or knowledge that differs from what comes before, and it brings new designs and products while encouraging firms to enter new markets or create new channels of distribution to meet the needs of emerging users or markets (Benner and Tushman, 2003; Raisch and Birkinshaw, 2008). We draw from the above literature to examine how organisational ambidexterity as a strategy can help firms respond to environmental opportunities and undertake GI.

In addition to examining whether the interplay of exploitation and exploration can facilitate GI, another distinct research objective in this study is to understand the role of big data analytics capability (BDAC) in the relationship between ambidexterity and GI. Due to recent rapid technological development, firms are able to harvest a huge amount of data from various sources and identify patterns within “Big Data”, with a significant implication on dynamic capabilities, competitiveness and, more broadly, firm performance (Braganza et al., 2017). Big data analytics (BDA) describes a holistic approach to manage, process, and analyse data to create valuable ideas that enhance performance and establish competitiveness (Wamba et al., 2015). According to Mikalef et al. (2018), there is a need for firms to leverage the rapidly expanding data in terms of volume, velocity, and variety, qualifiers that can be applied to techniques and technologies for data storage, analysis, and visualisation. Other studies also emphasis that this type of dynamic capabilities enable to create, extend, and modify the ways in which firms innovate and function in changing and uncertain situations (Helfat and Peteraf, 2003; Teece et al., 1997).

Nevertheless, only recently have scholars begun to pay attention to the capabilities firms need to adapt their GI practices. For instance, Mousavi et al. (2019) claim that sensing, seizing, and transforming are three key dynamic capabilities to significantly influence a firm's sustainability-oriented innovation processes. These capabilities are also key for recognising GI opportunities (Demirel and Kesidou, 2019). However, the scarcity of empirical evidence on BDAC from the IT-business perspective makes it difficult to appreciate the green value of BDAC in a business environment, and leaves practitioners struggle to understand it conceptually, and uncertain about the implementation of such initiatives in their firms. Therefore, it is important to understand the role of BDAC in environmental management and how it affects GI. This paper acts to bridge existing knowledge gaps in the literature, drawing upon prior BDAC studies to clarify the concepts of BDAC and conduct an empirical analysis to uncover the role of BDAC in GI. Specifically, we focus on firms who apply big data capability technologies in their GI. Therefore, the second aim of this research is to examine the moderating role of BDAC on the relationship between ambidexterity and GPI.

Previous research has understood the influence of BDA on business growth, drawing on resource-based theory (RBT), the knowledge-based view (KBV) and information processing view (IPV) (Wang et al., 2019). RBT has been used to conceptualise the BDAC by orchestrating tangible and intangible big data and human resources to business processes, therefore explaining how BDAC impacts operational and strategic operations (Gupta and George, 2016; Wamba et al., 2017). Some scholars have drawn on KBV to explain why BDA can be used to acquire and harness firms' knowledge effectively, while also allowing firms to improve organisational agility and competitiveness (Côrte-Real et al., 2017). A number of scholars adopted IPV to understand how to use BDA to manage task complexity and adapt to ever-changing environments through information-processing mechanisms (Srinivasan and Swink, 2018). However, limited research has explored the full complexity of BDAC implementations or examined under what conditions BDAC can help to achieve GI from a holistic perspective, especially in the context of Chinese firms. Grounded in previous research which states that deriving value from BDA requires the orchestration of complementary organisational resources, this study further examine the relationship between ambidexterity, BDAI and GI by arguing that, depending on the context of examination, certain BDAC aspects implemented with exploitation and/or exploration may have greater or lesser significance in GI (Gupta and George, 2016; Mikalef et al., 2019). Complexity theory and configuration theory are adopted to suggested that organisations can develop different approaches to leverage their BDAC resources alongside exploitation and exploration towards the attainment of sustainable goals (Woodside, 2014). A configurational approach is applied through the methodological tool Fuzzy-set qualitative comparative analysis (fsQCA) to examine this complex phenomenon.

Last but not least, although the empirical discourse examining the relationship between sustainable development and firm performance has grown, the results are inconclusive. Green management approaches, particularly GI, may not be cost effective. To persuade a practitioner to conduct GI practices, it is vital to clearly describe what benefits it could bring to the firm. As a result, it is worthwhile to investigate how the adoption of GI affects organisational performance. Meanwhile, the lack of an underpinning theoretical framework and difficulties in obtaining data have been identified as barriers to further understanding the association between environmental practices and firm performance (Dangelico and Pujari, 2010; Zhang and Walton, 2017). To address this, the study also focuses on firms' triple bottom line, which includes environmental performance (EP), social performance (SP), and financial performance (FP). Particularly, due to the limited and inconclusive empirical studies in the relationship between GI and FP, the indirect effects of GI in improving FP via EP and SP are examined.

1.2 OVERVIEW OF RESEARCH GAP

One particular research gap that has remained unclear is the association between adopting ambidexterity and achieving GI (Hojnik et al., 2018; Kawai et al., 2018). Although a handful of papers tried to investigate this question, few has focused on a specific strategy, i.e., ambidexterity, as an antecedent to improving GI. Since previous research generally supports that organisational ambidexterity has been proven to significantly affect innovation (Andriopoulos and Lewis, 2009; Gibson and Birkinshaw, 2004; He and Wong, 2004), this study further extends the field of research and justifies whether ambidexterity can also be applied to support firms' GI.

Another research gap is the lack of understanding of how the adoption of BDAC has transformed businesses (Wamba et al., 2017), especially in the area of green management. The concept of Big Data has attracted the attentions of scholars in Operations Management, and studies have provided evidence that the use of Big Data can improve profitability by exploiting data holding and data analytics (McAfee and Brynjolfsson, 2012a). There is not much existing literature that seeks to understand the ever-changing managerial processes as a result of adopting data-led strategies (Sena et al., 2019). In spite of its practical relevance, there is still a calling for a clear understanding of how management research conceptualises BDAC, and more importantly, how this data-driven management mechanism could work well with ambidexterity to achieve better GI. Besides, there is limited research that is capable of explaining the full complexity of BDAC implementations or examining how and under what conditions BDA can work with other strategies to achieve GI from a holistic perspective. Therefore, another method, fsQCA, is also applied to further discover how exploitation, exploration and BDAC can work together to improve GI.

A third gap in the literature is understanding the impact of GI on a firm's triple bottom line. Researchers and stakeholders typically view GI as a beneficial operation in which green-oriented firms achieve better performance in business practice (Tang et al., 2018; Tseng et al., 2013; Zhang and Walton, 2017). Financial and environmental performance have attracted the attention of most academics (de Giovanni, 2012). However, the relationship between GI and firm's financial performance is controversial (Chan et al., 2016a; Huang and Li, 2017), and knowledge about how firms contribute to society is limited. Moreover, there is limited research that considers the impact of GI on the three dimensions of performance: financial, environmental, and social. It is important to understand the triple bottle line of business as it reflects the accumulating anecdotal evidence of greater long-term profitability, and its core value of sustainability has become compelling in the business world. Given that the willingness of firms to integrate green management into their operations is highly influenced by the promise of better performance, it is important to provide empirical evidence on how triple bottom line is influenced by GI.

1.3 RESEARCH QUESTIONS AND RESEARCH OBJECTIVES

Based on the research gaps above, this study strives to answer the following four research questions in order to contribute to the knowledge in the area of GI. The main research questions are stated as follows:

- RQ1: Does ambidexterity as an underlying antecedent positively influence GI?
- RQ2: Does BDAC moderate the relation between ambidexterity and GI?
- RQ3: Under what conditions, can exploitation, exploration and BDAC help to achieve high level of GI?
- RQ4: Does GI bring a firm better performance in the context of China?

Besides, the main research objectives are stated as follows:

- RO1: To examine the relation between ambidexterity and GI on a large-scale basis.
- RO2: To understand the role of firm's BDAC between ambidexterity and GI, and to evaluate the value to develop this capability for achieving higher GI.
- RO3: To discover the combinations of elements that enable firms to achieve high level of GI.
- RO4: To investigate the influence of GI on firm's triple bottom line.

RO1 aims to validate the impact of ambidexterity as an antecedent to improve GI. RO2 aims to understand the moderator role of BDAC in the association between ambidexterity and GI from a dynamic capability point of view. RO3 aims to examine the different patterns of elements including exploitation, exploration, and BDAC that lead to high performance of green produce innovation (GPDI) and green process innovation (GPCI). Specifically, element refers to variable in fsQCA. Core elements indicate a strong causal relationship with the outcome, and peripheral elements indicate a weaker relationship (Fiss, 2011). RO4 aims to investigate the effect of GI on firm financial, social and environmental performance.

In attempt to answer these questions, this study builds a theoretical model with rational measurement scales that supported by RBT, KBV, and IPV. Then the model is tested with a sample of 375 survey response from senior managers and director in Chinese firms. Structural equation modelling (SEM) is conducted to simultaneously examine the relationship between ambidexterity and GI, the moderator role of BDAC in the association between ambidexterity on GI, and the impact of GI on firm performance. Considering that a particular outcome may be caused by different combination of elements, and that these combinations of elements may differ depending on context, this research then employs configurational approach through a novel methodological tool fsQCA to examine the patten of exploitation, exploration and BDAC, and other organisational elements simultaneously combine to achieve high levels of GPDI and GPCI. This method complements the results of SEM by investigating the complex phenomena and shows the interplay of element of a messy and non-linear nature (Mikalef et al., 2019).

1.4 SCOPE OF RESEARCH

This research concentrates on the development of GI in China. Since global warming and environmental degradation continue to pose severe challenges to the workforce, GI has grown in popularity in recent years. Firms can capture benefits in product design and manufacturing processes that save energy, reduce pollution, avoid penalties, and lessen negative effect on environmental protection by achieving a higher degree of GI (Tang et al., 2018). There is no question that turning green has become increasingly important; yet, there are a few reasons why enterprises in China face challenges in attaining GI. To begin with, innovation is often expensive; strong investment in green innovation may result in greater costs than rivals, resulting in an unsustainable market position (Dangelico, 2016). Furthermore, China is still in the stage of rapid development, and achieving short-term benefit is usually more appealing than pursuing long-term success. However, green innovation takes a long time to develop and may not yield large profits, so firms lack economic incentives to achieve in this region (Song et al., 2020).

Consider the challenges that businesses face while generating green innovations, that is, breaching environmental norms and regulations can result in corporate closure, and failing to fulfil consumer wants and public expectations can also result in significant economic losses. At the same time, firms are also being advocated to develop green innovations in a broader policy context. Research on how to guide firms in effectively developing green innovation can assist them in resolving this dilemma. Because the majority of GI research has undertaken in Europe, and most academic studies have focused on developed nations, research in developing countries such as China has been insufficient (Dangelico et al., 2017), more empirical GI research in emerging markets has been required (Zhang et al., 2021).

The study follows the streams of Chen et al. (2006) and Tang et al. (2018) that classify GI into GPDI and GPCI; this distinction does not include other types of GI examined in other research, such as green technological innovation and green managerial innovation. Also, different types of ambidexterity can be found in management literatures, so it is worthwhile to state that this study follows the study of Cao et al. (2009) and focuses on the combined dimensions of ambidexterity. The research scope does not aim to develop new methods to improve big data analysis capabilities, but to verify whether proposed big data analysis can improve GI.

1.5 SIGNIFICANCE OF THIS RESEARCH

This research presents a theoretical model to enrich previous studies on the antecedents and consequences of GI. The findings will contribute to the general literature on GI and growth by concentrating on firm-level data. The study first looks at the direct influence of ambidexterity on GI. This study will have an impact on the development of GI in China, as many firms are having problems implementing exploitation and exploration in order to achieve operational excellence and GI efficiency. This study will also determine the role of BDAC from the perspective of dynamic capacity and assess its efficacy in contributing to the association between ambidexterity and GI. This is the first quantitative research to analyse the relationship between ambidexterity and different forms of BDAC in achieving GI, and it will be useful to more businesses as more firms incorporate DBAC into seeking GI. Furthermore, this study examines the relationship between GI and company performance. Firm performance improvement indicates attempts to focus not just on economic goals, but also on environmental and social implications. Given the common understanding that GI may enhance the environment, our empirical conclusion will demonstrate whether GI of Chinese manufacturing firms can produce long-term advantages for the triple bottom line. Additionally, in order to further provide evidence of how different relational aspects interact with each other to create high performance in GI, the configurations of elements are also identified in this study. To the best of my knowledge, as yet, no previous studies have considered the complex interactions among ambidexterity, BDAC and other organisational elements driving GI in the Chinese context. This research therefore adds values to the IG development in China by extending and deepening the understanding of how ambidexterity and BDAC can be implemented to improve GI in practice, as well as the impact of GI on firm performance. The results of this research can be used as the basis for practical guidance for practitioners, outlining a variety of paths that they can follow, depending on their specific circumstances. Additionally, from a standpoint of methodology, this study adds value by demonstrating the complementary of fsQCA on regression-based methods. Since the regression-based technique is appropriate for describing the causal paths by which factors influence GI, fsQCA provides a more in-depth justification of the complex, non-linear, and synergistic effects of ambidexterity, BDAC, and other organisational elements on firm's GI.

1.6 CHAPTER OUTLINE

The thesis comprises of eight chapters. The first chapter is the introduction which has provided the incentive for this study and outlined its key aims and research questions. Chapter 2 considers the theoretical perspective of the study and provides an in-depth review of existing literature in GI, ambidexterity, BDAM and firms' triple bottom line. Then, the development of the theoretical model and hypotheses will be presented in Chapter 3. In the next two chapters, the two different methodologies adapted in this study, SEM and fsQCA, are explicitly explained. In Chapter 5, the philosophical foundation of the research methodology is presented to explain why quantitative methods are used in this research. Then, the flow of scale development and different techniques used in survey study are illustrated, e.g., Equation Factor

Analysis (EFA), Confirmatory Factor Analysis (CFA), and SEM. This is followed by the results of the model in Chapter 5, which includes the direct impact of ambidexterity on GI (i.e., GPDI and GPCI) and the moderator role of three types of BDAC in the relationship between ambidexterity and GI. In Chapter 6, the fsQCA methodology is described and the configurations that lead to high GPDI and GPCI performance are presented. The next section further discusses the results of SEM and fsQCA, and also presents the theoretical and practical contributions of the study. Finally, Chapter 8 concludes this study, explains its limitations, and offers recommendations for future research in this field.

CHAPTER 2 LITERATURE REVIEW

2.1 INTRODUCTION

Green innovation (GI) is a form of innovation that focuses on making significant and demonstrable progress toward the objective of sustainable development, such as lowering environmental impact or achieving more efficient and responsible use of natural resources (European Commission, 2008). Given GI is new to many established firms, it is uncertain how to incorporate green practises into product and process innovation. Ambidexterity has been offered as an effective strategy to increase organisational learning and accomplish innovation (O'Reilly III and Tushman, 2013; Raisch and Birkinshaw, 2008), however research on its influence on GI has yet to be completed. As a result, based on relevant research, this chapter describes the underlying processes of ambidexterity and demonstrates the link between ambidexterity and GI. On the other hand, with the rising utilisation Big Data in product and process innovation, effective big data analytics capability (BDAC) is recognised to enhance knowledge development and forecasting, allowing to meet environmental standards and market expectations. Despite the fact that several types of BDAC are described in the literature, the debate might be extended to their value in reaching GI (Gupta and George, 2016). This chapter examines BDAC from a dynamic capacity viewpoint and describes the generally utilised theories to expose the value of BDAC in realising sustainable goals for organisations.

Aside from identifying the practises that could enhance GI, the outcomes of GI are equally significant since improving firm performance is what motivates firms to embrace GI. That's being said, firms will only invest in GI if it is beneficial, hence it is critical to ensure that the objective of GI is incentive-compatible (Tang et al., 2018). The question then becomes whether investments in environmentally friendly innovation can boost business success. Current literature yields inconsistent conclusions that are highly dependent on sample size, analytic technique, and empirical design (Fernando et al., 2019; Huang and Li, 2017; Palmer et al., 1995). Therefore, this dissertation research seeks to draw a parallel with a theoretical foundation on which practices potentially enhance GI, as well the impact of GI on firm performance in the context of China.

This chapter discusses the literature review, which includes presenting concepts and existing research related to this dissertation. By critically analysing the existing knowledge, this chapter exposes limits of perspective of view, and further identifies research gaps. This chapter is structured into six main sections. Section 2.2 describes previous research on GI that addresses environmental concerns, as well as a full discussion of two fundamental features of GI, green product innovation (GPDI) and green process innovation (GPCI). Following that, the study discusses the fundamental mechanism of ambidexterity, as well as the relationship between ambidexterity and GI in section 2.3. In section 2.4., this study analyses research related to BDAC from the standpoint of the dynamic capability, and also presents the key elements of BDAC. Section 2.5 further reviews and discusses relevant theories, including resource based theory (RBT), Knowledge based view (KBV) and information processing view (IPV) in order to better comprehend the business value of BDAC. These theories are included in the literature review as they are utilised to support the arguments in later chapters. In section 2.6, the research gaps that this study aims to fill are highlighted. Last but not least, chapter 2 is concluded in section 2.7.

2.2 GREEN INNOVATION IN CHINA

2.2.1 Innovation

Based on a systematic review of literature published over the past three decades, Crossan and Apaydin (2010) defined innovation as “production or adoption, assimilation, and exploitation of a value-added novelty in economic and social spheres; renewal and enlargement of products, services, and markets; development of new methods of production; and establishment of new management systems. It is both a process and an outcome”. Innovation refers to the multi-stage process whereby organisations transform ideas into new and improved products, services, or processes, with the purpose to advance, compete and differentiate themselves successfully in their marketplace (Baregheh et al., 2009).

Since innovation is a necessary but challenging managerial responsibility, it requires an intricate knowledge management process to identify and utilise new ideas, tools, and opportunities, then firms are able to generate new ideas or improved products and process (Andriopoulos and Lewis, 2009). Furthermore, innovation considers environmental, social, and economic factors, and provide new way of processes, operating procedures and practices, business models and systems thinking (Adams et al., 2016). The research of innovation mainly covers aspects like new product innovation (Bouncken et al., 2018; Mothe et al., 2018), new firm growth (Mas-Verdú et al., 2015) as well as process efficiency (Trantopoulos et al., 2017). With customer demand and lifestyle changes, innovation capitalise on these new opportunities by developing new technologies and organisational strategies to meet customer needs, which constantly create business advantages and economic growth for firms (Baregheh et al., 2009;

Wamba et al., 2017). Therefore, innovation is a critical for firms' survival and success.

2.2.2 Green innovation

Academics have Scholars have offered different reasons why GI needs to be developed (Kraus et al., 2020; Zhang et al., 2019; Qi et al., 2013). To begin with, legislation play a key role that drives such innovation activities. Many international and domestic regulations have been laid down to curb polluting behaviour in order to avoid worsening the situation (Bansal and Roth, 2000). Internationally, the most influential convention is the Paris Agreement of December 2015, where 195 countries signed a contract for environmental protection. In domestic, Chinese government made the environmental law to enforce strict penalties, for instance, the Environmental Protection Tax Law requires the enterprises or other operators who directly discharge pollutants to the environment to pay environmental pollution tax. Since penalties, fines, and legal costs have escalated over recent twenty years, firms can avoid expensive capital losses by obeying environmental regulations (Zhang et al., 2019).

Besides, stakeholders' demand for green products is also a motivator towards implementing GI practices (Qi et al., 2013). Having witnessed the damage that industrial manufacturing activities brings to the environment, more people believe that change human behaviour could save our environment. With decrease developing natural resourced have been accepted by raised by customers, local communities, environmental interest groups (Kraus et al., 2020), more stakeholders have gradually started to value products based on their environmental impact. Managers can avert negative public attention and earn stakeholder support by being responsive (Bansal and Roth, 2000).

Due to the above reasons, "going green" has gradually become a trend among companies, with a growing number of firms considering “green” as a core value. When merging environmental concerns in product innovation, researchers and practitioners have paid greater attention to GI, also known as eco-innovation. Many attempts have been made to define GI, as presented in Table 2.1. In general, these definitions stress that GI lessens the environmental effect produced by consumption and production activities, regardless of whether the main motivation for their development or deployment is environmental (Carrillo-Hermosilla et al., 2010).

Table 2.1 Definition of GI

Paper	GI definition
European Commission (2008)	Eco-innovation is the production, assimilation, or exploitation of a novelty in products, production processes, services or in management and business methods, which aims, throughout its lifecycle, to prevent or substantially reduce environmental risk, pollution, and other negative impacts of resource use (including energy).
Oltra and saint Jean (2009)	In a broad sense, environmental innovations can be defined as innovations that consist of new or modified processes, practices, systems, and products which benefit the environment and so contribute to environmental sustainability
OECD (2009)	Eco-innovation represents innovation that results in a reduction of environmental impact, no matter whether that effect is intended or not. The scope of eco-innovation may go beyond the conventional organisational boundaries of the innovating organisation and involve broader social arrangements that trigger changes in existing socio-cultural norms and institutional structures.
Tseng et al. (2013)	GI is the process of modifying an existing product design in order to reduce the negative impact on the environment during the product’s life circle assessment.

Chen et al. (2014)	GI is defined as new or improved practices, processes, techniques, systems, and products aimed at preventing or minimising environmental damages. These actions may involve energy-saving and pollution-prevention policies, as well as green product designs or configurations that facilitate waste recycling or corporate environmental management.
Huang and Li (2017)	GI is a type of innovation that brings to a decrease of reduce the environmental risk, pollution, and other negative impacts on resource use, without considering whether that is intended
Albort-Morant et al. (2017)	GI is a type of innovation whose main objective is to mitigate or avoid environmental damage while protecting the environment and enabling companies to satisfy new consumer demands, create value, and increase yields

Indeed, GI embraced dual goals of enhancing firms' sustainability performance and helping to solving societal issues, and firms need to seek out innovation in a certain direction to ensure that the results have a beneficial influence on sustainability. Environmental improvement ranges from incremental improvements by improving existing products and processes to a radically new product or process which have no harm to the environment (Rehman et al., 2021a). Through reducing their environmental impact, firms can integrate environment benefits and meet eco-requirements, so GI is deemed as a key strategic tool to maintain firms' long-term development in response to growing environmental pressure (Sun and Sun, 2021; Tang et al., 2018)

In order to further understand GI, different typologies of GI are proposed by academics. Chen et al. (2006) published the pioneering paper, which classified GI into GPDI and GPCI. GPDI refers to new or improved products that integrate environment concerns, such as green design, energy-saving, waste minimisation, and so on. GPCI means producing environmentally friendly products by eco manufacturing processes and systems, like waste recycling, energy-saving or waste recycling (Kammerer, 2009). Afterwards, Chen (2008) further divided GI into three categories, GPDI, GPCI, and green managerial innovation, in which GI focuses on the process of identification, implementation and monitoring, in order to increase the competitiveness of a process as well as enhance the environmental performance of a firm (Abdullah et al., 2016). Furthermore, green technology innovation was added into the type of GI in the research of Tseng et al. (2013), which emphasises the investment in green equipment and the installation of advanced green production technology.

Despite the fact that there are several classifications for GI, this article is in line with the studies of GI that classify GI into GPDI and GPCI (Chen et al., 2006; Kammerer, 2009; Tang et al., 2018). This typology stresses that GI strives to achieve harmony between environmental, economy and production processes through new or improved products or processes to conserve raw materials, energy, and resources. The reasons for choosing this classification are as follows: firstly, it is the most commonly used categorisation, and recent research, such as the article of Kraus et al. (2020), employs it. The second reason is that some publications divide green technology innovation into GPDI and GPCI categories. For instance, Wang et al. (2021) describes green technological innovation as the whole process of applying green ideas into product innovation and process innovation, and also releasing green product into the market that are consistent with the purpose of sustainable development. Green technology innovation in Wang et al. (2021)'s study is a similar concept as GI in the study of Chen et al. (2006), which is a higher-level concept of GPDI and GPCI. We believe that GI is a better fit than green technology innovation for this article. Third, this research focuses on the context of China, where the application of GPDI and GPCI is more common (Tang et al., 2018). The classification of GI in this article is based on the grounds stated above. Following that, the concepts, implementation, and impact of GPDI and GPCI will be thoroughly explored.

2.2.3 Green product innovation

GPDI is a type of product innovation where environmental factors (material consumption, energy consumption, etc.) are incorporated into product design considerations for new and existing products, with the main objective of reducing negative environmental impacts during the life cycle of the product (Chan et al., 2016b). Although no consumer product has no impact on the environment, GPDI aims to protect or improve the natural environment by saving energy or resources, reducing the use of toxins, and preventing pollution and waste (Ottman et al., 2006). Successful GPDI leads to the development, production and marketing of new products that outperform conventional products in terms of environmental friendliness and novelty.

Compared to traditional product innovation, GPDI is more focused on environmental protection. Companies are investing more in areas such as energy conservation, pollution prevention and waste recycling to reduce pollution (Chen et al., 2006). In addition, companies are doing more research on extending product life cycles to minimise the environmental damage caused by discarded waste (Pujari et al., 2003). For the same reasons, namely to reduce environmental risks, pollution and negative impacts on resources throughout the life cycle of the product, they are paying more attention to design for after-use applications than for conventional goods.

In China, the growth rate of GPDI is still relatively low and its development is problematic from various aspects (Song et al., 2020). The most important reason is that companies lack the economic incentives to actively invest in this region. Although GPDI is beneficial to companies, some companies remain on their current path, considering GPDI an unnecessary expense and ignoring their environmental responsibilities. The lack of attention and investment intentions on the part of companies has limited the development of GPDI.

Another reason, related to the previous one, is the high financial cost of implementing GPDI. A company's high investment in green products could lead to it having higher product costs than its competitors, perhaps resulting in an unsustainable market position. Thus, the reasons why companies reject GPDI are probably not due to a lack of technology or knowledge, but to expensive R&D and production costs (Dangelico, 2016a). Small and medium-sized enterprises may be particularly reluctant to invest in GPDI. There is also a risk that GPDI will be phased out. This could be due to products not meeting customer requirements, consumers not being able to bear the high prices, or a failure to incorporate environmental principles into product development (Peters and Buijs, 2021). GPDI involves some risk, but some cautious companies that are only looking for short-term economic development may prefer to invest in other prospects than GPDI.

The third reason is the difficulty of combining environmental protection with traditional product attributes (Dangelico and Pujari, 2010), which poses a number of challenges for companies, such as trade-offs between product quality and green attributes or product function and green attributes. A long-term process is usually necessary when it comes to appropriately integrating green ideas into a product, as companies seeking short-term profits may not be attracted to GPDI. Therefore, it is necessary to carefully analyse the impact of GPDI on business performance and find out how to achieve good GPDI.

Enterprises play an important role in pollution and GPDI practises in China and are responsible for green development. Nevertheless, most enterprises prefer to pursue strategies that have immediate impacts (Song et al., 2020), while green development requires enterprise transformation, which implies long-term upgrading and stable development (Dangelico et al., 2017; Dangelico and Pujari, 2010; Zhang et al., 2021), which is contrary to the habits of enterprises that limit themselves to their immediate interests, display strong market speculation, and have no sense of urgency for enterprise transformation. Therefore, companies might not have a strategic perspective on developing and promoting GPDI (Stucki et al., 2018). In terms of the external environment, companies could avoid penalties by adhering to environmental commitments and regulations despite the immense pressures and constraints imposed by international and national laws and conventions. Furthermore, when companies go green in the production of their products, they often enter into partnerships with other companies. For example, McDonald's works with HAVI Global Solutions to reduce pollution from packaging. Companies can acquire external knowledge and skills by working with a wide range of partners, while also expanding their own internal knowledge base by integrating external sustainable knowledge and skills (Dangelico et al., 2017). A broad knowledge base with more environmental information can significantly improve design and operational efficiency in new product development.

2.2.4 Green process innovation

GPCI refers to any change or adaptation within the manufacturing process that contributes to reducing negative environmental impacts during any stage of production, including material sourcing, manufacturing or delivery (Albort-Morant et al., 2017). GPCI can be additive solutions or integrated into production processes through input substitution, production optimisation and output recycling. GPCI involves both improving existing production processes and adding new processes to minimise environmental impacts. Implementing GPCI usually requires more internal procurement and involves higher costs, but it is also more effective than other green practises. Moreover, GPCI can be an additive solution (e.g., chimney scrubbers) or integrated into the production process by replacing inputs, improving production or recovering outputs (Xie et al., 2019). Robotics is an example of a GPCI that is a key technology for process innovations that increase the efficiency of companies' production processes. During the process of integrating new technologies into GPCI, resource consumption and waste are drastically reduced, and both energy and errors are reduced (Wang et al., 2021; Wicki and Hansen, 2019).

Compared to traditional process innovations, GPCI includes more environmental requirements in the design and manufacturing process to protect ecosystems from aspects such as raw material extraction, energy consumption, waste generation, health and safety risks and ecological degradation. The GPCI includes a number of new activities, such as reducing air and water emissions, improving resource and energy efficiency, reducing water consumption, switching from fossil fuels to clean energy, etc. GPCIs enable companies to develop new production methods, search for new business methods and adapt organisational structures and work processes (Peters and Buijs, 2021). By improving existing production processes or adding new processes to minimise harmful environmental impacts, GPCI improves the production process that turns raw materials into usable products, improves corporate environmental compliance and helps companies gain a differentiation advantage.

There is a controversial opinion about the use of GPCI in China. Part of the literature points out that GPCI activities are often associated with high levels of uncertainty and risk due to their potential externalities, leading to negative impacts of process innovation on operational concerns. The study by Carrillo-Hermosilla et al. (2010) supports the "end of pipe" idea that GPCI has a negative impact on production costs compared to a traditional innovation process. Furthermore, Genc and Giovanni (2017) support this view from a green perspective, showing that investments in green R&D can significantly increase the marginal cost of production, leading to a delayed decision to invest in GPCI.

However, another group of scholars believes that process innovation can have a positive impact on operations, especially on reducing marginal production costs (Ghosh et al., 2020). As many Chinese companies are reluctant to develop GPCIs due to the high investment and uncertain benefits, academics argue that GPCIs reduce the marginal cost of production. Marginal cost of production is defined as a state variable that can be reduced through investment in research and development (R&D) (Cellini and Lambertini, 2009). Cassell et al. (2016) give an example of how the introduction of a recycling and remanufacturing process for a car body minimised aluminium waste, reducing overall production costs and improving environmental performance. In addition, the study by Sanni (2018) shows that improving final treatment equipment or processes helps to control pollutant emissions towards the end of production. Green process innovation aims to systematically improve the entire operational and management process to use resources and energy more efficiently, promote the design and production of green products, and lay the foundations for green product innovation. Green process innovation can help companies successfully produce green products by leveraging innovation advantages. At the same time, it can help them improve product quality, expand product categories or produce new products to increase their market share.

2.3 AMBIDEXTERITY

2.3.1 Definition of ambidexterity

The term "ambidexterity" in common use refers to the ability to use both the left and right hand equally. In the field of management, it indicates an organisation's capability to use both exploration and exploitation techniques to achieve success (Gupta et al., 2006). When Duncan (1976) first introduced the term "organisational ambidexterity", exploration and exploitation were deemed as two competing organisational behaviours. Firms confirm their organisation's current viability via exploitation behaviours, such as refinement, choice, production, efficiency, selection, implementation, and execution, while they also ensure future viability through search, variation, risk-taking, experimentation, flexibility, discovery, or innovation (March, 1991; O'Reilly III and Tushman, 2013; Raisch and Birkinshaw, 2008).

As a broad managerial concept, ambidexterity has reached growing interesting in innovation management, strategic management and organisational literature (Andriopoulos and Lewis, 2009; O'Reilly and Tushman, 2008; Raisch and Birkinshaw, 2008). Most empirical research about ambidexterity attempts to test whether ambidexterity is associated with a firm's performance, and the results suggest that the application of ambidexterity helps firms achieve improved sales growth performance, higher subjective ratings of performance, innovation and market valuation, as well as better firm survival (Cao et al., 2009; O'Reilly III and Tushman, 2013; Raisch and Birkinshaw, 2008; Wei et al., 2014a).

2.3.2 Logic between exploitation and exploration

Existing knowledge have proven that a one-sided focus may bring negative effects to a firm (Hansen et al., 2019; Andriopoulos and Lewis, 2009; Cao et al., 2009). The reason of exploitation is organisational inertia, and both internal pressures (e.g., irreversible managerial commitments and historic decisions) and external pressures (e.g., institutional legitimation) could cause inertia results (O'Reilly III and Tushman, 2013). When a new problem emerges, firms usually base their solutions on past experience. These reliable solutions tend to reduce risk and improve short-term performance but may cause the firm's ability to adapt to environmental changes to wither (Peters and Buijs, 2021; Ahuja and Curba Morris Lampert, 2001). This leads to competency traps, inertia and ultimately obsolescence, with organisations ultimately becoming "trapped in suboptimal stable equilibria" (March, 1991). Meanwhile, exploration is not only facilitated by the desire of invention, but also the intention to glean external knowledge. The ability to value, assimilate and apply external knowledge can help firms to achieve exploration (Also-Simo et al., 2020). However, identifying external opportunities and employing external knowledge is a cost-efficient and time-consuming process. If firms are too wholly focused on exploration, they may gain a few innovation opportunities, while they may also fall into an endless cycle of search and unrewarding change

(Hansen et al., 2019; Volberda and Lewin, 2003). As a result, the balance of the poles of exploitation and exploration effectively eliminate innovation tensions and create a better organisation (Andriopoulos and Lewis, 2009).

Ambidexterity is hard to accomplish because firms are easily struggled by resource discrete, categories contrast, or one-side focus on exploration or exploitation (Also-Simo et al., 2020; Cao et al., 2009; Duncan, 1976). There are two conflicting streams of literature in terms of the incompatible or complementary logic between exploitation and exploration, and discussion of how to integrate them in innovation (Chang et al., 2020a; Wei et al., 2014). One stream of research holds a balanced dimension of ambidexterity, which emphasises the difficulties in achieving ambidexterity (Hansen et al., 2019). This viewpoint believes that exploitation and exploration are fundamentally incompatible because they compete for limited organisational resources. Exploitation and exploration are two ends of one continuum and firms need to determine the best relative exploratory point along the continuum. While another stream of research is the combined dimensions of ambidexterity, which emphasises that exploratory and explorative processes are not necessarily in fundamental competition (Gomes et al., 2020). Therefore, firms can attempt to engage in higher levels of both exploitation and exploration to gain these potential complementary effects (Peters and Buijs, 2021). Cao et al. (2009) suggest that the balanced ambidexterity benefits firms with constrained resources, whereas combined ambidexterity is suitable for firms with greater access to internal or external resources. Considering that this study focuses on firms which use information technology, which usually have more resources than traditional companies, this study therefore mainly considers combined ambidexterity rather than balanced ambidexterity.

2.3.3 Ambidexterity and green innovation

Since March published his iconic paper (1991), organisational ambidexterity has received growing attention in innovation research, and many researchers have demonstrated ambidextrous organisations' ability to excel at innovation (Andriopoulos and Lewis, 2009; Wang et al., 2020). Some studies posit that all learning and innovation activities are classified as examples of exploration, and therefore the term exploitation ought to be reserved for activities in which the primary purpose is to use past information rather than to go down any type of learning trajectory (Rosenkopf and Nerkar, 2001; Vassolo et al., 2004). Such research focuses on the R&D process and patenting activities, which emphasise exploration over exploitation. However, even if organisations do nothing but repeat their past actions, they can still accumulate experience and learning in an incremental manner. Therefore, this research builds on March's (1991) logic which argues that both exploitative and explorative activities include at least some learning (Gupta and George, 2016).

Moreover, later literature further summarized the key objectives of both exploitation and exploration, which are learning, improvement, and acquisition of new knowledge (Gupta et al., 2006). The difference between the two notions is whether new learning follows the same path as previous learning (exploitation) or follows a completely different one (exploration). The tension of exploration and exploitation is a prominent matter for firms to manage because it usually triggers innovation and helps firms outperform competitors (Andriopoulos and Lewis, 2009). As a result, ambidexterity has been recognised as a key managerial process necessary for achieving short-term success and long-term sustainability with the ability to be aligned and efficient in business demands while being adaptive to environmental changes (Duncan, 1976; Gibson and Birkinshaw, 2004).

Even though the importance of ambidexterity in pursuing innovation has been extensively discussed, there is limited understanding on ambidexterity as an influential precursor to GI in the literature. In order to build a more complete picture of the relationship between ambidexterity and GI from existing literature, academic papers published in the last five years with these are presented in Table 2.2.

Table 2.2 Literature in GI and ambidexterity

Author	**Journal**	**Method**	**Theory**	**Research objective**
Arranz et al. (2019)	Journal of Cleaner Production	Secondary data from the Spanish Technological Innovation Panel (PITEC)	Dynamic capabilities theory	This paper studies the incentives and inhibiting factors of eco-innovation capacities in the firm.
Cegarra-Navarro et al. 2019)	Technological Forecasting & Social Change	An empirical investigation of 161 of Apple's customers	None	This study examines the extent to which business performance in global enterprises can be influenced open-mindedness, environmental produce innovation and addressing privacy concerns.
Wicki and Hansen (2019)	Business Strategy and the Environment	Case study in a well-established German engineering firm.	Organisational learning theory	How established firms use their core competences to diversify their business by exploring and ultimately developing green technologies
(Chang and Gotcher, 2020a)	International Business Review	Survey of 124 OEM suppliers in Taiwan	Resource-based view, dynamic capability theory, and institutional theory	This study develops a conceptual model focusing on the effects of co-production on eco-innovation, the mediating effects of environmental innovation ambidexterity, and the moderating role of institutional pressures.

Silvestre et al. (2020)	International Journal of Operations & Production Management	Multi-case studies and secondary data analysis	Contingency and evolutionary theory	This paper explores how organisational capabilities and path dependence affect the implementation of supply chain (SC) sustainability initiatives.
Wang et al. (2020)	Journal of Cleaner Production	Survey of 206 OEM suppliers in China	Resource-based theory	This study proposes a moderated mediation model to examine the relationship of green learning orientation and ambidextrous GI.
Zameer et al., (2020)	Journal of Cleaner Production	Survey of 320 managers and 320 customers in China.	Stakeholder theory, institutional theory, resource-based theory, ambidexterity theory	The study explores the key reinforcing factors (i.e., green creativity, customer pressure, regulatory pressure) of green competitive advantage among equipment manufacturing enterprises in China.
Alos-Simo et al. (2020)	Sustainability	Panel data from 449 firms over five years from the telecom industry in Spain.	None	This study analyses the factors that affect eco-innovation, as well as eco-innovation's effects on dynamic ambidexterity.
(Sun and Sun, 2021)	Sustainability	Survey of 166 middle and senior managers in Chinese manufacturing companies.	Resource Dependence Theory	This research examined the relationship between GI strategy and ambidextrous GI, and the mediating role of green supply chain integration is investigated.
Peters and Buijs (2021)	Business Strategy and the Environment	A qualitative research approach including multiple cases and several sources of rich empirical data.	Organisational learning theory; ambidextrous learning theory	To examine the reasons why manufacturing firm struggle with green product innovation, and how a firm's capabilities shape its green product innovation practices.

According to the above papers, several theoretical frameworks and different perspectives have been developed to explain the relationship between GI and ambidexterity. For instance, the empirical results of produced by Wang et al. (2020) show that green learning orientation positively effects both exploitative and exploratory GI, and that the effect of exploratory GI is stronger than exploitative GI. Also, a new concept "environmental innovation ambidexterity" was introduced in the study of Chang and Gotcher (2020). This capability helps firm to achieve efficient use of pollution-prevention technologies and the innovation of pollution-prevention technologies, therefore contribute to environmental protection and pursue eco-innovation outcomes. Their study also uncovers that the relationship between co-production and GI ambidexterity is stronger when institutional pressures are high. Alos-Simo et al. (2020) and Sun and Sun (2021) also examine how ambidextrous GI is determined by the GI strategy. Alos-Simo et al. (2020) demonstrate that eco-innovation facilitates ambidexterity by allowing exploration and exploitation to alternate dynamically in the pursuit for economic advantage. While Sun and Sun (2021) prove that the GI strategy has a positive influence on both exploitative and exploratory GI, the impact on exploratory GI is greater than that on exploitative GI. Besides, Silvestre et al. (2020) examine green initiatives from the supply chain perspective, the results show that simultaneously implementing both exploitation and exploration capabilities in supply chain sustainability initiatives can improve learning and achieve a superior supply chain sustainability trajectory in the short and long term.

Meanwhile, other publications just mention the relationship between organisational ambidexterity and GI in the discussion without delving into it in depth. For example, Arranz et al. (2019) include ambidexterity as one of the inhibiting factors of eco-innovation capacities for firm. Cegarra-Navarro et al. (2019) claim organisational ambidexterity improves a firm's alignment to new user needs, and the adaptability of ambidexterity in socio-economic context can be facilitated through both internal orientation and external engagements with stakeholders.

Besides, Zameer et al. (2020) explore the factors of firm's green competitiveness in the manufacturing industry and mention that creative organisations prefer green production as this fosters a green brand image and improves sustainable competitiveness at the exploitation stage of ambidexterity.

The literature shows that some papers only mention the relationship between GI and ambidexterity in the discussion or conclusion section, lacking further investigation of the principle behind the relationship (Arranz et al., 2020; Cegarra-Navarro et al., 2019; Zameer et al., 2020). In terms of papers that provide a deeper understanding of ambidexterity and GI, some of them combine the two concepts into one, i.e., environmental innovation ambidexterity or ambidextrous GI (Chang and Gotcher, 2020b; Sun and Sun, 2021). This differs from the view of this study, which follows the stream of ambidexterity research that considers ambidexterity as an antecedent to achieving GI. As a result, our research will investigate this previously unexplored subject.

2.4 BIG DATA ANALYTICS CAPABILITY IN GREEN INNOVATION

2.4.1 Big data analytics

In the recent decades, information technology has developed rapidly and lead various industries into a new information era. Meanwhile, new technologies produce "big data", or rapidly assembled data sets that are of incredible size and complexity. Big data has received increasing discussion amongst scholars and practitioners over the last decade, but the term "big data" was first introduced in computer science literature in relation to scientific visualisation in the late 1990s (Cox and Ellsworth, 1997). The notion of big data first appeared in the business domain a few years later, with the works of Doug Laney (2001). Laney identified three major characteristics of big data: volume (data that requires a huge amount of storage or detailed records), variety (data generated from different sources and in different formats), and velocity (rapidity of data generation, modification, transfer, and delivery). The definition model was then developed by introducing two more characteristics, veracity (data governance in relation to their reliability to highlight importance of quality data trust level of the data sources) and value (the process of extracting valuable knowledge and extracting economic benefit from data by means of BDA. This leads to the formulation of the 5Vs framework (Fosso Wamba et al., 2015).

Big data can be generated from multiple sources and is generated either intentionally or unintentionally. Data intentionally generated by internet users includes search engine queries, financial transactions by retailers, non-financial transactions (as on government websites), information spread through company websites and apps, and social interactions through online review platforms, social networking, and blogs. Other sources of data which are created by the user unintentionally includes internet usage data (web cookies), customer location data (GSM, GPS, Bluetooth signals) and personal data that can be retrieved by websites though purchases (Mariani and Fosso Wamba, 2020).

Existing literature proves that big data has the potential to transform the entire business process and is regarded as the next frontier for innovation, competition, and productivity (Fosso Wamba et al., 2015; Gupta and George, 2016). By collecting, storing, and mining big data, firms can create significant value, enhance productivity, and creating a substantial economic surplus for consumers. Moreover, big data enables the transformation of decision-making process by improving the visibility of firm operations and developing better performance measurement mechanisms (McAfee and Brynjolfsson, 2012).

BDA is regarded as a holistic approach to managing, processing, and analysing big data, so that creating actionable ideas for delivering sustained value, measuring performance, and establishing competitiveness (Wamba et al., 2017). According to Kwon et al. (2014), BDA includes technologies (e.g., database and data mining tools) and techniques (e.g., analytical methods) that a company can employ to analyse large-scale, complex data for various applications intended to augment firm performance in various dimensions. Similarly, Ghasemaghaei (2019) described BDA as a tool applied to large and dispersed datasets for obtaining meaningful insights. The use of BDA has also received much attention in IS research given its capacity to improve organisational performance, for instance, George et al. (2016) demonstrated how to develop analytical insight and prediction models from structured and unstructured big data, as well as the emerging opportunities and business outcomes that big data provides.

Due to the wide application of BDA among different industries, the study of BDA in driving organisational decision making has attracted greater academic attention in recent years. Existing literature proves the ability of BDA to enable better data-driven decision making and innovative ways to organise, learn, and innovate, therefore, improving customer relationship management, inventory optimisation, operational and supply chain risk management, and operational efficiency and competitive advantage improvements (Kiron, 2013, Mariani and Fosso Wamba, 2020).

2.4.2 Dynamic capability

The capacity of an organization is its demonstrated and potential ability to accomplish against the opposition of circumstance or competition (Grant, 1991). Teece et al. (1997)firstly propose the idea of dynamic capability, which was in line with Schumpeterian idea that firms compete on the basis attribution (e.g., product design, product quality, process) while developing new capabilities to improve long-term competitive outcomes. Teece (2018) explicitly descripts that "dynamic capabilities, which are underpinned by organisational routines and managerial skills, are the firm's ability to integrate, build, and reconfigure internal competences to address, or in some cases to bring about, changes in the business environment". The overall outline of dynamic capabilities derives from the relationship of resources, capabilities, and organisational routines, together with factors of coordination, configuration, and renewal (Braganza et al., 2017). Moreover, the work of Teece et al. (1997) also claimed that the core step to defining dynamic capabilities is "to identify the foundations upon which distinctive and difficult-to-replicate advantages can be built, maintained, and enhanced". The capacity of an organisation is its demonstrated and potential ability to accomplish against the opposition of circumstance or competition, and the creation or development of distinct capability which distinguish it from the other is the key for firm's success (Teece, 2007). Dynamic capabilities thus reflect an organisation's ability to achieve new and innovative forms of competitive advantage given path dependencies and market positions.

However, not all the academic agrees with Teece's theory and definition of dynamic capability. Another mainstream of dynamic capabilities is proposed by (Zollo and Winter, 2002) with the reason that Teece's theory failed to explain "where the dynamic capabilities come" and put “rapidly changing environments” as necessary prerequisite. From Zollo and Winter (2002)’s position, they pointed out learning mechanisms is the initial step that create and evaluate of dynamic capability, they also narrow the focus on operating routing and the object on which dynamic capabilities operate, as well as specifically identified the structured and persistent characteristic of dynamic capabilities. In contrast, Teece (2007)emphasis more on the importance of firm’s competencies and their impact on addressing and adapting environmental changing and building long-term competitive advantage. After comparing the two main streams of dynamic capabilities, Teece et al. (1997)’s proposition is adopted because it provides a more general idea of what dynamic capabilities are for and how they work, and in this research, we are not research the prerequisite mechanisms for BDAC, so it is not necessary to highlight the learning mechanisms in the definition. Moreover, Teece’s theory set the rapidly changing environments as background while Zollo and Winter (2002) include both high and low rate of change in environment, our study focuses on high-tech industry which is usually been characterised by fast developing and rapid changing, so it is more appropriate for Teece’s presume.

Follow the stream of Teece (2007), dynamic capability of organisation brings together talents, data, technology, and experience to produce revenue-generating products and services, or to increase efficiency. The importance of dynamic capabilities stems from their capacity to adapt to changing consumer, technology opportunities, and the environment in which the firm operates (Teece, 2018). It also contributes to the expansion of new products and processes, as well as the design and implementation of sustainable business models (Teece, 2007). The development of dynamic capability requires tacit accumulation of experience and knowledge, which articulated through collective conversation, problem-solving sessions, and performance evaluation processes. The possession of dynamic capabilities is especially relevant to the environment that exposed to the opportunities and threats associated with rapid technological change, and the technical change itself is systemic in that multiple inventions must be combined to create products and/or services that address customer needs, especially in high-technology sectors. Therefore, this study argues that BDAC is an enterprise-level competitive advantage that boost firms' competitiveness in the rapid technological change.

2.4.3 Big data analytics capability

It is not enough to just know BDA, because a company must have BDA-related capabilities to improve its operations and performance (Sena et al., 2019). BDAC is defined as an organisation's ability to effectively deploy green technologies and talents to capture, shop and analyse data and ultimately generate timely business value and insights (Mariani and Fosso Wamba, 2020; Mikalef et al., 2020). Recently, numerous research papers have been published demonstrating the impact of BA on businesses in the areas of product innovation, process innovation, production models, green HRM practises and market decisions (Bag et al., 2020). Specifically, green operational excellence in the manufacturing industry can be improved by developing BDAC (Waqas et a., 2021). First, Big Data should be collected in large quantities from internal and external information relevant to environmental protection. After processing this kind of data, the results will provide suggestions for improvement in the development of GPDI and GPCI and the advantages of developing GI compared to the traditional and existing products or processes. Secondly, BDAC will enable the companies to communicate the changes in the current decisions on GI and manage the processes of GPDI and GPCI accordingly.

Academics suggest integrating a multidimensional perspective into studies on the value of IT capabilities (Bharadwaj, 2000). Therefore, it is necessary to understand the IT capability before BDAC. IT capability has been defined as "the organisation's ability to mobilise and deploy IT -based resources in combination or co-presence with other resources and capabilities" (Bharadwaj, 2000). The study of IT capability is consistent with the study of dynamic capability and usually uses the idea of RBT, i.e. a firm's competitive advantage is achieved through the deployment and use of distinctive, valuable and inimitable resources and capabilities (Yu et al., 2021). Moreover, the distinctive capabilities are hard to replicate and lead to sustainable competitive advantage, so companies selectively invest in various types of IT assets to ensure their long-term competitiveness.

Wamba et al. (2017) treat BDAC as a key organisational capability that leads to sustainable competitive advantage in the big data environment. Based on the classification of resources proposed by Grant (1991), these can be divided into tangible (e.g. financial and physical resources), intangible (e.g. organisational culture) and human capabilities (e.g. the knowledge and skills of employees). The study of Bharadwaj (2000) also provides a framework to classify IT capabilities accordingly into three, i.e. (1) the tangible resources which include the physical IT infrastructure components, (2) the intangible resources are the IT -capable resources such as knowledge assets, customer orientation and synergy, (3) human-based resources and the human IT resources which include the technical and managerial IT capabilities. This classification has been widely cited in business and management journals

(Barton and Court, 2012; Davenport and Prusak, 1998; Kiron, 2013; McAfee and Brynjolfsson, 2012).

Meanwhile, BDAC has similar elements to IT. Table 2.3 shows the elements of BDAC from previous studies. The majority of studies classify BDAC from three perspectives: management, personnel, and technology. Although there are alternative classifications, such as Wang et al. (2019), this study focuses on healthcare businesses, which may focus on different aspects of BDAC than other industries. This study follows the mainstream of BDAC literature and classifies BDAC as big data infrastructure analytics capability (BDAI), big data analytics management capability (BDAM) and big data analytics personnel capability (BDAP). Each element is explained in detail in the following sections. The following discussion will be based on three main types of BDAC, which become types of organisations that are able to adapt to environmental and regulatory changes in a very short time by reorganising their internal and external processes related to green production and various resources based on their current capabilities.

Table 2.3 Elements of BDAC

Author	**Publisher**	**Elements of BDAC**
McAfee and Brynjolfsson (2012)	Harvard business review	Personnel management Technology infrastructure Corporate decision making
Davenport et al. (2012)	MIT Sloan Management Review	Big data management capability Human resource capability IT infrastructure capability
Barton and Court (2012)	Harvard business review	Big data management ability IT infrastructure

		The expertise
Kiron (2013)	MIT Sloan management review	Organisation culture Analytics platform Employees' analytics skill
Wixom et al. (2013)	MIS Quarterly Executive	Strategy Data People
Akter et al. (2016)	International Journal of Production Economics	Organisational (i.e., BDA management) Physical (i.e., IT infrastructure) Human (e.g., analytics skill or knowledge)
Wamba et al. (2017)	Journal of Business Research	Infrastructure flexibility (e.g., infrastructure, IS, and data) Management capability (data-driven culture, governance, social IT/business alignment) Personnel capabilities (e.g., data analytics knowledge and managerial skills)
Wang et al. (2019)	British Academy of Management	Data integration capability Analytical capability Predictive capability Data interpretation capability

2.4.3.1 Big data analytics infrastructure capability

In this study, we follow the classification of BDAC by Wamba et al. (2017) and argue that infrastructure flexibility, management capability and human resource capability are the three aspects of BDAC. First, it is often mentioned that data analysts are concerned with the quality and availability of the data that the organisation uses (Mikalef et al., 2019). BDAI is "the capability of the BDA infrastructure, such as applications, hardware, data, and networks, that enables BDA staff to quickly develop, deploy, and support the system components necessary for an enterprise" (Wamba et al., 2015; Kim et al., 2012). For the flexibility of BDAC's infrastructure in supporting GI, green data itself is the most important resource. In addition to the three characteristics of Big Data, i.e. its volume, variety and velocity (Wamba et al., 2017), the quality of green data also plays a particular role in terms of its accuracy, format, timeliness, reliability and perceived value. The development of BDAI makes it possible to add value to green products, improve green production processes, achieve sustainable competitive advantage and optimise sustainable business performance (El-Kassar and Singh, 2019). For example, the American multinational parcel delivery company UPS used BDA to optimise each driver's delivery route based on constraints and delivery times, road regulations and restrictions. This project significantly reduced energy consumption and vehicle emissions, even saving over $300 million in one year, and the efficiency improved the company's competitive advantage over its rivals (Sena et al., 2019).

2.4.3.2 Big data analytics management capability

Moreover, BDAM is the ability of the BDA unit to handle routines in a structured way to manage IT resources in accordance with business needs and priorities (Kim et al., 2012; Wamba et al., 2017). The study by Bag et al. (2020) indicates that manufacturing companies should adopt and develop green manufacturing processes by applying BDAM to optimise sustainable supply chain performance (Bag et al., 2020). BDAM relies on people who not only understand that problems need to be bought together with the right data, but also have problem-solving techniques to use it effectively. In studies on BDAM, governance and data-driven culture are the two most discussed terms. Specifically, analytic organisations create, prioritise and track analytic efforts and manage different types and categories of data related to analytics (Espinosa and Armour, 2016). This means that the governance of BDA establishes rules and controls that participants must follow when conducting their activities. To use BDAM to improve GI, leadership teams should set clear targets for green goals, define what green success means, and ask the right questions about why and how to improve green performance. An effective leadership team pools important information and decision-making power.

Furthermore, existing literature argues that a data-driven culture is one of the most important outcomes for BDMC practises (Shamim et al., 2020). Furthermore, data-driven organisations emphasise "What do we know?" over "What do we think?". This requires that organisations do not act alone and discard bad habits, such as pretending to be more data-driven than they actually are. An example of a data-driven culture is the UK fashion retailer Jaeger, which experienced a general downward trend in the market due to information leaks in 2009 (Sena et al., 2019). To combat this, the company developed a centralised system that collected data from multiple internal systems, including points of sale, warehouses and shop alarms. Statistics showed that the company was able to significantly reduce the number of redundant productions and even turn a profit nine months after the project began.

2.4.3.3 Big data analytics personnel capability

BDAP is broadly defined as the professional ability of BDA personnel, such as skills or knowledge, to perform assigned tasks (Fosso Wamba et al., 2015; Kim et al., 2012). Personal capability can then be further divided into technical knowledge, business knowledge, relational knowledge and technological knowledge. The ability to use Big Data technologies and tools is highly dependent on human capabilities (Mikalef et al., 2019). Data technologies can be used to cope with the volume, velocity and variety of Big Data. However, these techniques require a skill that may be new to IT departments, namely the integration of all relevant internal and external data sources. The most important skills are cleaning and organising large data sets, creating new types of data in structured formats and using visualisation tools and techniques to make data visible. This type of work requires both data scientists and computer scientists to work with very large data sets. Expertise in experimental design is required to bridge the gap between correlation and causality. The successful application of Big Data analytics requires a specialised and capable workforce to derive the intended benefits from the implementation (Fosso Wamba et al.).

The study by Bag et al. (2020) confirms that BDAP has a significant positive effect on workforce development and sustainable supply chain performance in the South African manufacturing industry. The key techniques for BDA are rarely taught or trained in traditional statistics courses, making data scientists and other professionals critical to working with big data. As more environmental data is collected, the ability of staff to analyse data becomes more valuable. BDAP has had a direct and significant impact on human resource development by influencing the working style of companies and enhancing the skills of employees. The difficulties of human resource development have intensified in modern enterprises due to environmental changes and the control of the huge amount of new green data at every level of operation. Moreover, experienced data scientists can comfortably communicate in the language of business and help leaders reframe challenges using Big Data (McAfee and Brynjolfsson, 2012). Ongoing practitioners have an interest in understanding the benefits of environmentally relevant data and technologies for driving green innovation.

China's manufacturing sector accounts for more than 30% of GDP and more than 26.4 trillion, and the country has excellent infrastructure and a fast-growing economy. Despite all this expansion and contribution, Chinese manufacturing companies still face the following shortcomings: Lack of GI, weak creative capabilities, weak adoption of BDAI, BDAM and BDAP, heavy reliance on key core technologies, low-quality mass production, high waste generation, high energy consumption, inadequate resource management, serious pollution problems and lagging digital infrastructure development. These shortcomings adversely affect the sustainable growth of the industrial sector in China. Therefore, this study will examine how the development of BDAI affects enterprises GI.

2.5 THEORY

2.5.1 Resource-based theory

RBT has been adopted in OM research studies to clarify the strength and capabilities that enable firms to maintain competitiveness (Grant, 1991; Helfat and Peteraf, 2003). From the perspective of RBT, the meaning of "resources" that form the sources of competitive advantage have four key attributes: value, rarity, imperfect imitability, and non-substitutability (Barney, 1991). RBT posits that a competitive advantage is contingent on the nature of the product and technology, and a firm's competitive advantage does not last forever. A competitive advantage may no longer be valuable for a firm due to the unanticipated change in the economic structure of an industry. When experiencing an unanticipated change in the industry, existing resources that provide a basic competitive advantage may not be useful anymore. Firms have the responsibility to determine which resources should maintain their competitiveness in the new environment before their competitors.

The changing nature of competitive advantages is recognised as the proponent of dynamic RBT, which states that RBT must consider the evolution of the resources and capabilities that form the foundation of competitive advantages (Helfat and Peteraf, 2003). In line with this dynamic view of RBT, organisations ought to evolve with their product circle as resources that provide competitive advantage are different over the product circle. In addition, firms need to change organisational capability dynamically in line with disruptive changes, including both organic changes (e.g. product and process) or exogenous changes (e.g. industries and markets). This requirement for firms to develop capabilities to adapt to changing environments has been enshrined in the dynamic capabilities approach to competitive advantage. From another perspective of resource-based theory, companies access scarce resources, and make good use of rare resources to achieve a competitive advantage.

RBT was used to provide rationale for the study in two areas. To begin, it is used to explain the fundamental principle of ambidexterity in promoting GI. Given the disadvantages of focusing solely on exploitation or exploration, firms that put emphasis on ambidexterity are able to develop firm-specific assets that are valuable and difficult to imitate (Helfat and Peteraf, 2003). Second, RBT is used to better understand the role of BDAC as a moderator in the relationship between ambidexterity and GI. According to RBT, BDAC is a firm's tangible and intangible resources, and the resources are valuable, scarce, non-imitable, non-substituteable, and non-transferable (Gupta and George, 2016; Barney, 1991). More detail explanation on how

RBT supports the argument can be found in 3.2 AMBIDEXTERITY AND GREEN INNOVATION and 3.3.1 Resource based theory in big data analytics capability respectively.

2.5.2 Knowledge-based view

KBV can be explained as the generation of sustainable competitive advantage from knowledge (Herden, 2020). Knowledge has two forms, namely explicit knowledge, and tacit knowledge. Any knowledge that can be codified, verbalised, communicated, and expressed is considered to be explicit knowledge; explicit knowledge often exists in written form such as reports, books, or manuals, and it is easy to articulate and communicate, transmittable without loss of integrity. Tacit knowledge, on the other hand, is unwritten knowledge that exists in people's minds and is gained by experience and interaction with others. Tactic knowledge is more difficult and costly to communicate to others than explicit knowledge (Abbas and Sağsan, 2019). Furthermore, knowledge gives organisations with a sustainable advantage because it enables for revenue growth and competitive maintenance. Even if competitors always match the market leader's product quality and price, organisations that are knowledge-rich or knowledge-managing can raise their quality, creativity, and efficiency to a higher level.

Early study held that knowledge is an intangible asset that plays a significant impact in the success or failure of any organisation. Later works define it as the process of converting tacit knowledge into explicit knowledge in order to enhance the flow of organisational knowledge (Yang, 2008). Knowledge involves the comprehension of varied scientific and engineering information, as well as specialised skills required to operate technological systems; hence, knowledge can be incorporated in both technical systems and physical capital resources

(Carrillo-Hermosilla et al., 2010). Knowledge is typically created and held by individuals in KBV, with organisational members carrying, generating, and preserving knowledge, which is then embedded within the firm's structures and moved between the process of creating knowledge and embedding it into the firm's knowledge pool (Öhman et al., 2021). As a result, a firm may be conceived of as a coordinated body of information, and the integration and generation of knowledge can be considered as the core responsibility of the firm and the key capacity that organisations must acquire.

Knowledge can be categorized into three forms: knowledge creation, knowledge transfer, and knowledge integration. Individuals have tacit experience and information, which is valuable because it is difficult to copy or transfer to competition. Meanwhile, individual tacit knowledge must be conveyed and incorporated within the firms. According to research on the use of IT technology in decision-making, the integration of technical and business knowledge necessitates strategic alignment inside businesses, emphasising the need of knowledge sharing between business managers and technology managers (Öhman et al., 2021). Knowledge integration goes beyond information sharing because it is dependent on the knowledge that all members of an organisation share owing to their connection with the organisation, and it also needs to be synchronised in sharing knowledge with the involved parties inside corporations. It is also proposed that sharing information promotes communication and planning procedure integration. Neither having information without integrating it nor attempting to integrate knowledge that does not exist may provide a competitive advantage.

This study uses key insights from the KBV perspective to better understand how the development of BDAC affects the impact of ambidexterity on GI. According to this study, the development of BDAC would improve knowledge creation, transfer, and integration. Knowledge enables dynamic organisational learning in natural environments, whereas relational capability can augment alliance partners' resources to create, extend, or modify their resource bases (Öhman et al., 2021; Teece, 2007). As a result, the development of BDAC enables the generation of data-driven insights and assists firms in making efficient GI decisions. 3.3.2 Knowledge-based view in big data analytics capability contains more explanations of how KBV is used to support the argument.

2.5.3 Information processing view

Information processing refers to the "gathering, interpreting, and synthesis of information in the context of organisational decision making" (Tushman and Nadler, 1978). From the perspective of information processing view theory, the fundamental goal for organisations is to manage uncertainties like task complexity and the rate of environmental change by deploying information processing mechanisms. The information processing view highlights the importance of matching information processing requirements with information processing capabilities: the greater the task uncertainty, the more information that has to be processed. As a results, businesses should build their structures or processes to make it easier for decision makers to process large amounts of data, allowing them to make better decisions, reduce costs, and enhance organisational performance.

Based on the information processing view and business analytics studies, information processing capability is explained as organisation's capability to capture, integrate, and analyse data and information, and also use the insights extracted from data and information in the context of organisational decision making. BDAC are proposed as a type of information processing capability in literature, and IPV is used for explaining BDAC's impact on organisational decision making (Srinivasan and Swink, 2018).

From the standpoint of information processing, this study contends that BDAC enables firms to access the high volume, variety, velocity, veracity, and value of big data, as well as process and analyse green data, . Data can be transformed into knowledge, allowing businesses to collect, evaluate, synthesise, and coordinate information across the organisation. Moreover, firms can develop BDAC to create analytically driven business processes and organisational structures, as well as to use data-driven insights to evaluate firm's business practises and make intelligent decisions. 3.3.3 Information processing view in big data analytics capability provides a more detailed explanation of how BDAC influences ambidexterity on GI.

2.6 RESEARCH GAP

2.6.1 Research gap in green innovation

Even though the importance of GI has attracted increasing attention both by academics and practitioners, little research has explored the implementation and the impact of GI, including by some of the most common research methods. This study focuses on a specific strategy as an antecedent of GI in order to help firms effectively adopt it. This strategy is ambidexterity, which is as an important strategy for firms to pursue short-term increment innovation and long-term radical innovation (Andriopoulos and Lewis, 2009; Gibson and Birkinshaw, 2004; He and Wong, 2004). Ambidexterity has been proved to significantly facilitate new product innovation by researchers (Wei et al., 2014a), and this study aim to further investigate how ambidexterity supports firms to achieve better GPI.

Furthermore, many existing studies define GI activities broadly but find no subdivisions (Stucki et al., 2018). GI, on the other hand, encompasses a variety of practises, the most common of which are GPDI and GPCI. Although both activities are aimed at environmental protection and resource conservation, the core of GPDI is focused on product and GPCI is focused on process technology improvement (Song et al., 2020). Because these two components have different emphases and are at different stages of innovation, they should be measured using different indicators. Confusion between these two practises may cause research results to be distorted (Stucki et al., 2018), so this study will treat both GPDI and GPCI as research objects, making the results more reliable.

According to (O'Reilly and Tushman, 2008), it is almost impossible to achieve corporate success without conducting both exploratory and exploitative innovation. In fact, some researchers have provided empirical evidence to support the view that ambidextrous organisations are more capable of excelling in innovation, that is, exploring new opportunities for radical innovation and exploiting existing products for incremental innovation (Andriopoulos and Lewis, 2009). Ambidextrous innovation can be classified in two fields: "(1) the proximity to existing technologies, products, and services, and (2) the proximity to existing customer or market segments" (Jansen et al., 2006). Exploration seeks new resources or knowledge, and it brings new designs and products, and encourages firms to enter new markets or create new channels of distribution for the purpose of meeting the needs of emerging users or markets. Exploitation emphasises meeting the requirements of existing customers and markets (Benner and Tushman, 2003). This approach aims to develop existing knowledge and skills; improve established designs, products and services; and promote the efficiency of existing distribution channels. We draw from the above literature to examine how organisational ambidexterity as a strategy can help firms respond to environmental opportunities and undertake GPI (Zhang and Walton, 2017).

Moreover, this research pays attention to firms that apply big data capability technologies in their GI. BDA is a holistic approach to manage, process, and analyse data to create valuable ideas in terms of performance enhancement and competitiveness establishment (Wamba et al., 2015). There is a wide adoption of BDA-enabled tools, technologies, and infrastructure in different areas, like social media, mobile devices, automatic identification technologies, relevant technologies such as internet of things and cloud-enabled platforms have been used in firm's operations to achieve competitive advantage improvements (Wamba et al., 2017). BDA has been considered a tool to improve business efficiency and effectiveness due to its high operational and strategic potential. With the ongoing revelation from traditional industries to intelligent industries, there will be more firms adopting this new technology to improve decision-making processes in business, thus, it is important to understand how BDAC influence a firm's strategies. In this research, the moderating role of BDAC will also be examined within the relationship between ambidexterity and GI. By understanding whether developing BDAC will positively influence the relationship between ambidexterity and GTI, managerial implications will be provided in terms whether BDAC should be adopted to achieve GI.

The majority of researchers and participants consider GI as a profitable operation whereby green-oriented firms enjoy a better performance in both environmental and business practices (Klassen and Vachon, 2003; J. Zhang et al., 2018). However, some debate can be found as to the relationship between GI practices and firm performance. For example, some literature reports an unexpected result, i.e. significant investments are made in GI practices which ultimately cause economic burden to their companies (Chan et al., 2016a; Huang and Li, 2017). Moreover, insufficient literature could be found for some other aspects of firm performance, e.g. social performance. Given the fact that a firm's willingness to integrate green management into its operations will be greatly influenced by the promise of improved future performance, it is important to understand how GI practices affect this. In this study, we will fill the above gaps by testing the relationship between GPI and the Triple Bottom Line (TBL); that is, simultaneously understanding the impact of GPI on financial performance, environmental performance, and social performance. The promotion of TBL reflects the firm's efforts to not only focus on economic targets but concern about environmental and social impacts. By proving the impact of GTI on TBL for firms, customers are more likely to buy products that contribute to environmental and social issues, so other market competitors have to adjust their strategies or develop new strategies to achieve non-economic targets. By incorporating environmental and social bottom line in the study, it is possible to measure how the adoption of GTI achieve firm's goals of environmental responsibility and corporate social responsibility.

2.6.2 Research gap in the context of China

There are two main reasons why industrial enterprises in China provide a perfect background to empirically test the research hypotheses and conceptual framework formulated above. First, China has experienced unprecedented economic growth since its economic reform and opening-up policy forty years ago. However, this has come at a price, and sustainability has gradually become a serious concern in recent years (D. Zhang et al., 2019). Economic progress has been significantly dependent on energy consumption, especially fossil fuel consumption. As a result, environmental problems have become increasingly threatening (Orzes and Sarkis, 2019). To respond to the growing pressure from both sides of the debate, the Chinese government has set explicit strategic goals to promote green development. Green development and energy innovation became fundamental principles for the future in the 13th Five-Year Plan of 2016. However, the country's energy intensity is still well below that of developed countries (Zhang et al., 2021) and requires further efforts. Furthermore, Song et al. (2015) show that there are significant reginal differences in the relationship between economic development and green innovation in China. The large differences among industrial enterprises in terms of green transformation provide a diversified sample. Under the pressure of resources, environment and society, the Chinese government attaches great importance to the transformation of industrial enterprises, and some industrial enterprises have achieved rapid development through GI. As a large number of Chinese companies are anxious to transform themselves into green companies, they are ideally suited as a target for the study of GI.

Second, most of the research on GI focuses on developed countries where environmental regulations are stricter than those in developed countries. Therefore, many conclusions and implications of the existing literature are not applicable to most developing countries (Song et al., 2020). China, as a typical developing country characterised by rapid economic growth, low per capita income, weak legal protection and imperfect taxation system, was selected as the research object of this study to fill the research gap in the field GI. This study can also serve as a reference for the transformation and development of GI in other developing countries. Since China is such an important player in product manufacturing and global economy in almost all industries, both academic and industrial fields can benefit from the knowledge contribution of a GI study in China. However, although GI is a hot topic in OM research, we know relatively little about GI in China and even less about how Chinese companies use GI and how effective it is. As China's share in the global economy increases, it is even more important that we better understand BDAC in China and that it also benefits Chinese companies. There is therefore an urgent practical need to take a closer look at the practises of GI in the Chinese context.

2.7 CHAPTER SUMMARY

The chapter analyses existing literature and reveals research gaps which this study aims to address. Separate sections describe GI, ambidexterity, and BDAC, with definitions and explanation. The aim is to introduce and clarify the key concepts in the research, as well as present existing knowledge in literature that contributes to the understanding of this research. Also, theories including resource-based view, knowledge-based view, and information processing view are discussed in this chapter as these theories will be used in the theoretical development sections of the following chapters to help to identify the moderating role of BDAC. Moreover, research gaps are further explained and elaborated in section 2.6 following the critical literature review. This section provides further support for identifying research gaps in the study and further justifications to the relevancy of the research questions mentioned in the previous chapter.

CHAPTER 3 HYPOTHESES DEVELOPMENT

3.1 INTRODUCTION

Despite a large number of studies that investigate why firms should be more sustainable and how critics can measure the greenness of firms, literature regarding how firms can transfer from traditional innovation to more sustainability are still limited (Wicki and Hansen, 2019; Zollo et al., 2013). Additionally, there is no unified view on whether green innovation (GI) can boost firm performance, and controversial conclusions about the impact of GI on different types of performance can be found (Zhang and Walton, 2017). This raises the important issue of further investigating the antecedents and consequences of GI – in order to better understand its value and discover means of improvement. For achieving this purpose, firms must address the difficulties of developing GI. To answer all of the research questions, this study employs two methods: a survey and fuzzy-set qualitative comparative analysis (fsQCA). More specifically, a survey study will investigate the direct and indirect relationship between independent variables and dependent variables, whereas fsQCA will investigate the synergistic relationship between different elements on how they work together to achieve better green product innovation (GPDI) and green process innovation (GPCI). This chapter develops hypotheses to investigate ambidexterity as a determinant of improvement and investigates the moderating role of big data analytics capability (BDAC) in achieving higher levels of GI. Specifically, BDAC has been divided into three categories: big data analytics infrastructure (BDAI), big data analytics management (BDAM), and big data analytics personnel (BDAP). BDAI refers to a company's capacity to use BDA-related infrastructure to enable BDA professionals to swiftly build, implement, and maintain system components for a company (Kim et al., 2012; Wamba et al., 2017). The capacity of management units to handle routines in an organised manner in order to manage BDA resources in line with business demands and priorities is emphasised by BDAM (Kim et al., 2012; Wamba et al., 2017). The capacity of technical workers to complete specified duties is referred to as BDAP (Kim et al., 2012; Akter et al., 2016). Furthermore, the impact of GI on a firm's triple bottom line is also discussed in this chapter. To the best of the author's knowledge, this thesis is the first attempt to simultaneously examine the impact of ambidexterity and BDAC on GI as well as studying the effect of GI practices on the firm's performance in the area of green study.

In this chapter, the theoretical model of the study is proposed for explaining the relationship between GI, its antecedents, and consequences (see Figure 3.1). These are:

(1) The direct effect of ambidexterity on GI (e.g., GPDI and GPCI)

(2) The moderator role of BDAC on the relationship between ambidexterity on GI

(3) The direct effect of GI on firm performance

(4) The mediator role of EP and SP in the relationship between GI and FP

Moreover, multiple theories – resource based theory (RBT), Knowledge based view (KBV) and information processing view (IPV) - are adopted to explain how developing different types of BDAC could facilitate the impact of ambidexterity on GI from a theoretical perspective.

Thus, several research questions are addressed in the survey study:

(1) Does ambidexterity affect GPDI and GPCI?

(2) Do different types of BDAC, i.e., BDAI, BDAM and BDAP, moderate the

impact of ambidexterity on GPDI and GPCI?

(3) Does GPDI and GPCI affect a firm's triple bottom line?

These questions are incorporated in the theoretical model shown in Figure 3.1 and integrated into hypotheses in this chapter.

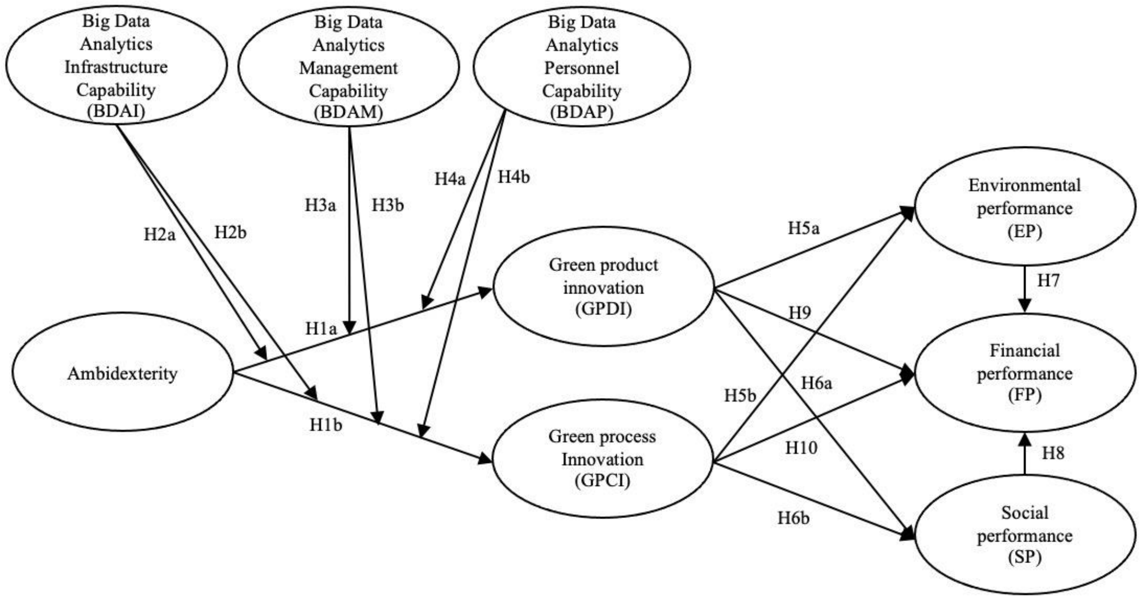


Figure 3.1 Theoretical model

3.2 AMBIDEXTEIRY AND GREEN INNOVATION

In the literature, two major viewpoints exist with regards to the influence of ambidexterity on GI. One stream of study argues that ambidexterity may lead to failure for firms. The work of Peters and Buijs (2021) evaluates whether ambidexterity, as a powerful and favoured method, shapes GI for firms. The results also show that strategic ambidexterity often fails to achieve GI due to a variety of factors. The uncertainties that firms face in GI exist by raising by the utilisation of both internal and external sources. In addition, when firms choose between a highly uncertain and high-risk strategy (exploration) and a more conservative and less green strategy (exploitation), the latter option is preferred in most cases. It has been proven that one-sided focus may bring negative affect to firms; that is to say that too much exploitation improves short-term performance by exploiting existing products but hampers the ability to adapt to environment changes (Ahuja and Curba Morris Lampert, 2001). On the other hand, devoting attention preferentially to exploration could help firm explore innovation opportunities, but organisations may fall into a trap of an endless cycle of search and unrewarding change.

Nevertheless, similar to the conflict in conservative ambidexterity research, some scholars hold the view that ambidexterity can improve a firm's GI. Many studies posit that ambidexterity is a powerful and favoured method for firms to learn and innovate under uncertainty (O'Reilly III and Tushman, 2013; Raisch and Birkinshaw, 2008; Wicki and Hansen, 2019). Ambidexterity competencies enable firms to develop incremental or radical green products and/or to create new markets for those green products. The new processes, in turn, can be used to discover and experiment with new competencies (Danneels, 2002). The paper written by Wicki and Hansen (2019) first used a case study in an engineering firm to examine the distinction between exploration and exploitation. Compared with short-term exploitation, they found that GI requires a long-term exploratory process without guarantee of success and even a likelihood of exploration failure. To increase the chance of success, firms need to improve the efficiency of exploration through creating a failure-friendly organisational culture, deliberately experimenting, and learning from failure. As a result, effectively conducting exploitation and exploration is the key to eliminate innovation tensions and create a better organisation in terms of achieving innovation. Since organisational scholars have realised the importance of balancing exploitation and exploration simultaneously (Chang and Gotcher, 2020b), this research evaluates whether adopting exploitation and exploration simultaneously to pursue GI is practical for most firms.

In this study, we align with the latter stream of research, which posits that firms can achieve successful GI when employing both exploitation and exploration. Further, we posit that ambidexterity improves GI through organisational learning and efficiency improvement (Wei et al., 2014b). When firms adopt exploitation, attention has to be paid to short-term perception, efficiency, and incremental improvement. Exploitative activities pursue learning by local search, experimental refinement, and selection and reuse of existing routines. This improves resource efficiency and makes the product and green process more environmentally friendly. It is possible that there are a lot of duplicated green resources across multiple departments, which could be combined as these activities promote a better understanding of existing resources. This effectively frees up the resources to be used in the firm. With increasingly efficient use of resources, firms are able to share recouped resources on a regular basis, improve commonalities and simplify organisational processes. That being said, exploitation in a GI-emphasised firm's endeavours on developing new linkages within existing green competencies, technologies and products, and those processes improve more efficient use of resources. High efficiency in deploying resources makes products and processes better, cheaper, and greener, which allows firms to exploit existing green products and processes for incremental innovation. This is aligned with the research from (Jakhar et al., 2020), who claim that GI usually respond to stakeholder environmental pressures with short-term oriented sustainability practices.

On the other hand, exploration in GI refers to firms' efforts in terms of discovery, experimentation and variation to generate new and greener competencies for reacting to external changes (Peters and Buijs, 2021). Explorative activities stimulate firms' GI ability by applying new knowledge, skills, and technologies. In other words, when the "green" concept comes to the firm, it is requiring inter or intra organisational green learning. In addition to the collaboration mentioned above, this brings greater possibilities to create new products with high levels of sustainability. Although some studies claim exploration could lead to failure, firms can adapt to new business environments and develop new GI during the process of exploration because firms learn from failure (Wicki and Hansen, 2019). Small failures are necessary conditions for effective organisational learning, and purposeful experimentation to trigger leaning from failure is encouraged. The dead-end experiments in the process are part of an exploratory journey which derives more knowledge about green products and processes. This helps firms to become faster and more effective at exploration and reduces high economic risks. When exploring new opportunities in improving green products and processes, firms are able to understand what the market needs, aiding fast decision-making. Therefore, we suggest that firms need to invest in exploration intelligently to be successful at developing GI.

The above arguments shows that exploitation and exploration separately improve GI, while this study argues that working on exploitation and exploration simultaneously can also improve GI. Firstly, maintaining efficiency and creating radical GPDI/GPCI complements each other, resulting in a higher level of operational excellence and efficiency. When applying ambidexterity, firms rely on current competencies in one area (exploitation) while exploring new competencies in another area (exploration). This can be served as a mean to overcome difficulties in integrating different learning modes, and facilitate the operations efficiency (Filippini et al., 2012).

Secondly, the practice of ambidexterity also improves firms' creativity and adaptability to the new green technology or changes in external regulations. This is due to the fact that ambidexterity includes two distinct mechanisms related to the way organisations obtain knowledge, i.e., exploiting existing knowledge and learning new knowledge (Peters and Buijs, 2021), which optimises knowledge management through knowledge sharing and knowledge creation. The improved knowledge management enables firms to create new GI ideas or improving current green produce or process that are satisfy the demands of customers and markets (Filippini et al., 2012).

Thirdly, ambidexterity also enables firms to foster cross-fertilisation between exploitation and exploration both within and across organisational functions (Hansen et al., 2019). With employees spend time between innovative activities and business unites, as well as dynamic innovation team membership, knowledge and ideas are sharing among the organizations. Since employees devote a significant amount of time to the innovation process, information is shared within teams. Moreover, when new members join the dynamic innovation team, they can bring new ideas and knowledge to the board (Herden, 2020). To sum up, exploitation enables firms to be aligned and efficient to meet business and sustainability demands, but at the same time exploration should also be developed to help firms adapt to environmental change and survive long-term. Working on exploitation and exploration simultaneously allow firms to be aligned and efficient in meeting the business demands, adapting the fast-changing environment, and also stimulate the mix of resource and knowledge for achieving a better GI.

From the perspective of RBT, the underpinning principle of ambidexterity is leveraging (Hansen et al., 2019). Firms can leverage existing resources and competencies that come with exploitation in some areas of GI, while working with uncertainties and lack of experience that come with exploration in other areas of GI (Voss and Voss, 2013). In terms of cross-functional ambidexterity, if a company has the competencies to exploit current markets, assessing market potentials for radical new green products and processes becomes easier. Similarly, if a company excels in discovering radical new market demands, it will become easier to capitalise on existing technical competencies connected to GI or processes. The same principles apply to within-function ambidexterity, in which a part of current green technical (or market) competencies can be exploited while a portion of existing green technological (or market) competencies can be regenerated via exploration. Specifically, a firm can investigate new green-related competencies and technologies for a whole new set of functionalities or a new type of environmentally friendly material that will be applied in an existing product platform and offered in an existing market. Meanwhile, a firm may investigate competencies that are connected to a new green business model in order to offer an existing product as a service to an existing client base (Peters and Buijs, 2021).

Hypothesis 1a: Ambidexterity positively affects GPDI

Hypothesis 1b: Ambidexterity positively affects GPCI

3.3 THE MODERATOR ROLE OF BIG DATA ANALYTICS CAPABILITY

In this study, BDAC is deemed to positively moderate the relationship between ambidexterity and GI, implying that when a firm adopts BDAC, the relationship between ambidexterity and GI tends to be stronger. This section begins with an overview of BDAC's moderator effect from the viewpoints of RBT, KBV, and IPV, then provides detailed information on how each type of BDCA moderates the influence of ambidexterity on GI.

3.3.1 Resource-based view in big data analytics capability

RBT is widely regarded as one of the most powerful and renowned theories for defining, explaining, and forecasting organisational interactions in all business disciplines (Kozlenkova et al., 2014). RBT views an organisation as a collection of resources and provides a powerful framework for bringing together different and disparate resources, which can then be merged to achieve competitive advantage (Gupta and George, 2016).

Previous research has provided empirical evidence that RBT is a suitable theory in various business disciplines to explain the link between organisational resources and firm performance. For example, (Gu and Jung, 2013) describe RBT as a rigorous framework that allows for the identification and classification of IS resources, as well as the measurement of the impact of these resources on a firm's competitive advantage and performance. Similarly, (Dubey et al., 2019) use a resource-based view to design a model that emphasises the relevance of resources in developing competencies, skills, and a big data culture, as well as enhancing cost and operational performance. As a result, RBT is an important tool for examining the link between organisational resources and performance, both conceptually and experimentally

(Gupta and George, 2016).

According to RBT, a firm has a collection of tangible and intangible resources, but only valuable, uncommon, inimitable, and non-substitutable resources can provide a competitive advantage (Gupta and George, 2016). In terms of the context of BDAC, tangible resources are those that can be sold or purchased in the market. BDAC's key tangible resources are as follows:

(i) Data, which includes internal data (enterprise-specific data generated as a result of an organisation's corporate activities) and external data (population-level statistics). As data and information enable firms to make better business decisions and get a better understanding of their customers, modern organisations are keen to collect more information regardless of data quantity, data structure, or data creation pace (Manyika et al., 2011).

(ii) Technology, which refers to innovative technologies that are capable of dealing with the issues provided by massive, diversified, and fast-moving data (Kaisler et al., 2013).

(iii) Basic resources, such as the standard approach for implementing big data initiatives (Wixom et al., 2013).

(iv) Human resources, which include workers' experience, expertise, problem-solving talents, and leadership capabilities, amongst others (Chae et al., 2014).

(v) Technical skills, which refers to the knowledge necessary to employ new forms of technology to extract insight from large amounts of data. This resource necessitates some capabilities, such as machine learning, data extraction, data cleansing, statistical analysis, and understanding of programming paradigms (Davenport et al., 2012).

(vi) Managerial skills, which develop as a result of strong interpersonal relationships among organisational personnel who collaborate. These competencies are highly firm-specific and deeply embedded in an organisational setting (Bharadwaj, 2000)

Meanwhile, intangible resources are viewed as critical to a firm's performance, particularly in a volatile market. Intangible resources cannot be represented on a firm's financial statements because they lack clear and visible boundaries, and their worth is extremely context dependent. In BDAC, there are two major intangible resources:

(i) Data driven culture, which is described as "the extent to which organisational members make decisions based on the insights gleaned from data" (Gupta and George, 2016). A well-developed data-driven culture enables activities ranging from huge amounts of data collection to the acquisition of technology to the development of technical and management skills; moreover, it enables the culture diffusion of data-driven decision-making to all levels (Iivari and Huisman, 2007).

(ii) Intensity of organisational learning, which refers to the capacity to reconfigure resources in response to changes in the external environment provides a corporation with a lasting competitive edge (Teece et al., 1997). Firms with a high intensity of organisational learning typically have stockpiles of organisational knowledge that can be exploited to create BDAC.

As the study views the deployment of BDAC as an essential necessary resource for maintaining competitiveness, further discussion regarding the moderator functions of BDAC in influencing the impact of ambidexterity and GI will be provided.

3.3.2 Knowledge-based view in big data analytics capability

From the perspective of the KBV, knowledge resources are complicated and hard to duplicate. Previous research has laid the groundwork for the use of KBV, indicating that knowledge management provides comprehend data-driven insights and helps firm make efficient decisions within organisations (Ghasemaghaei, 2019). This study also draws key insights from the KBV perspective, to understand how the development of BDAC can influence the impact of ambidexterity to GI.

Firstly, knowledge is the key strategic resource of an organisation, and valuable knowledge resources are embedded internally in information technologies and systems. This could include the internet, data warehouses, open systems, networking mechanisms, software applications and data mining techniques (Awan et al., 2021). When firms apply BDA in resource utilisation, they can gather product data (product material recyclability, product energy consumption, etc.), process data (consumption of sewage discharge, toxic gas discharge, etc.), environmental data (hydrogeological data, environmental surveillance data, economic statistics, meteorological data), and so on (Song et al., 2017). The collected data can subsequently be utilised to modify production plans or policies, for example, environmental data can be used to have a holistic and integrative management of water pollution and climate change reduction. When firms develop BDAC, their green operations will be enhanced by correlation analysis, the causation and necessity of data can be determined, and accurate predictions and better judgments can be made (Song et al., 2017). Furthermore, by collecting multi-functional resources and reconfiguration resource bundles, firms extend their resource portfolios, which allow exploitation and exploration activities conducted in a more dynamically environment.

Aside from resource utilisation, KBV implies that BDA considerably improves the efficiency of the application of knowledge through boosting organisational learning (Lam, 2000). In knowledge management practice throughout the firm's departments, organisational learning is particularly important as it influences organisational ambidexterity. This is because obtaining, processing, interpretation, and synthesis information improves firm performance and competitiveness (Awan et al., 2021). More specifically, both exploration and exploitation require organisational learning, and there is a strong emphasis on the various processes of learning that occur at different levels within organisations, which can be seen as the transition between these processes from the individual level toward the organisational level (Morland et al., 2019). Recent research found that BDA contributes to individual and organisational learning by providing data insights to accomplish various learning outcomes (Ghasemaghaei, 2019). For instance, this could promote real-time learning to solve emergent challenges. BDA also increases organisational learning by improving information processing and interpretation. As a result, BDA contributes to the generation of valuable and hard-to-imitate knowledge resources, which in turn build a firm's sustainable competitive advantage. as well as enhancing GI with the learned and harness knowledge.

Moreover, BDA's data-driven insights have recently gained attention for their ability to generate deep data insights (Ghasemaghaei, 2019). The application of BDA minimises the complexity of creating data insights and improves comprehension of the optimal set of actions based on descriptive, prescriptive, and predictive data insights. Three approaches can be used to create data-driven insight, including descriptive insights (using aggregation and mining techniques on historical data to provide insights into the past), predictive insights (using statistical models and forecasting techniques to provide insights into what could happen in the future), and prescriptive insights (using optimisation and simulation algorithms to provide an overview of possible outcomes and understand what to do). Following KBV, knowledge embedded in information technology requires managers using BDA to demonstrate what has happened in the past, what could happen in a given situation, and what to do in certain circumstances. It also emphasises generating insights on how to contribute to existing resources to improve future outcomes. Fostering effective data-driven decision making requires managers, technical personnel, and other key workers to have strong learning capabilities. In addition, decision making has been identified as a mean of shaping ambidexterity through five stages in the exploitation: commercialisation routes; resource partnering; product design and production; international market development; and customer identification. It's also key for three stages of exploration: problem solving, product development, and market experimentation (Evers and Andersson, 2021). Therefore, through employing computer-supported systems to collect, interpret, and disseminate valuable knowledge, firms can produce valuable knowledge and insights for better decision making in attaining ambidexterity, thereby promoting GI.

3.3.3 Information processing view in big data analytics capability

According to the information processing view, BDAC is an organisational capability that enables a firm to process and analyse green data. BDAC allows firms make use of the high volume, variety, velocity, veracity, and value of big data. By employing different BDA approaches, firms are able to collect, evaluate, synthesise, and coordinate information throughout the organisation. These can include advanced statistical techniques and quantitative methodologies to process, visualise, and analyse data in a systematic way. This information provides opportunities to draw associations or identify hidden factors, and aids in reducing uncertainty about green products and processes (Yu et al., 2021). Because there is less uncertainty that a firm needs to fulfil its objectives, green-related knowledge, environmentally friendly materials and financial flows can be leveraged more effectively. With collection information in demand, sales and operations for green products and green processes, both exploitative and explorative activities benefit from more effective information interpretation.

Meanwhile, when an organisation's structure and business processes are built to improve its BDAC and so meet its data processing requirements, it has a better chance of making effective decisions. The processing requirements of big data are challenging because they necessitate dealing with high volume, diversity, and velocity data. The big data processing is burdensome to organisations since it is difficult for individuals to fully handle enormous volumes of information (Yu et al., 2021). Furthermore, standard systems lack the capacity to capture, store, and analyse big data; hence, companies want new and novel types of BDAC that are projected to provide superior and unique data storage, management, analysis, and visualisation technologies (Wamba et al., 2017). Thus, through developing BDAC, organisations could build an analytically driven business processes and organisational structure.

Moreover, when a firm implements a powerful BDAC to meet the demands of data processing, it could expect to have data-driven insights to evaluate its business practises and make intelligent decisions. Organisations with BDAC not only increase internal company efficiency, but also generate new green products or processes, obtain shorter cycle times and better flexibility, and/or greatly enhance their performance (Yu et al., 2021). This is consistent with the findings of the strategic decision-making study (Awan et al., 2021), which assumed that if an organisation has comprehensive and accurate knowledge about the relationship between options and outcomes, it is more likely to make good decisions, develop effective organisational plans, and improve performance. Prior authors explained that the lack of a positive relationship between IS investment and firm performance could be explained by a lack of appropriate data, time lags between IS investments and the business values generated by the investment, and a failure to consider indirect values brought about by IS investment. Scholars have claimed that BDAC is a moderator that helps to obtain higher performance (Wamba et al., 2017). We aim to add to this information by investigating the moderator function of BDAC in the context of the link between ambidexterity and GI.

3.3.4 The moderator role of big data analytics infrastructure capability

When BDAI is well-developed in the firm, the company usually has superior equipment and software applications for accessing high volume, variety, and velocity data. According to RBT, BDAI includes tangible resource of firms, such as the big data equipment and systems. BDAI enable the implement of big data initiatives and technologies to solve issues by big data. With enhanced infrastructure, professionals can make greater use of collected data by recording more data, filtering out unnecessary data, and analysing data more precisely (Dubey et al., 2019). Meanwhile, advanced network systems allow employees in different departments to effortlessly share data or information (e.g., data from an existing green products or green processes) across organisations, regardless of department locations. This allows professionals to gather information easily from a variety of sources and platforms. High connectivity for analytics, on the other hand, enables the more efficient communication between firms and stakeholders, allowing for a quicker understanding of stakeholder demands.

Given the features mentioned above, we argue that BDAI strengthens the impact of ambidexterity on GI by improving corporate knowledge acquisition and knowledge creation. According to the KBV, knowledge acquisition indicates organisational activities to acquire, extract, and organise knowledge from various sources (Abbas and Sağsan, 2019). BDAI provides the necessary conditions to record diverse and fast-moving data from different platforms and transform diverse data into knowledge (Mikalef et al., 2018). Knowledge can be understood as a mixture of various elements, and BDAI provides sufficient facilities and technological supports to record knowledge in documents or repositories.

In addition, the development of BDAI increases organisational access to various sources, either by generated data with their own IT architectures, or purchasing data of their preference for a particular purpose. Due to the connectivity of BDAI, employees acquire knowledge from both internal sources and external sources. Internal sources include colleagues, managers, or CEO in the enterprises, while external sources include customers, competitors, suppliers, partners, and experts (Mothe et al., 2018). In other words, BDAI acquires knowledge and provides a rich understanding of stakeholder needs related to ecosystem protection and their experience with a firm's products or current processes. This knowledge then can be transferred into unique, green-related knowledge and resources. By integrating unique knowledge and resources into explorative and exploitative activities, organisations are able to make changes to improving existing GI or create new GI.

Moreover, BDAC also facilitate the process of knowledge creation, which could improve the impact of ambidexterity on GI. Knowledge creation is understood as a consequence of interaction between knowledge and the act of knowing, and can be accomplished via activity, practice, and engagement with other organisational members (Abbas and Sağsan, 2019). Advanced infrastructure provides technical and IT systems to facilitate communication or brainstorming. Employees are able to recognise different knowledge types that are shared and converted, then create knowledge through practice, collaboration, interaction, and education. It is particularly essential for firms to allocate adequate resources to the creation of new knowledge in order to improve their innovation skills and the development of new technologies, which will eventually help firms attain sustainability. Developing big data infrastructure enables companies to obtain higher-quality data in terms of different elements. Knowledge creation is also supported by relevant innovation and data which can improve decision making and serve as building blocks in GI. In the context of this study, the accuracy of the interaction of knowledge can be improved when relevant data from green products or processes are transformed into knowledge - therefore, firms can exploit this valuable knowledge to improve existing GPDI and GPCI. At the same time, dynamic firms devote their time to developing knowledge creation environments that encourage employees in knowledge interaction. When providing effective infrastructures or platforms for data generation, employees are able to identify new knowledge, and explore hidden knowledge and introduce new ideas or solution to promote GI.

Hypothesis 2a: BDAI moderates the relationship between ambidexterity and GPDI

Hypothesis 2b: BDAI moderates the relationship between ambidexterity and GPCI

3.3.5 The moderator role of big data analytics management capability

BDAM reflects a firm's ability to manage IT resources, and the adoption of BDAM enable to achieve the routines arrangement in a structure manner (Wamba et al., 2017). From the perspective of RBT, is can be understood as a tangible resource, e.g., leadership big data capabilities. Analytic-based organisations develop BDAM to manage different types and categories of data related analytics in accordance with business needs and priorities, e.g., green purpose, and specific rules and controls are established for participants to comply with during the projects.

Previous studies have found that the capability of big data management has considerably enhanced companies' data governance (Kim et al., 2012). Data governance is the policies and procedures adopted to manage data in an organisation, and it covers aspects like data measure and monitor quality, data scope determination, communication and data management. By applying data governance, the right sets of data can be sent to the right people whenever the need arises, so that right decisions can be made. Thus, the data that needed for ambidexterity can be delivered in time to identify new GI ideas. Meanwhile, a set of governance policies, processes and standards are framed by managers for effectively managing and ensuring big data's availability, usability and consistency. Since effective governance must follow a top-down approach and requires commitment to data-driven decisions from top management to employees (Vidgen et al., 2017), an executive manager's environmental consciousness would also influence other staff. This would potentially encourage them to think in an environmentally friendly way to innovate products or processes.

Moreover, the governance of BDA is a serious concern for innovation because its successful implementation could reduce risks. Risks are not limited to corporate data integrity and data quality, but also IT professionals' problems in transiting from original data sets to big data due to the lack of big data governance framework. While only high quality and timely data could deliver accurate knowledge for exploitation and exploration, GI can be improved by the development of environmental governance.

When developing BDAM capabilities, organisational members must make data-driven decisions and imprint the depth and richness of a data-driven culture through specific practices (Kim et al., 2012), thereby, facilitating the development of intangible resources. When a data-driven culture is created, firms treat data as the main resource for leveraging insights in every department of the organisations, and employees are expected to use data to enhance their daily work and to fully utilise the company's potential by making decisions more successfully. The purpose of data-driven culture is to collaborate to move data to the centre of decision making. It starts from data owner to the data scientist, then the data is analysed and sent to employees who use it. Data-driven culture has been regarded as an essential factor in determining firm's overall success for different reasons:

(i) It promotes collaboration between different teams in the organisation. Even though the key insights gained through advanced and predictive analytics by the data science team, the insights can also help other members in the different departments. This could include the advancement of data interpretation skills and critical thinking, as well as exploiting and exploring green ideas (LaValle et al., 2011).

(ii) It helps to foster data democratisation. When the IT department is the only owner of data, other members cannot access and make use of the data, so a data-driven culture helps to democratise data for more business users with exploitation and exploration.

(iii) It develops products and processes based on company data. Without the data-driven culture, firms usually reply on managerial experience or intuition rather than information extracted from data analysis. Instead of developing a new product or process on the drawing board without any knowledge of sustainability, a firm with a data-driven culture can greatly reduce employees' reliance on their instincts in favour of big data analysis to obtain accurate knowledge in the development of a successful GI (Shamim et al., 2020).

Considering stakeholder opinions, dynamic firms follow environmentally friendly practices. Existing products and processes can be evaluated and customised based on customer needs, and research and development activities carried out to introduce new processes and technologies. This also enable firms to produce high-quality products by reducing the consumption of resources, which not only benefits the environment, but also the firm itself (Abbas and Sağsan, 2019).

Hypothesis 3a: BDAM moderates the relationship between Ambidexterity and GPDI

Hypothesis 3b: BDAM moderates the relationship between Ambidexterity and GPCI

3.3.6 The moderator role of big data analytics personnel capability

Similarly, this study asserts that the development of BDAP strengthens ambidexterity's impact on GI. BDAP can be regarded as the intangible resources of the firms, including human resources and technical skills. Problem-solving talents and IT professionals make use of a variety of skills and technical knowledge to handle large amounts of data and programs to improve decision-making capabilities and relational green knowledge. Moreover, newly generated knowledge not only provides new interpretations of business problems and the development of appropriate technical solutions, but also allows for seamless communication with stakeholders.

BDAP stress the technical person ability in using computer science skills to generate statistics and modelling knowledge. They are expected to create valuable and actionable insights in entrepreneurial and business domain knowledge. Additionally, technical person need to possess effective communication skills in order to report the results to the managers and share outcomes with other organisational employees (Chatfield and Reddick, 2018; Mikalef et al., 2019). Employees' understanding of technology, business, and innovation grow as their professional ability to use big data technologies develops. Meanwhile, when employees have a good understanding of what each department is doing, the information gap between teams can be reduced, resulting in increased communication efficiency. This indicates that increased personal competence can also lead to more effective information exchange (Mikalef et al., 2018)

As mentioned, not only data scientists need to understand business problems and use relevant data sources to generate ideas based on models and visualisation tools; employees throughout the organisation also need to have the ability to think analytically about data and have the relevant ability and skills. Advanced BDAP is not limited to IT professionals, but also benefits other members. According to Bocanet and Ponsiglione (2012), organisational members interact with each other through organisational codes. In the model of March (1991), employees in an organisation are initially endowed with different set of beliefs, while organisational code is developed through interaction. That is to say, organisational code is learnt from people in the organisation, and people learn in turn from the code. As a result, organisational learning improves as time goes by. In this process, exploration can be achieved by the faster learner, who learns and uses higher-performing ideas and routines quickly, improving organisational learning efficiency. Fast learners also tend to converge prematurely on a homogenous set of ideas or routines, hindering long-term learning and leading to a suboptimal equilibrium in the organisation. On the other hand, exploration is achieved by slow learners, who explore new knowledge and ideas in a relatively long period of time. Explorative employees allow the organisation to keep a greater diversity of beliefs, and therefore increases the possibility of improving the quality of organisational knowledge over the long term (Bocanet and Ponsiglione, 2012).

Moreover, with continuous improvement of a team's overall BDAP, knowledge sharing will continue to strengthen. Knowledge sharing is the process through which explicit or tacit knowledge is communicated to an individual or group of people. This term can also be understood as a mean of social interaction in organisations. In some dynamic organisations, experiential results are available to both employees and public, so that organisations could share manufacturing process and experiment results to earn customer trust. In this process, employees with high BDAP are particular important as they solve issue in a creative manner and provide good support for strategies design, decision making, and learning environment development (Abbas and Sağsan, 2019). What's more, effective knowledge sharing can also improve employees' social responsibility and awareness. Once executives acquire those skills and knowledge of human resource, this knowledge and information will allow more flexible use of ambidextrous activities with the purpose of decreasing the environmental impact of GI.

Hypothesis 4a: BDAP moderates the relationship between Ambidexterity and GPDI

Hypothesis 4b: BDAP moderates the relationship between Ambidexterity and GPCI

3.4 HYPOTHESIS DEVELOPMENT OF THE DIRECT EFFECT MODEL BETWEEN GREEN INNOVATION AND TRIPLE BOTTOM LINE

3.4.1 Green innovation and environmental performance

Environmental performance refers to a company's ability to reduce carbon dioxide and other hazardous gas emissions as a result of its operations, such as manufacturing and transportation (Dubey et al., 2019). GI is widely recognised as one of the most effective solutions for reducing environmental harm because it incorporates environmental considerations into product designs and packaging (Dangelico et al., 2017). GI means looking out for ways to modify an existing product design to reduce its potential environmental harm during the whole product life cycle. From the perspective of processes, GI can be improved by any change of the manufacturing process that minimises the environmental impact of steps like material acquisition, production, and delivery (Chiou et al., 2011). Firms may minimise waste and emissions in manufacturing, for instance, by creating products made of environmentally friendly materials or reducing CO2 emissions during product manufacturing (Tseng et al., 2013; M. Zhang et al., 2018).

The work of Chen et al. (2006) points out that innovation related to green products and processes improve firms' competitiveness and the green image of an organisation. Chiou et al. (2011) further argue that both GPDI and GPCI are positively associated with environmental performance. GI generates advancements in knowledge that can be absorbed into green intellectual capital, not only incrementally but also by radically transforming products and processes in a more environmentally friendly way (Rehman et al., 2021a). This study suggests that the GI can improve a company's environmental performance by lowering the environmental consequences of the resources used in manufacturing. Several papers have looked into the positive relationship between GI and environmental performance (Abu Seman et al., 2019; Chiou et al., 2011).

Hypothesis 5a: GPDI has a positive effect on EP

Hypothesis 5b: GPCI has a positive effect on EP

3.4.2 Green innovation and social performance

According to Cooper (2004), social performance refers to a firm's behaviour in terms of shared social values when implementing its goals into action, including evidence of corporate social responsibility on issues like environmental degradation and preservation. Drawing on (Ranganathan, 1998), who suggested four fundamental characteristics of social performance, we present further explanations of how GI improves enterprises' social performance. To start, GI entails not only the creation of green goods and processes, but also the execution of tight regulations to create a better working environment that prioritises employee safety and protects them from the impact of harmful pollution(Zhang et al., 2021). Second, corporations demonstrate their social responsibility and contribute to an environmentally friendly community by adhering to rules or regulations, such as limiting resource waste and environmental harm (Y. S. Chen et al., 2006). Third, under the burden of institutional pressure, choosing whether or not to harm the environment in the pursuit of corporate goals becomes a moral decision. GI provides an ideal approach for addressing ecologically related ethical dilemmas by developing new goods that do minimal harm to the ecosystem.

Under the pressure of green regulations and pressures, businesses are expected to develop environmental ethics and see environmental protection as a social obligation; otherwise, the company's image will not be organically associated with green values(Zhang et al., 2021). Since a favourable cooperative image and reputation are essential for a firm's long-term success, a green image could consistently meet consumers' demands for environmental preservation, which has a long-term beneficial impact on a firm's profitability (Chen, 2008). Meanwhile, eco-labelling, which is derived from a green image, is described as an important tool for stakeholders to include environmental features on products, and it aids in reducing information asymmetry between stakeholders and consumers, as consumers are more likely to be aware of stakeholders' efforts to pursue environmental sustainability and to choose products with eco-labelling amongst competitors (Qi et al., 2013).

Hypothesis 6a: GPDI has a positive effect on SP

Hypothesis 6b: GPCI has a positive effect on SP

3.4.3 Environmental performance and financial performance

A high level of EP is associated with considerable improvement in a firm’s overall environmental situation and its compliance to environmental standards. EP is often achieved by a significant reduction in air pollution emissions, energy consumptions, wastewater, and hazardous materials (Zailani et al., 2012). This study supports Zhu and Sarkis’s (2007) argument that the development of EP reduces costs and improves resource efficiency, therefore improves FP. Previous research points out that EP may be achieved through the employment of green technology, and environmentally friendly technologies enhance EP by lowering the company's expenditure on dealing with waste disposal, pollution control, and energy usage (Feng et al., 2018). Besides, the large reduction in waste and hazardous substances assist firms in avoiding penalties for violating environmental regulations and laws, therefore reduce costs associated with environmental spillage and liability (J. Li et al., 2016). Moreover, Feng et al., (2018) contend that high EP provides firms with legitimacy to operate and may even enhance revenues by introducing new industry standards. This argument is consistent with RBT, indicating that when competitors are unable to meet the same level of EP, firms' products will have a competitive advantage and may gain more market share (Zhang et al., 2021). As a result, pursuing EP can boost firm's total profit margin and market share at a lower cost.

Hypothesis 7: EP has a positive effect on FP

3.4.4 Social performance and financial performance

SP has been found in the influence of an organization's behaviour on different aspects fo society, for instance, health and safety employee, incentives and engagement for local employment, economic development of community, the collaboration with supply chain partners, etc. This study posits that having a high level of SP also improves FP (de Giovanni, 2012). The main reason for this is that when companies raise their environmental awareness and integrate green concepts into their business development, SP can be improved by satisfying stakeholders' needs for environmentally friendly products and services, which supports origination's ability to provide high FP. For example, improving the company's environmental protection standards can lessen environmental pressure on other firms in the supply chain, or lowering waste generated in the manufacturing process can improve the labour safety and working conditions. The satisfaction of various stakeholders improves the company's competitiveness and FP (Alfred and Adam, 2009). A stronger contact with the external society would be developed by benefiting various stakeholders in terms of their environmental protection demands. By making the company's SP more widely known, a positive reputation can spread across stakeholders or the industry, enhancing financial performance by raising the likelihood of receiving investment from banks or investors (Zhang et al., 2021). Therefore, this study posit that SP is positively associated with FP.

Hypothesis 8: SP has a positive effect on FP

3.4.5 Mediating effect of environmental performance

In an institutional context, setting a high priority on social responsibility is likely to be opposition to, or even outright rejection of, products or processes that are seen to be harmful. Such products or processes may violate environmental regulations or just fail to meet customer expectations. Incorporating ecological or green concerns into firm operations, on the other hand, not only complies with formal institutional requirements, but also improves overall efficiency by reducing waste, energy consumption, and hazardous substance emissions (Zhang and Walton, 2017), thus avoiding the costs associated with implementing invalid practices or even manufacturing substandard products.

Unlike traditional product innovation, which focuses on economic growth or cost efficiency, GI considers both economic and environmental advantages, and integrates consumers' environmental concerns throughout the whole business proces). Such improvements in both environmental and societal dimensions can bring higher consumer satisfaction, as well as improved profit and market share (Dangelico, 2016a). Furthermore, GI frequently necessitates the deployment of innovative technology. According to the resource-based theory (RBT), when a business develops unique knowledge and resources that are difficult to duplicate, the focused firm benefits more from its innovation and becomes more competitive than its competitors (Zhang and Walton, 2017). Given that customers prefer to buy products that do not hurt the environment, GI may enable enterprises to increase product sales and so ensure more consistent profits.

In addition to providing their functional needs, green products may satisfy people's psychological demands in terms of environmental conservation (Pujari et al., 2003). If firms keep creating traditional products and processes rather than GI, they are refusing to assume social responsibility for the environment, which will result in major issues in the future (Tseng et al., 2013). As a result, companies with a high GPI capability and a brand image connected with an environmentally friendly idea will have an easier time competing in the market than their more traditional counterparts.

Generally, we claim that GI is not oriented towards directly assisting businesses in increasing revenue and lowering expenses. GI is used to improve social perceptions and achieve environmental sustainability. Green practices, according to Feng et al. (2018), do not immediately contribute to better financial success. Instead, enterprises may indirectly improve their financial performance by booting their environmental and social performance as a result of GI development. As a result, we claim that GI has an indirect influence on financial success through increasing environmental and social performance.

3.4.6 Mediating effect of social performance

A high degree of environmental performance is linked to lower levels of pollution, hazardous material usage, and environmental incidents (Feng et al., 2018). Strong environmentally positive behaviour leads to cost savings and resource efficiency, and so to better financial results (Zhu and Sarkis, 2007). According to Feng et al. (2018), ecological technological solutions can improve environmental performance by preventing pollution and lowering costs associated with environmental spillage and liability. Explicitly, firms will be able to save money on waste disposal, pollution control, energy, and material consumption. Meanwhile, significant reductions in waste and hazardous chemicals aids businesses in avoiding penalties for breaking environmental rules and laws (J. Li et al., 2016). Furthermore, earlier research (e.g., Feng et al., 2018; Kraus et al., 2020; Ranganathan, 1998) suggests that high environmental performance provides businesses with legitimacy and even increases profit margins by establishing new industry norms. When competitors are unable to meet the same high level of environmental performance, environmentally aware businesses might acquire greater market share. As a result, pursuing environmental performance may boost a company's overall profit margin and market share while lowering costs.

The social dimension of sustainability is found in the influence of an organisation’s behaviour on different aspects of society, including its employees, customers, community, supply chain, and business partners (Alfred and Adam, 2009). This study implies that social performance effects financial success in a beneficial way. This is because excellent social performance satisfies diverse stakeholder groups by assessing and resolving environmental issues in a fair and reasonable manner, therefore boosting the firm's competitiveness and benefiting organisational financial performance (Xie et al., 2019). When increasing environmental performance, social excellence ensures the organisation's license to operate and satisfies evolving stakeholder needs for environmentally responsible (Ar, 2012; Barney, 1991; Cooper, 2004)goods and services, which supports the organisation's capacity to produce a high-quality economic performance. Furthermore, strong social performance improves a company's operational efficiency and managerial abilities, which impact organisational culture, structure, technology, and human resources, and has both internal and external advantages (Barney, 1991; Kraus et al., 2020). Furthermore, increasing communication surrounding environmental protection and GI helps the firm build a positive reputation and goodwill with external stakeholders, improving financial performance by attracting more investment from bankers or investors, facilitating the appointment of better employees, and expanding the customer base (Cooper, 2004). As a result, this study argues that social success and financial performance are favourably associated.

Hypothesis 9: The effect of GPDI on FP is fully mediated by EP and SP.

Hypothesis 10: The effect of GPCI on FP is fully mediated by EP and SP.

3.5 CHAPTER SUMMARY

This chapter proposes a conceptual framework to examine the antecedents and consequences of GI. The model consists of a set of ambidexterity and BDAC practices for organisations to improve GI, and the impact of GI on the triple bottom line. In addition, a detailed explanation based on existing knowledge that support the hypotheses is provided to explain the theoretical model.

In particular, hypotheses 1a and 1b, assume that ambidexterity improves GPDI and GPCI, and the relationship between ambidexterity and GI is explained by how exploitation, exploration, and the combination of these two elements improve GPDI and GPCI. The RBT is used to demonstrate how ambidexterity improves firm competence and resources, and thus improves innovation ability in an environmentally friendly manner. This chapter also explains why BDAC moderates the relationship between ambidexterity and GI from the perspectives of BDAI, BDAM, and BDAP. It also assesses the value of BDA in developing this capability for higher GI. It combines RBT, KBV, and IPV to demonstrate that the ability to use BDA improves ambidexterity and GI. In terms of the hypothesis development, BDAI moderates the relationship between ambidexterity and GPDI/GPCI, that according to hypotheses 2a and 2b; BDAM moderates the relationship between ambidexterity and GPDI/GPCI, as per hypotheses 3a and 3b; and BDAM moderates the relationship between ambidexterity and GPDI/GPCI, as according to hypotheses 4a and 4b. Finally, we will investigate the direct impact of GI on the triple bottom line, i.e., financial, environmental, and social performance, as well as how environmental and social performance can mediate the impact of GI on financial performance, thereby scrutinising the benefit of GI on firm performance from various perspectives. Hypotheses 5a and 5b assume that GPDI/GPCI has a positive effect on EP; hypotheses 6a and 6b assume that GPDI/GPCI has a positive effect on SP; hypotheses 7 and 8 assume that EP/SP has a positive effect on FP; and hypotheses 9 and 10 assume that GPDI/effect GPCI's on FP is fully mediated by EP and SP. The proposed model serves as the foundation for the subsequent empirical research in GI, and it will be tested in the sections that follow.

CHAPTER 4 METHODOLOGY

4.1 INTRODUCTION

The methodology of this green innovation (GI) study is described in this chapter. Research methodology refers to the procedural framework for the conducted research (Amaratunga et al., 2002). It can be used to explain the procedure for selecting appropriate techniques to identify, select, process and analyse information to solve research questions. The methodological process enables researchers to plan and examine the underlying logic of the selected methods, to assess the appropriateness of different research techniques, and to evaluate the possibility of the study design contributing to knowledge in a constructive way (Amaratunga et al., 2002). The research methods will be thoroughly defined in this chapter by offering a robust research methodology, making the study easy to understand.

There are multiple reasons to support quantitative methodology as the appropriate choice for this research. The main reason is that GI and BDAC is a relatively new combination in operations management, and a context-free generalisations are more appropriate than a subjective perspective from practitioners who interpret their realities of GI and BDAC practices. Furthermore, objectivism represents generalisable results, by using a quantitative approach, the proposed key concepts can be operationalised and measured by a number of measurement items, so the dimensionality of key constructs can be investigated. Moreover, the large amount of sample data collected from practitioners can provide valid and reliable results (Flynn et al., 1994).

Nevertheless, there is no perfect methodology for all studies, as each study focuses on different research domains and has its particular characteristics and concerns. Each methodology collects and analyses data in different ways, with different advantages and limitations. For instance, a quantitative approach has the ability to address a wide range of situations, and the statistical analysis of quantitative study is usually aggregated from a large number of samples, which allows the results have a significant impact on decision making. However, quantitative methods fall short when it comes to explaining factors in depth. These methods also tend to be inflexible and managing the speed, progress, and end point of the study can be more difficult (Amaratunga et al., 2002). In order to solve all the research questions and enhance the research possibilities, this study adopt two methodologies, surveys and fsQCA. This chapter focuses on the description of survey methods; a detailed explanation of why and how fsQCA was adopted as well as its results will be presented in Chapter 6.

This chapter aims to describe the methodology used in this research. It begins with the philosophical foundation of the research methodology and explains the reason for adopting a quantitative methodology and surveys. Then, this chapter provides more details of the survey including the questionnaire design, sampling, and analysis techniques employed. In addition, the key techniques adopted to analyse the primary data collected from the surveys are explained, including exploratory factor analysis (EFA), confirmatory factor analysis (CFA) and structural equation modeling (SEM). The methodology of scale development, and the moderating and mediating effects testing of the structural model, are also discussed.

4.2 PHILOSOPHICAL FOUNDATION OF RESEARCH METHODOLOGY

As mentioned, there is no single accepted methodology which can be applied to all studies. As each method has its own strengths and weaknesses, it becomes particularly important to select the appropriate research methodology according to the paradigm that can guide research activity. These could be categorised based on views about the nature of reality and humanity (ontology), the theory of knowledge that informs the research (epistemology), and the particular ways of knowing reality (methodology) (Guba, 1990). Ontology represents "the study of reality or things that comprise reality", epistemology can be defined as "a theory of knowledge concerned with the nature and the scope of knowledge" (Slevitch, 2011), and methodology is understood as a research strategy in which epistemological and ontological principles are turned into rules and show how research is conducted. When discussing the nature of social science research, the consideration of ontology, epistemology and methodology need to be seen as the central feature since these elements provide shape and definition to the conduct of an inquiry (Popkewitz, 2012).

There are two broad epistemological positions in social science research: interpretivism and positivism, see as Figure 4.1 (Tuli, 2011). Interpretivism believes that individuals are intricate and complex, and different people experience and understand the same objective in different ways. Interpretivist research aims to gain in-depth insight into the lives of respondents and as well as have an empathetic understanding of why individuals act in the way that they do. Qualitative methods are therefore preferred since they allow for closer interaction with respondents. The nature of qualitative methods is interpretive, and the purpose of inquiry is to understand a particular phenomenon, since it allows complex interpretations, consisting of multiple viewpoints amongst individuals. From an interpretivist-constructivist perspective, the theoretical framework for a majority of qualitative research thinks of the world as constructed, interpreted, and experienced by people in their interactions with others and with wider society (Maxwell, 2005).

Meanwhile, positivism posits that society shapes individuals and that people's actions are influenced by the social norms they have been exposed to through their socialisation. The aim of positivist research is to uncover the laws that govern human behaviour. The realist/objective ontology and empiricist epistemology contained in the positivist paradigm requires a research methodology that is objective and detached, which attaches great importance to measuring variables and testing hypotheses that are related to general causal explanations (Marczyk et al., 2005). The goal of positivist research is to develop the most objective methods to get the closest approximation of reality, thus, quantitative methods are preferred due to the reason that they allow for the research to remain detached from the respondents and generalise to a population. In addition, results from quantitative methods, such as questionnaires, tests, inventories and so on, provide the result of a single "true" reality with nomothetic conclusions.

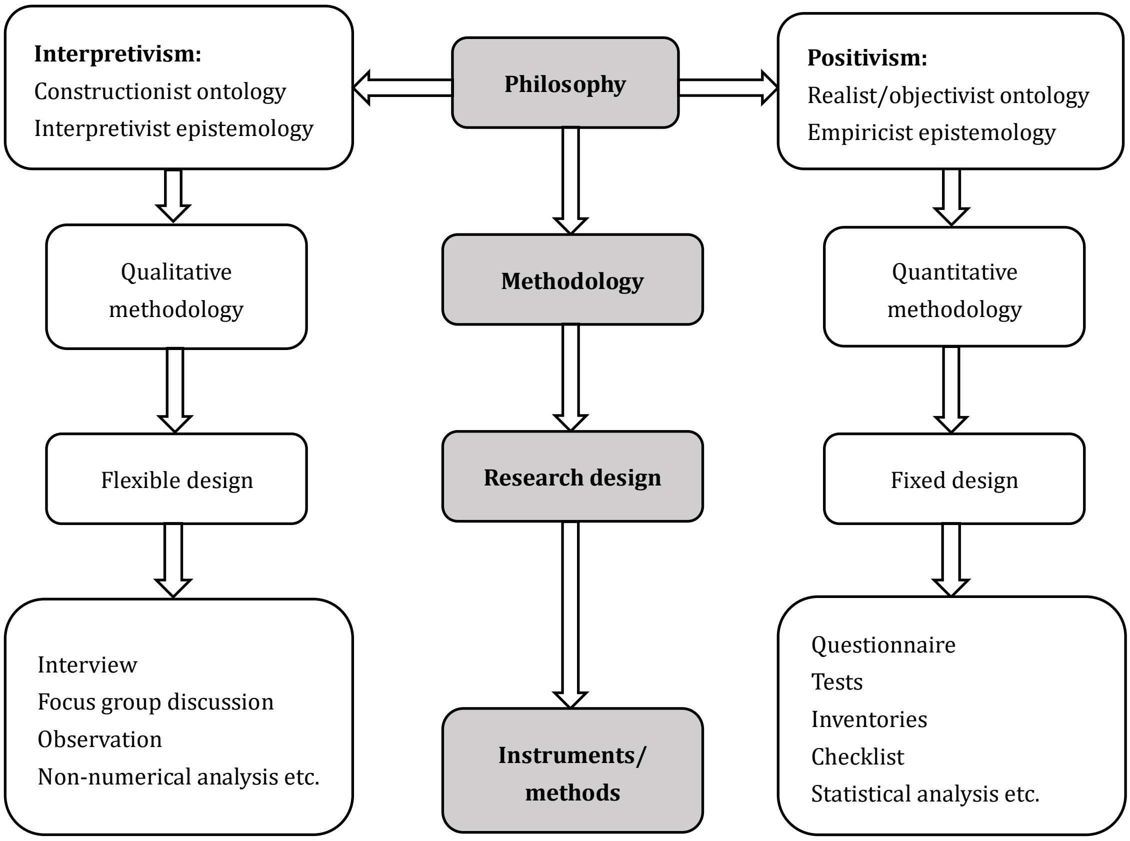


Figure 4.1 Foundation of research (Tuli, 2011)

The context of this research, according to the philosophical foundations of methodology, is Chinese firms that pursue GI. It posits that green related product and progress impacts organizational behaviour. As a result, objectivism is the suitable ontology for this study, rather than positivism, which from an epistemological perspective. Moreover, the objectivism perspective of quantitative approach reflects reality and represents a generalisable result. GI is a relatively new practice in real life settings, so context-free generalisations related to GI are more useful than subjective perspectives from practitioners who have adopted GI practices (Kraus et al., 2020; Abbas and Sağsan 2019). Therefore, quantitative research methods are more suitable in this study for examining the enablers of green technology innovation and its impact on firm performance. That is to say, this study fits quantitative philosophy as a quantitative approach, an extreme of empiricism in which ideas are justified not only by the extent to which they can be verified, but also focuses on the facts.

According to an objective perspective, quantitative methods can be used to develop key constructs' measurement, distinguish characteristics, elemental properties, and empirical boundaries (Amaratunga et al., 2002). Besides, this approach can formulate and test the hypotheses, therefore, the relationship between ambidexterity, green technology innovation, and firm performance can be scrutinised and analysed by statistical analysis techniques. A large-scale sample size is adopted to validate the proposed key constructs' practices and ensure the validity and generality of this research. Therefore, this study can benefit from this methodology in terms of the value of hypotheses and flexible in the treatment of data measure and allows to investigate what leads to good GI practice, how to adopt GI, and what are the best recipes for applying it.

In particular, surveys are adopted in this study to add to the body of knowledge in a certain field of interest. In the fields of business study, survey-based research is appropriate in exploratory settings and predictive theory, and the validity of contracts and their corresponding measurement items are supported by using previously published latent variables with psychometric properties (Mikalef et al., 2019; Straub and Gefen, 2004). Like other types of research technology, survey research contributes to the advance of scientific knowledge in different ways, including exploratory, confirmatory, and descriptive survey research. In this study, confirmatory survey research is selected to understand the knowledge of a phenomenon that has been stated in a theoretical form with well-defined concepts, models, and propositions. In this situation, surveys are designed to discover or establish the existence of a relationship, association, or interdependence between two or more aspects of a situation or a phenomenon. Information collection is conducted with specific aims of testing the adequacy of the concepts developed in the relation to the phenomenon, the hypotheses that link different concepts, and the validity bounty of the modules (Forza, 2002). Data are collected from individuals through activities like mailed questionnaires, telephone calls, personal interviews, and so on. These survey sampling processes allow information to be generated about large populations with a defined degree of accuracy, and more in-depth processes will be explained explicitly in the following sections.

4.3 SCALE DEVELOPMENT

There are two major challenges in multi-item measurement and scale development. One is reducing measurement error by providing a robust representation of complex variables, while another is selecting the appropriate measurement items that cover the construct domain with the desired reliability and validity (Menor and Roth, 2007). To address these issues, this study uses Menor and Roth (2007) scale development approach as the skeleton and combines it with stages suggested in the literature (Kaynak and Hartley, 2008; Netemeyer et al., 2003; Zhang and Walton, 2017) to develop and validate measures of ambidexterity, GI, BDAC, and firm performance. Figure 4.2 displays the specific steps.

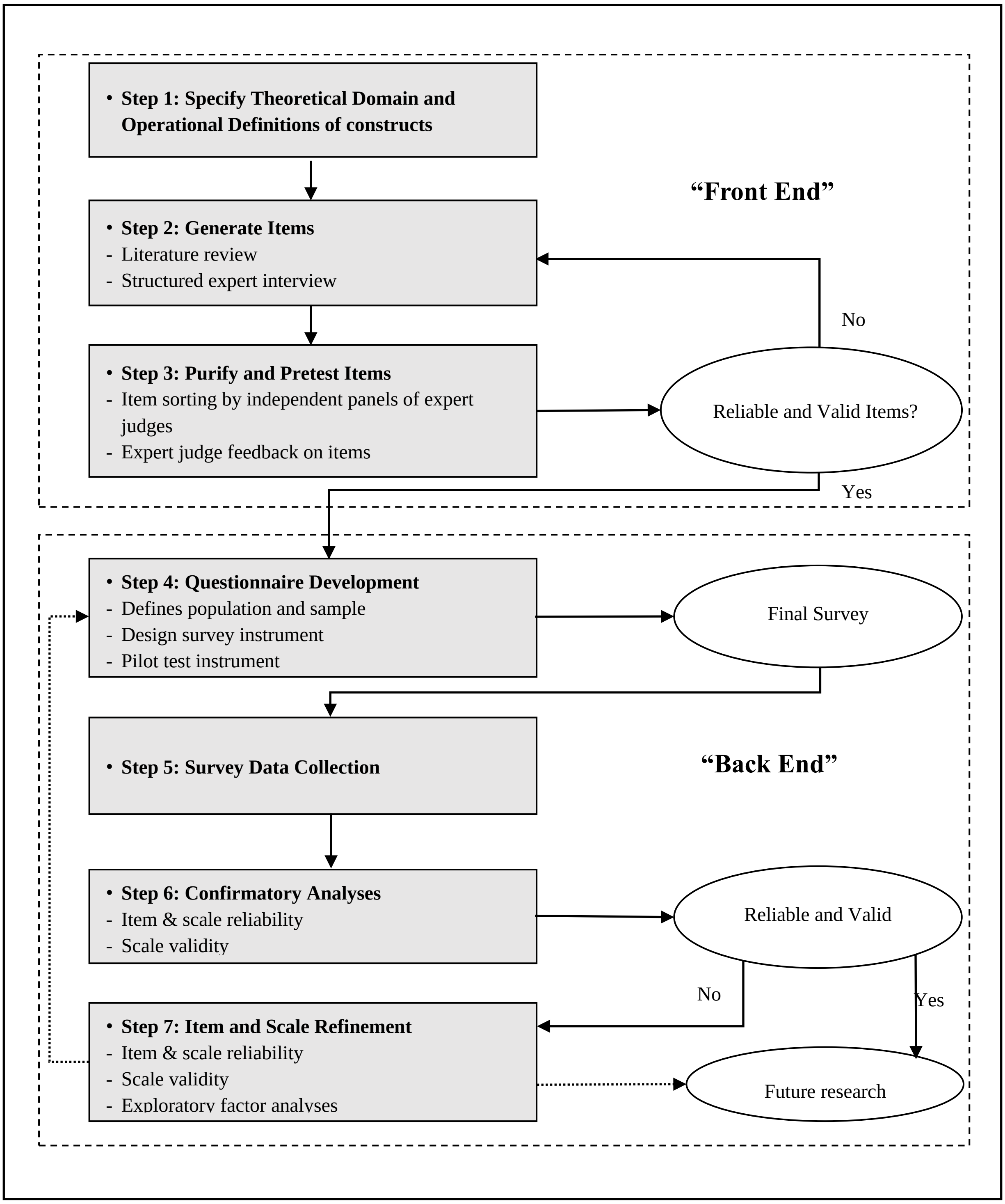


Figure 4.2 Flow of scale development

4.3.1 Specification of theoretical domain and operational definition of constructs (Stage 1)

In scale development, the first step is to define constructs clearly and concretely (Worthington and Whittaker, 2006a). The conceptualisations should be based on a thorough existing theory and researched to ensure information is collected in a cumulative manner and provides a strong foundation that reflects a variety of different themes or perspectives (Netemeyer et al., 2003). The qualities covered in the definition must be clarified by the researcher. This conceptualisation process creates the conceptual model for item measurement and scale development.

4.3.2 Item generation (Stage 2)

After the goal of scale development has been established, the next step is to create an item pool designed to the construct. Generally, the items need to be clear, concise, readable, distinct and reflect the purpose of the scale. Previous literature in the key terms of this study were reviewed, and the theoretical insights were obtained to compile the initial list of potential items (Worthington and Whittaker, 2006a). The goal is to generate a collection of items that can clearly and accurately represents the proposed construct of interest, thus ensuring content validity. Items that are not central to a construct or poorly worded could lead to potential sources of error variance, lower the strength of correlations among items, and even weaken the overall objectives of scale development. Furthermore, research shows that the items generated should not be either narrow or too wide, and scale elements should be developed to connect to the conceptual domain (Netemeyer et al., 2003).

4.3.3 Purify and pre-test item (Stage 3)

Following the item generation steps, the next step is to have structured interviews with expert panels to purify and pre-test the initial list of potential items (M. Zhang et al., 2018). In a structured interview, a group of knowledgeable experts review the items by assessing item quality. The experts are required to review content validity, which means examining the extent to which of a set of items reflects the content domain (Churchill, 1979). The reason to conduct content validity is to ensure that empirical scrutiny is sufficiently rigorous for the measurement items and construct definition. Content validity should be achieved through a comprehensive review of relative literature and through interviews with practitioners and academics. In this study, the review of literature is complemented by in-depth discussions with practitioners who are familiar with GI and BDAC practices in their manufacturing firms. The two-step content validity test proposed by Rungtusanatham et al. (1998) will be conducted for content validity, which includes (i) an inter-judge agreement percentage and (ii) the application of Cohen's kappa test.

In the first step, a panel of knowledgeable assessors is chosen for the test, consisting of three operations management (OM) academics and two industrialists. One academic is a professor at Wuhan University of Technology in China, while two OM academics are professors at University of York in the United Kingdom. Three academics can provide precise knowledge about the definition and measurement items of the potential constructs because they have extensive experience undertaking research in the fields of OM and innovation. In addition, the two industrialists work as directors of Chinese manufacturing companies Jianhua Materials Co., LTD and Wuhan Jinhua Foundation Engineering Co., LTD. Both industry professionals have extensive management and industry experience and have suggested improvements to the measurement items based on their practical experiences. Each possesses the appropriate knowledge, skills, and experience in GI. The instrument used for item sorting consists of a definition of each construct, and a randomised list of all measurement items (Hinkin, 1998; Menor and Roth, 2007). Experts are also asked to assess factors such as clarity, conciseness, grammar, reading level, face validity, and redundancy. At this stage, experts can provide suggestions for adding more items and extending the length of administration.

In the second step, the results of the sorting exercise are analysed by obtaining Cohen’s kappa (κ). The kappa statistic is the percentage of agreement that remains after chance agreement is eliminated, which is used to measure interrupter agreement among observers who grade dichotomous categories of data. Cohen's kappa (κ) is an indication of beyond-chance agreement amongst multiple judges for the overall task and to evaluate content validity (Wynd et al., 2003). The value of Cohen’s kappa (κ) index ranges between +1.00 and –1.00, with a positive kappa indicating that raters agree more frequently than can be expected by chance. A +1.00 means complete agreement across raters. A zero kappa demonstrates that agreements are no more than can be expected by chance. A negative kappa indicates that agreement occurs less frequently than would be expected by change, while a kappa of -1.00 reveals total disagreement (Wynd et al., 2003). After obtaining Cohen’s kappa (κ), the inter-judge agreement percentage is obtained. The inter-judge agreement percentage is the percentage of judges that assigned the item to the desired category. The cut-off ranging from 60% to 75% is treated as a minimum extent of agreement among judges for item retention (Hardesty and Bearden, 2004).

4.3.4 Questionnaire development (Stage 4)

Questionnaires are used to collect information (e.g., knowledge, attitude/beliefs/intention, cognition, emotion, and behaviour) in a standardised manner. When obtained from a representative sample of a defined population, they allow the inference of results to a larger group (Rattray and Jones, 2007). When designing a questionnaire, the development process should be defined in sufficient detail to allow practitioners to make an informed decision about whether or not to implement the findings. The three key points that need to be taken into consideration, as suggested by Hinkin (1998), are (i) the number of items in the construct, (ii) the selection of a Likert scale, (iii) negative wordings.

Because the target respondents were Chinese senior executives, the questionnaire was translated from English to Chinese. When translating the questionnaire items into the appropriate language for the respondents in this study, the forward and reverse translation method of the questionnaire was used (M. Zhang et al., 2018). Following the completion of the questionnaire design, it was given to practitioners for pilot testing of fine-tuning phrasing (See Appendix 2 for practitioner information.) The pilot test can also provide input on the questionnaire design. The major goal is to guarantee that practitioners have a thorough grasp of the measuring project's respondents.

4.3.5 Questionnaire administration and data collection (Stage 5)

At this stage, a questionnaire was distributed to the selected data pool's senior management. The questionnaire, together with a cover letter, was sent via email. Endorsement letters from the Product Development and Management Association (PDMA) in China, PDMA-CHINA, were also included in the email (Both letters are attached in Appendix 6.) Around four weeks later, an email was be sent to all possible recipients reminding them of the questionnaire. Following the distribution of the reminder emails, phone calls were made to request the recipients' involvement. After the data gathering, a data purification process was conducted.

It is worth mentioning why Chinese industrial enterprises provide an ideal setting to test the research hypotheses and the conceptual framework formulated empirically above. There are two key reasons. First, significant differences regarding green transformation can be found between industrial enterprises, which provide a diversified sample. Due to constraints imposed by resources, the environment, and society, the Chinese government places a high value on industrial enterprise transformation, and certain industrial firms have achieved rapid growth through GI (Wang et al., 2021). Secondly, environment costs can be reduced by GI, thereby expectedly increasing the financial performance of firms. An example could be the sewage charge system used in China which helps to balance the costs and benefits of GI.

4.3.6 Scale construction and purification (Stage 6)

Scale construction and purification are also widely used steps in empirical research. The goal of this stage is to remove items from multi-item scales. The exploration of scale development is necessary since scales were employed in a national culture that differs from the Western culture in which the scales were formed (Zhao et al., 2008). A two-step technique provided by Narasimhan and Jayaram (1998) is utilised. EFA is first performed on the original set of items to assure unidimensionality of the scale, then Cronbach's alpha is used to test reliability. EFA is used with principal component analysis to purify the scales, removing items that diminish the alpha value. To clarify the factors, Varimax rotation with Kaiser normalisation was utilised (Loehlin et al., 1998). Then the measurement items on the construct are compared, if any item is presented to measure other construct, the item need to be eliminated. Then, Cronbach's alpha is computed for each construct for internal consistency, with the cut-off point of Cronbach's alpha being greater than 0.70. Using the intercorrelation matrix, all factor loadings in EFA are considered to be larger than the cut-off value of 0.30, and items with correction values that are less than 0.30 are eliminated. All of the above steps are performed interactively.

4.3.7 Scale validation using CFA (Stage 7)

CFA is used to assess whether measurement variables are related to their corresponding constructs, in addition to verifying the unidimensionality of all indicators. The CFA test findings allow us to compare the developed theory to the reality offered in the data (Hair et al., 2010). Construct validity is essential to the perceived overall validity of the test as it assesses how well a set of measured items represents the theoretical latent construct that those items are meant to evaluate (Hair et al., 2010). Thus, construct validity is concerned with evaluating accuracy and provides evidence that the items measured correspond to the true population score. The validity of the scale is assessed in three ways: (i) model fit, (ii) convergent validity and (iii) discriminant validity.

4.3.7.1 Overall fit

The model fit is evaluated using absolute, incremental, and parsimonious measures to indicate "how well the estimated relationships in the model match the observed data (Shah and Ward, 2007a). Table 4.1 shows the suggested values of these indices for an acceptable model fit for three types of measurements that are often given to demonstrate the overall model. Absolute measures of fit indicate how well an a priori model reproduces the sample data; incremental fit measures evaluate the model's incremental fit compared to a null or worst-case model; and parsimonious fit measures evaluate the proposed model's parsimony by evaluating the model's fit versus the number of estimated coefficients required to achieve the level of fit (Hair et al., 2010; Shah and Ward, 2007a). Since many fit indices are impacted by sample size (e.g. GFI, NFI, and AGFI) and others by the manifest the ratio of variable/latent variable (e.g. NNFI and CFI), providing a broad selection of fit indices is recommended (Shah and Ward, 2007a). In this study, different measures of fit are provided to derive relevant conclusions about model fit, and we provide our findings as well as the recommended cut-offs for each of the metrics.

Table 4.1 Recommended values for acceptable model fit (adopted from Shah and Ward, 2007)

Measures of fit	**Statistics measures**	**Recommended values for acceptable model fit**
Absolute	χ^2-Test statistic (d.f.)	NA
	Root mean square error of approximation (RMSEA), point estimate	≤0.08
	RMSEA, 90% confidence interval	(0.00;0.08)
	p value H_0: close fit (RMSEA ≤ 0.05)	≥0.05
	Standardised root mean square residual (SRMR)	≤0.10
Incremental	Non-normed fit index (NNFI)	≥0.90
	Comparative fit index (CFI)	≥0.90
	Incremental fit index (IFI)	≥0.90
Parsimonious	Normed χ^2 (χ^2/d.f.)	≤3.0

Parsimony normed fit index (PNFI)	≥0.70

4.3.7.2 Convergent validity

Convergent validity reflects the extent to which indicators of a specific construct converge or share a high proportion of variance in common (Hair et al., 2010), and it can be used to uncover the extent to which two measures capture the same information. In other words, if the construct has a good convergent validity, the item measurement should correlate closely with other measures designed to measure the same construct (Churchill, 1979). The more similar the information measures capture, the more likely that they can produce equivalent research results. As suggested by Cheung and Wang (2017), this study adopted three approaches to assess the convergent validity among item measures: (i) factor loading, (ii) average variance extracted (AVE), and (iii) composite reliability. In detail, factor loading is one of the most important considerations for achieving a high degree of convergent validity. If the factor loading is statistically significant, convergent validity exists. The Fornell-Larcker criterion for convergent validity requires an AVE greater than 0.5. The Hair et al. (2010) criteria for convenient validity requires an AVE greater than 0.5 and standardised factor loading of all items higher than 0.5. Finally, composite reliability is used as a measure of convergent validity, with the rule of thumb being that it should be more than 0.7 for good reliability.

4.3.7.3 Discriminant validity

Discriminant validity is used to verify that scales developed to measure different constructs are truly distinct from other constructs (Hair et al., 2010). Discriminant validity indicates that a latent variable can explain for more variance in the observable variables associated with it than can a measurement error, equivalent unmeasured external effects, or other constructs within the conceptual framework (Farrell and Rudd, 2009). This is particularly essential when constructs are highly correlated and similar in nature. If different latent variables are highly correlated, they may measure the same construct rather than different constructs. Only low correlations between constructs suggests the presence of discriminant validity. For achieving a high discriminant validity, it is necessary to indicate "how much the construct correlates with other constructs in the model" and "how distinctly the measurement items only represent this single construct".

There are various approaches for determining discriminant validity, such as the paired construct test, the Fornell and Larcker technique, or multi-trait multi-method evaluation of constructs. While considering the need for more stringent evaluations of validity, the rigorous approach suggested by Hair et al. (2010) is adopted in this research. The AVE values of any two constructs are compared with the square of the correlation estimated by two constructs. Discriminant validity is assessed by the shared variance (squared correlation) between each pair of constructs compared with the average of the AVEs for these two constructs (Farrell and Rudd, 2009). When there is a high discriminant validity in the model, the estimated AVE is greater than the squared correlation. This implies that the latent construct explains more of the variance in its item measures than the variance shared with any other construct.

4.4 FACTOR ANALYSIS

Factor analysis is one of the most widely used multivariate techniques in quantitative studies, notably in the areas of social and behaviour sciences. This technique is applicable when there is a systematic interdependence amongst a set of observed or manifest variables. This approach can be used to discover something more fundamental or latent which creates this commonality (Kothari, 2004). The primary goal of this technique is to determine the number and nature of latent variables or factors that account for the variation, as well as the covariation among a set of observed measures, often known as indicators. That is, the observed measures are inter-correlated because they are impacted by the same underlying construct and share a common cause. In this study, factor analysis will be used to discover the latent variables that accounts for exploitation, exploration, green product innovation (GPDI), green process innovation (GPCI), big data analytics infrastructure (BDAI), big data analytics management (BDAM), big data analytics personnel (BDAP), environmental performance (EP), financial performance (FP), social performance (SP).

As there are more measured variables than the number of factors, factor analysis gives a more parsimonious comprehension of the covariation among a group of indicators. A factor represents an unobservable variable that impact numerous observed measurements and explain the correlations among observed measures (Brown, 2015). This study includes two main types of analyses: EFA and CFA. The purpose of both EFA and CFA are to reproduce the observed relationships among indicators with smaller set of latent variables, but they differ in terms of the number and nature of a priori specifications and restrictions made on the factor model.

EFA is used early in the topic's development, e.g., during the scale construction and construct validation processes. Researchers use EFA to identify the underlying or latent constructs (i.e., exploitation, exploration, GPDI, GPCI, BDAI, BDAM, BDAP, EP, FP, SP) that could have resulted in the observed pattern of variances and covariances among variables, therefore defining basic concepts and relationships and simplifying the current instrument by lowering the number of items (Forza, 2002). The associations between latent constructs and observed variables (test items) are characterised by a sequence of equations containing factor loading coefficients, which are comparable to standardised regression coefficients. As the aim of EFA is to search for structure among the variables in the analysis, there are no prior constraints regarding to the number of factors to be extracted (Hair et al., 2010). The results of EFA shows the number of common factors, and which measured variables are reasonable indicators of the latent dimensions according to the size and differential magnitude of factor loadings. For determining what is deemed a strong factor loading coefficient, exploratory factor analysis approaches rely on numerous rules of thumb, with factor loading cut-off criterion ranging from 0.30 to 0.55 (Forza, 2002).

CFA is commonly applied later, after the underlying structure has been established on EFA and theoretical grounds. Unlike EFA, which primarily seeks to identify the factor structure present in a collection of variables, CFA tests the measurement model and the hypothesised factor structure and assesses its fit to the data (Forza, 2002). The chosen measures define the latent variables in the measurement model (Weston and Gore, 2006). Before applying CFA, the researcher usually has a preconceived idea of structure of the data base of the proposed framework, and a framework includes theoretical considerations or empirical support from literature, therefore, CFA requires a stronger empirical or conceptual foundation to guide the specification and evaluation of the factor model. CFA is applied to evaluate the “fit” of the indicators that represent the latent variables, and can also specify the number of factors, the pattern of indicator-factor loadings, and other parameters like those bearing on the independence or covariance on the factors and indicator unique variances.

There are five important elements in CFA including latent variable (LVi), including exploitation, exploration, GPDI, GPCI, BDAI, BDAM, BDAP, EP, FP, SP in this study, measurement variable (indicator Xi), the item loadings on each construct (λ), the relationship amount constructs (ϕ), and indicator error (e). Since CFA only has correlational relationships, the arrows are represented as a two-headed curved arrow. Furthermore, there is no cross loading in CFA, the loadings theoretically link the measured variable to its corresponding latent variable (Hair et al., 2010). Researchers evaluate this pre-specified factor solution by knowing how well it reproduces the same correlation (covariance) matrix of the measured variables (Brown, 2015). Figure 4.3 shows a path diagram of a CFA model. Each ellipse represents a latent variable, and the rectangular boxes indicate the measured variable.

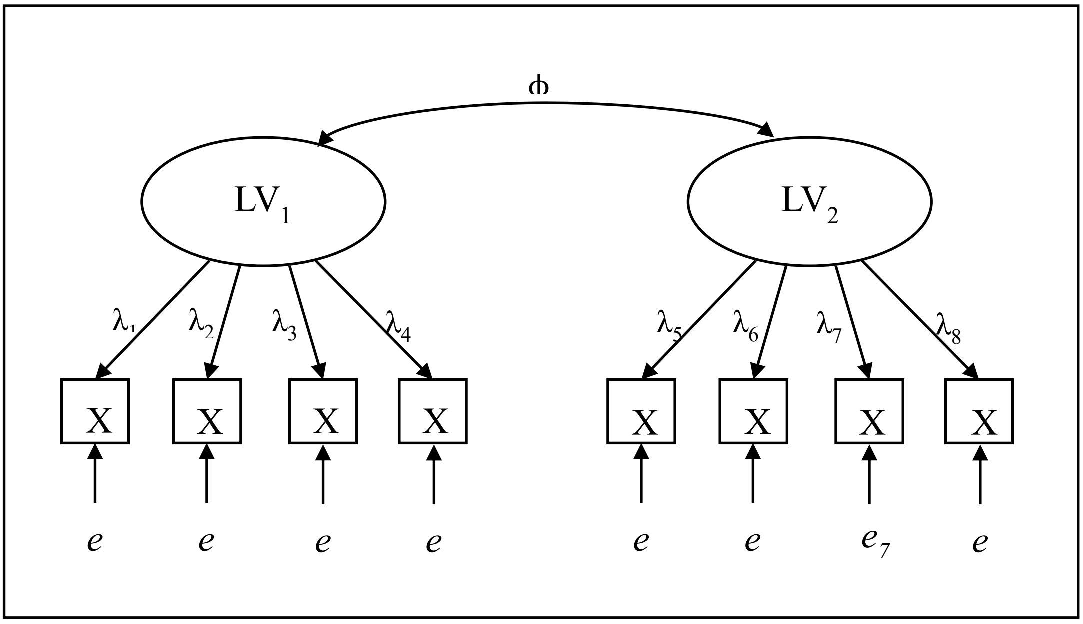


Figure 4.3 The illustration of a CFA model

4.5 STRUCTURE EQUATION MODELING

Since this study establishes theory-based linkages between item measurements and constructs based on the literature, confirmatory factor analysis was performed. Then, the SEM method was used to examine the correlations between the constructs. In details, SEM will be adopted to investigate the impact of ambidexterity on two types of GI, i.e., GPDI and GPCI, the moderator role of BDAC in the relationship between ambidexterity and GI, as well as the influence of GI on firms' triple bottom line. SEM is consisting of a structural model evaluating the measurement of latent variables and testing the relationship between latent variables (Zhang et al., 2018). More specifically, it is regarded as a confirmatory technique for specifying, estimating, and evaluating models of linear relationships between observable variables in terms of a (usually lower) number of unobserved variables (Shah and Goldstein, 2006a). Hair et al. (2010) provide a comprehensive description of SEM as "(1) the estimation of multiple and interrelated dependence relationships, (2) an ability to represent unobserved concepts in these relationship and account for errors in the estimation, and (3) defining the model to explain the entire set of relationships." In essence, SEM is a statistical method that allows researchers to propose hypotheses to develop a model and test these assumptions at the same time to assess model-data coherence. It's an advanced multivariate methodology for statistical estimation because it doesn't overlook measurement error (Hair et al., 2010). Moreover, SEM considers multiple equations simultaneously, which means that it combines a great variety of statistical procedures, such as multiple regression, factor analysis, ANOVA, and allows researchers to testify direct effect and moderator effects in the same model (Zhang et al., 2021).

By applying SEM, the fit-statistics assessment can evaluate whether the predicted measurement models and structural models are supported by the data. It requires that the connections represented by the model be well established, and capable of reliable measurement in the population (Shah and Goldstein, 2006a). Although no model can perfectly describe the real world, a favorable SEM analysis indicates that the hypothesized model provides a good approximation of real-world phenomena by data sampling. Moreover, when a desirable outcome cannot be obtained from the initial model, SEM techniques provides for a "specification search" that enables researchers to modify their model to improve its fit to the data (Shah and Goldstein, 2006a).

The two-step testing SEM technique suggested by Hair et al. (2010) is used in this study. CFA is the pre-step to the path analysis that provides evidence for the validity of individual measures based on model fit and other evidence of construct. However, as CFA is restricted to analysing the nature of relationships between constructs, a structural model then needs to be examined after the validation of CFA. Figure 4.4 provides an example of a structural model of SEM. The structural model in Figure 4.4 is similar to the CFA model in Figure 4.3.

It is worth mentioning that there are a few differences between CFA and structural models (Hair et al., 2010). Firstly, CFA uses a two-headed curved arrow because it represents a correlational relationship, while SEM uses a single-headed arrow because it represents a dependence relationship. Second, the constructs in the structural model are classified identically: exogenous (LV_1) represents the independent latent variable, and endogenous (LV_2) represents the dependent latent variable. In order to show the differentiation between the endogenous item measures and the exogenous item measures, the item measures in the endogenous latent variable are then renamed from X_i to Y_i in the structural model. Thirdly, the error variances of the measurement items are renamed to match the endogenous-exogenous distinction. The observed covariance model stays unchanged in the transition from CFA to a structural model, and the differences of model fit are associated only with the different relationships represented in the structural model (Hair et al., 2010).

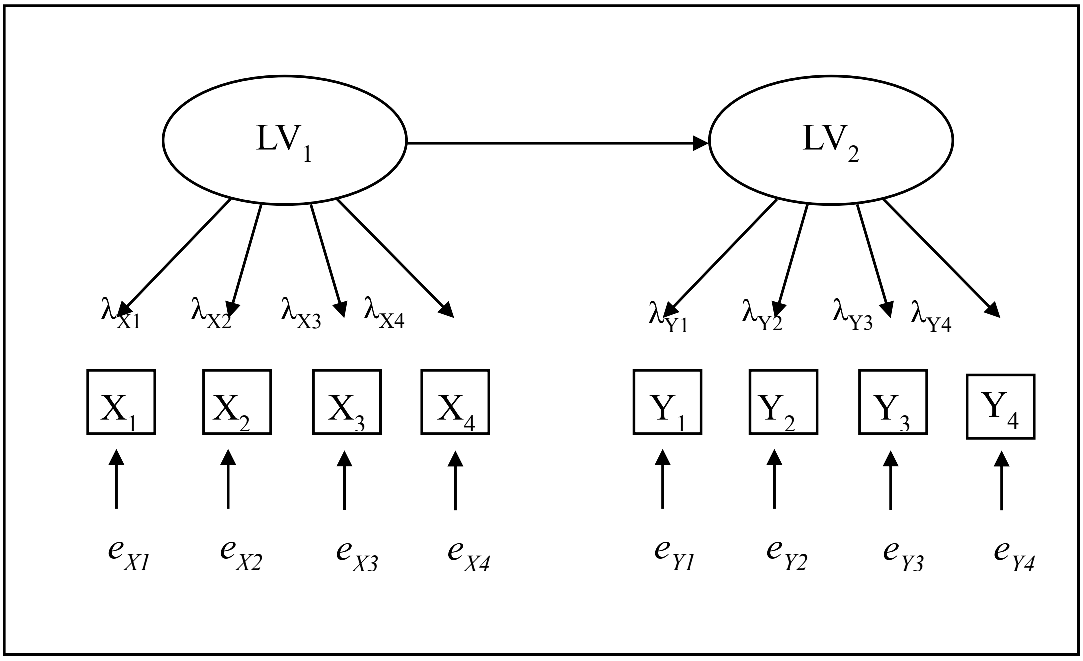


Figure 4.4 The illustration of structural model in SEM

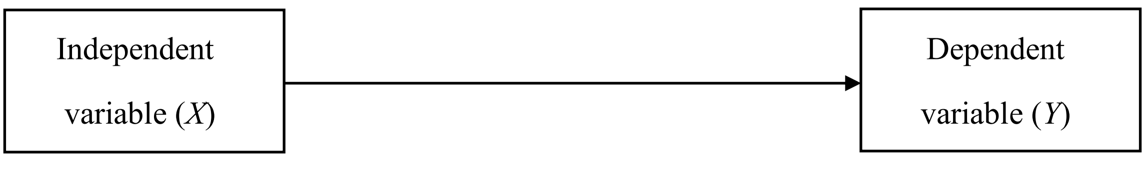
Additionally, the single-headed arrows in the structural model represent structural regression coefficients, and therefore indicate the impact of one variable on another variable (Hayne, 1998). As shown in Figure 4.2, the single-headed arrow points toward LV_2, indicating that the factor LV_1 "causes" the factor LV_2. Likewise, the four single-headed arrows leading from LV1 to each of the indicator variables (X1, X2, X3, X4) indicates that the regression coefficients (λ1, λ2, λ3, λ4) are influenced by LV1. Furthermore, the regression coefficients (λ1, λ2, λ3, λ4) show the degree of expected change in the indicators (X1, X2, X3, X4) for every change in the related latent variables (LV1).

The SEM technique has been one of the most prominent empirical research methodologies in OM fields in the last decade and one of the favourite data analysis methodologies among empirical operation management academics. This is reflected in the publishing trends in top-tier operations management publications such as Management Science, Journal of Operations Management, Production and Operations Management, International Journal of Production Research, International Journal of Production Economics, and so on. Many empirical researchers advocate employing SEM as a more appropriate path analysis methodology to examine the links among OM practice and performance. For instance, Dangelico et al. (2017) use a structural model that links sustainability-oriented dynamic capability to market performance to solve the questions of the types of sustainability-oriented dynamic capability needed to develop GI and eco-design capabilities, and the specific capabilities that lead to prior market performance of green products. Zhang et al. (2018) proposed a hierarchical structure to understand sustainable supply chain management and developed a multi-item measurement scale to reflect management practices in the field of sustainable supply chain management. Gomes et al. (2020) used online survey data and SEM techniques to investigate the impact of quality management exploitation and exploration on supporting environmentally sustainable production development. Tse et al. (2021) examined the mechanisms between uncertainty factors and supply chain quality risk and investigated the moderating role of supply market thinness with the SEM method.

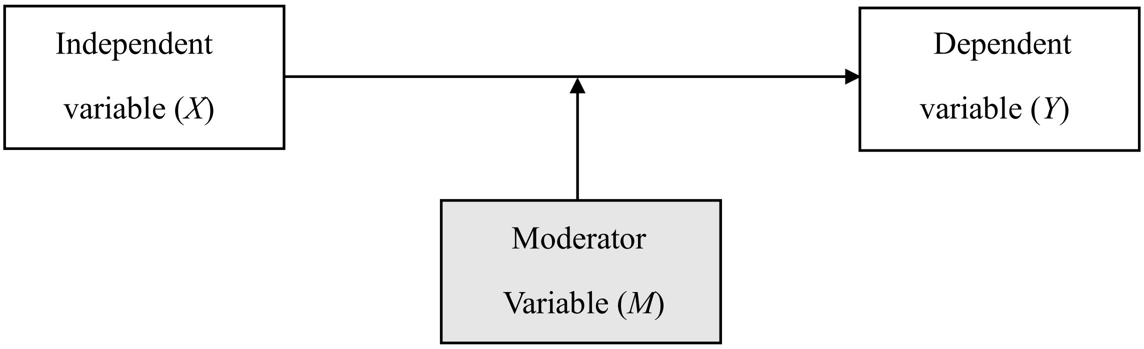
The preceding explanation described how the quantitative research approach will be used in this investigation. Since SEM is not typically recommended for exploratory research when the measuring framework has not yet been determined or when the theory behind patterns of interactions among latent variables has not yet been clearly established (Dangelico et al., 2017; Shah and Goldstein, 2006a). As a result, a scale development process is carried out prior to SEM in order to analyse the measurement structure and the underlying pattern of the main construct. This research will begin with scale development for constructs, i.e., exploitation, exploration, GPDI, GPCI, BDAI, BDAM, BDAP, EP, FP, and SP. Scale development will include (1) conceptualization and operationalization from existing literature in the field of ambidexterity, green innovation, BDAC, triple bottom line; (2) item generation from the item pool; (3) item purifying and pre-testing; (4) questionnaire development based on the finalised measurement times; (5) pilot study from a panel of knowledgeable assessors in the field of operations management; (6) data collection from a number of Chinese firms; and (7) checking for non-response bias and common method bias, confirmation analysis, item and scale refinement. Then, in this study, SEM will be used to investigate the relationships between ambidexterity, GI practises, BDAC, and firm performance, including the direct effect between ambidexterity and GPDI, the direct effect between ambidexterity and GPCI, the direct effect between GPDI and EP/FP/SP, and the direct effect between GPCI and EP/FP/SP. More information may be found in sections 5.2 SCALE DEVELOPMENT and 5.3 SEM RESULTS.

4.6 TESTING THE MODERATING AND MEDIATING EFFECT

A. Direct effect



B. Moderator effect



C. Mediating effect

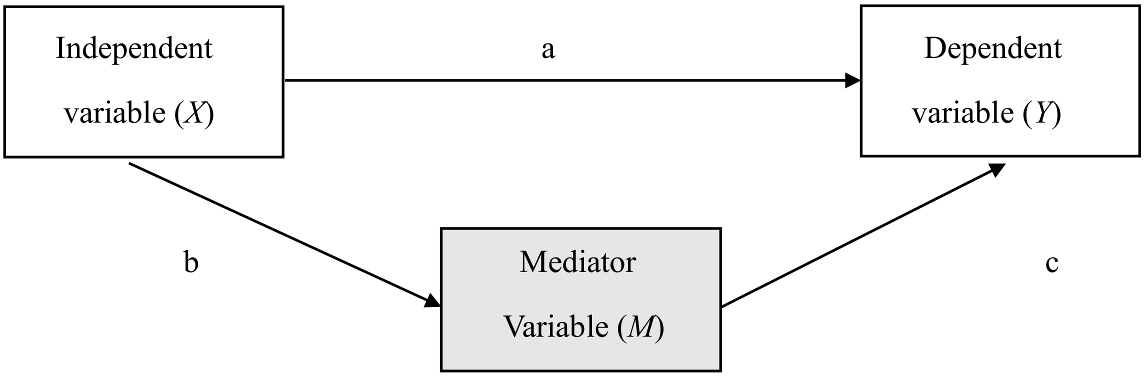


Figure 4.5 Diagrams of direct, moderator effects and mediator effects

As shown in Figure 6, direct effect answers research questions of the form “Does variable *X* predict or cause variable *Y*?” However, it is important to move beyond this type of basic question in both research and practice. One way to do this is by examining moderators of these effects. Questions involving moderators have been proposed to address “when” or “for whom” a variable can strongly predict or cause an outcome variable. Moderating variables are at the heart of theory in business and social science (Cohen et al., 2003), and the identification of important moderators represents the maturity and sophistication of a field of inquiry. A moderating variable refers to a variable that “influences the nature… of the effect of an antecedent on an outcome”, and a moderator effect can be understand as an interaction in which the effect of one variable depends on the level of another (Frazier et al., 2004). Compared with a direct effect, which only includes independent/predicting variable (*X*) and dependent/outcome variable (*Y*), the conceptual model (Figure 4.5) consists of an independent/predicting variable (*X*), an outcome dependent/variable (*Y*), and a moderator (*M*). The moderating variable is connected to the dependent and independent variables by an arrow which points to the relationship between *X* and *Y*. However, the statistical visualisation is different from how it is conceptualised in the model graphically as it includes an interaction term depicted by *X***M* (*Z*) (Aguinis et al., 2017).

The statistical model for moderation is shown in Figure 4.6, in which an independent variable (*X*), a moderator variable (*M*) and an interaction term (*Z*) point to the dependent variable (*Y*). In general, a moderator can have different connotations. It can be referred to as categorical variable when a nominal or ordinal scale is used (e.g., male and female; foreign company and private company) or as continuous variable when an interval scale is used. Discrete data is often treated as a categorical variable in statistical analysis. In this study, the independent variable (X) is ambidexterity, the three moderator variables (M) are BDAI, BDAM, and BDAP, and the three interaction terms (Z) are ambidexterity * BDAI, ambidexterity * BDAM, and ambidexterity * BDAP, and these three interaction terms point to the three dependent variables (Y), which are EP, FP, and SP.

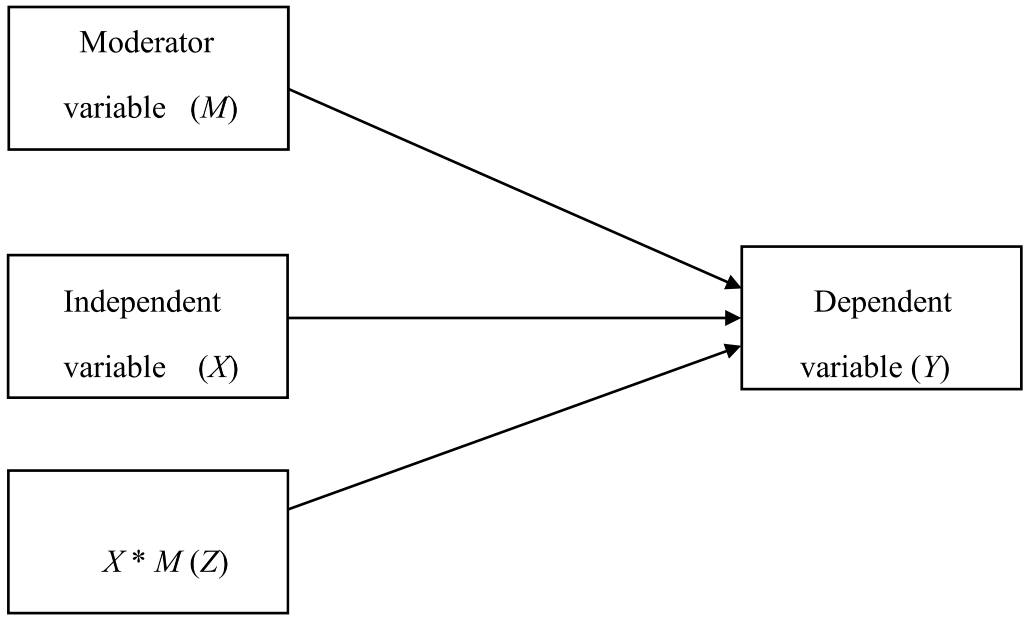
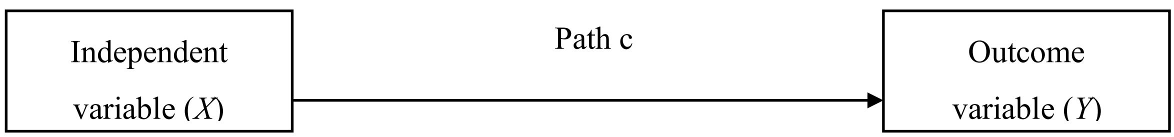


Figure 4.6 Statistic model of moderation

A mediator, on the other hand, is a variable that describes how an association occurs between an independent variable and an outcome variable, therefore, a mediator gives a substantive explanation of the underlying nature of the link between an independent and an outcome variable. Due to the reason that mediation analysis provides a story with a sequence of effects, it is always phrased in causal terms and implies a causal chain (Ro, 2012).

According to Baron and Kenny (1986), there are four conditions can be tested with three regression models, as shown in Fig 4.7. The first regression model is shown in the path c in Figure 4.7 A. Here, the independent variable should significantly influence the outcome variable ($X \rightarrow Y$) to indicate that there is an effect to mediate. The second regression model is shown in the path a in Figure 4.7 B. Here, the independent variable significantly influences the mediator in the mediation chain ($X \rightarrow Me$). The third regression model includes both independent and mediator variables entered with the outcome at the same time. If the mediator effect exists, two conditions need to be satisfied in the third regression analysis: (i) after controlling for the effect of an independent variable on the outcome, the mediator significantly predicts the outcome variable (Me $\rightarrow$Y; Path b in Figure 4.7 B), and (ii) the direct relationship of the independent variable to the outcome variable is significantly smaller in size than it was in the second regression model (Path c < Path c’) (Ro, 2012). Mediation analysis is utilized in this research to explore the role of EP and SP as mediators in the relationship between GPDI and FP, as well as the relationship between GPCI and FP. Using the previously mentioned methods, the first regression model is used to determine if GPDI and GPCI have a significant influence on FP. The second regression comprises four analyses: whether GPDI has a significant impact on EP; whether GPDI has a significant impact on SP; whether GPCI has a significant impact on EP; and if GPCI has a significant impact on SP. Finally, the third model of regression analysis includes both independent and mediator variables entered simultaneously with the outcome. (i) After controlling for the effect of GPDI or GPCI on the outcome, it is necessary to test whether the mediator (i.e., EP and SP) significantly predicts FP and (ii) whether the direct relationship of GPDI or GPCI to FP is significantly smaller than in the second regression. If so, EP and SP would act as mediators between GI and FP.

A.



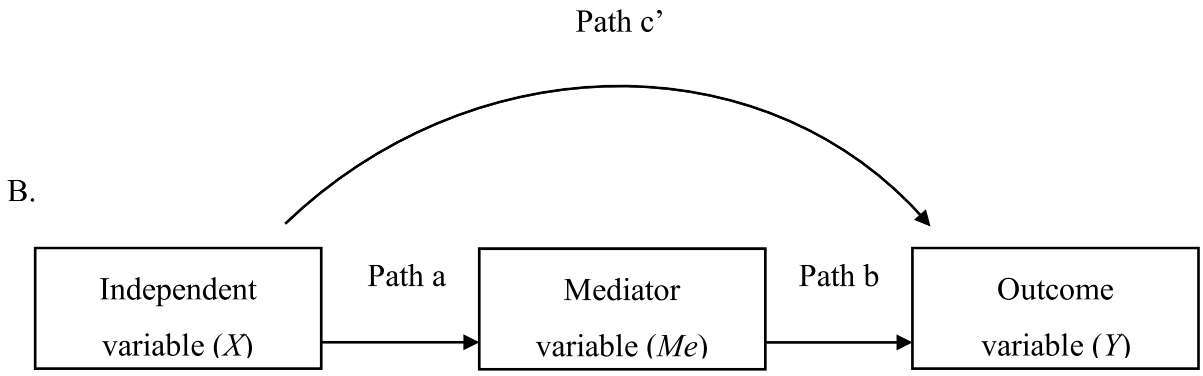


Figure 4.7 Statistic model of mediation

Three types of mediating effect are possible. Firstly, a complete (or full) mediation occurs when the relationship between the independent and outcome variables, after adjusting for the mediator, is zero (Path c is not significant). Secondly, a partial mediation occurs when the relationship between the independent and outcome variables is much weaker when the mediator is included in the model (Path c′) than when the mediator is not included in the model (Path c) but is still greater than zero. Finally, if none of the conditions are satisfied, there is no mediation (Ro, 2012).

4.7 CHAPTER SUMMARY

This chapter discusses scale development technique. A seven-stage procedure is a robust scale development process to ensure that the suggested items are reliable and valid. This chapter contains detailed instructions on how to carry out each step, and additional details on how each step works in this research is explained in the next chapter. Before the questionnaire is finished, an expert panel reviews it for content validity, appropriate translation, and feedback/comments on the final items. Furthermore, the suggested models in this study are assessed using the SEM approach, which statistically examines all hypotheses in the model at the same time to verify the model's consistency with the data.

This chapter has also offered details on the quantitative research methodology and research designs employed in this study. These methodologies are explored in depth in order to create measurement instruments and analyse the conceptual framework using the acquired data. Two statistical software tools, SPSS v27 and AMOS, are used for the research methodology. SPSS v27 is a software package used to perform EFA for identifying substantial cross-loadings. Amos is the primary software package used in more complex quantitative analysis, such as CFA and SEM. CFA is a second-generation method to assess convergent and discriminant validity between items and construct, and SEM is the principal approach for analysing the raw data acquired from the questionnaire survey delivered to Chinese manufacturing businesses.

In summary, this chapter provides a constructive theoretical basis for the next chapter. This scale development methodology will be used to develop the reliable and valid measure of the key constructs, then SEM testing approach will be used to access the theoretical model. More explanations of how these techniques are applied in this study will be presented in the next chapter.

CHAPTER 5 EMPIRICAL RESULTS

5.1 INTRODUCTION

This chapter includes two parts, scale development and the test of the theoretical model. Firstly, scale development is critical in this study in order to facilitate the development of a reliable scales. Followed the seven-step scale development introduced in the last chapter, a rigorous and comprehensive scale development procedures is presented in this section. The detailed information in each step is explicitly explained and it includes the steps (1) conceptualisation and operations for key constructs, including exploitation, exploration, green produce innovation (GPDI), green process innovation (GPCI), big data analytics infrastructure (BDAI), big data analytics management (BDAM), and big data analytics personnel (BDAP). (2) Item generation, (3) purify and pre-test items, (4) questionnaire development, (5) data collection, (6) confirmatory analysis, (7) item and scale refinement. These steps will equip both researchers and practitioners with a grasp of the ontology and methodology of scale development and validation, thereby improving the advancement of the understanding of the latent constructs.

5.2 SCALE DEVELOPMENT

5.2.1 Conceptualization and operationalization

The first step of scale development is to articulate the domains this study is aiming to measure, which including the aspects like key constructs' concept, attribute, or unobserved behavior that is relevant to the study. The term conceptualization is a multi-dimensional concept which can take different meanings depending on the context in which it is used (Mustar et al., 2006). Since word conceptualization is a hyponym for concept, it is frequently used to describe the process of forming a concept. Despite the fact that existing literature propose the concepts for terms in this study, it is still necessary to further conceptualized in the specific research setting.

The processes of conceptualization are based on thorough literature review. A great number of literatures in the field of green innovation (GI), ambidexterity, big data analytics capability (BDAC), firm performance is reviewed to have a general understanding the knowledge in the relevant area. Since the purpose of this research is to understand BDAC from a management position rather than a computer science stance, measuring items that assess BDAC from a technical perspective are not included. This step makes sure that all the concepts are developed by experts from the discipline and area of study. After reviewing the papers that in the research scope, existing instruments of each construct can be found, and existing concepts are revised carefully. The concepts that accurately express the meaning of the concepts are chosen, and then the concepts are refined in order to fit well in this research.

In details, the concept of exploitation and exploration proposed by March (1991) are chosen in this study. Using direct concepts from disciplinary experts shows that this study is using relevant and credible sources. The reason is that they are the universal concepts which have led to critical and reflective thinking for later ambidexterity research. Majority of studies in ambidexterity are based on these concepts, and therefore, it can easily link to relevant knowledge, like organizational adaption, trade-off between efficiency and flexibility, competitive advantage, etc. (Cao et al., 2009; Hansen et al., 2019; O'Reilly III and Tushman, 2013; Raisch and Birkinshaw, 2008).

Except from ambidexterity, other concepts are explained by quoted concept definitions in the new way, which demonstrates the understanding of complex disciplinary ideas, and can also better apply the concepts in this study. For instance, the selection of the GI and BDAC practices share different reasons, since these the practices of these two concepts are easier to understand and associate to organizational behavior, the chosen concepts are more content-specific that honor the curriculum and provide depth to the practice. Moreover, there are numerous concepts about firm performance in terms of the environment, social, and financial aspects, some of which highlight specific performance standards. For example, in the explanation of social performance, descriptions such as enhancing the quality and appropriateness of financial services, improving the social conditions of customers, and guaranteeing social responsibility to stakeholders might be included (Cooper, 2004). However, since this article focuses on the influence of GI on this performance, the definition of the term highlights the impact rather than the specific activities that the performance may include. Table 5.1 shows the concepts of each construct, the origins of the concepts.

Table 5.1 Conceptualization of key concepts

Term	**Literature**	**Concept**
GPDI	Chan et al., 2016; Dangelico and Pujari, 2010	The activity that takes the environmental factors into product design considerations for both new and (modification of) existing products, with the prime objective to reduce the negative environmental impacts over the products' life cycle.
GPCI	Chan et al., 2016; Chiou et al., 2011	Any adaptation to the manufacturing process that reduces the negative impact on the environment during material acquisition, production, and delivery.
Exploitation	March, 1991	Refinement, choice, production, efficiency, selection,

		implementation, execution.
Exploration	March, 1991	Search, variation, risk taking, experimentation, play, flexibility, discovery, innovation.
BDAI	Kim et al., 2012; Wamba et al., 2017	Organization’s ability of the big data analytics infrastructure that enable the BDA staff to quickly develop, deploy, and support necessary system components for a firm.
BDAM	Kim et al., 2020; Wamba et al., 2017	Big data analytics manager's ability to handle routines in a structured (rather than ad hoc) manner to manage IT resources in accordance with business needs and priorities.
BDAP	Kim et al., 2012; Wamba et al., 2017	Big data analytics staff's professional ability (e.g., skills or knowledge) to undertake assigned tasks.
EP	Zailani et al., 2012; Zhu and Sarkis, 2007	How well a firm contributes for the natural environment.
FP	Li et al., 2006	How well a firm fulfills its financial goals compared with the firm's primary competitors
SP	de Giovanni, 2012	How well a firm translate social goals into actions in line with the accepted social values.

After obtaining the scholarly definitions of a concept, operationalize the meaning of the concept then needs to be conducted for making the concept measurable. Operationalization is usually be applied as the final step in the conceptualization process (Hinkin, 1998). The term, operationalization, on the other hand, is frequently used to refer to the process by which the research defines a concept or variable in terms of its dimensions and indicators. In this context, dimensions are the specifiable aspect of concept, whereas indicator is the observation we select to use as a reflection of a variable we intend to investigate.

5.2.2 Item generation

Once the construct ideas have been specified, the item pool may be determined. The item creation process, also known as question development, was used in this study, and the deductive technique established by Hinkin (1995) was used for item generation. The deductive approach is focused on describing and identifying items in the relevant area. This study employed the deductive approach, which includes a review of the literature as well as an assessment of current scales and indicators in the field. Since the literature research provides the theoretical framework for defining the domain, a scale based on theoretical foundation is more suited to making specific operational judgements about the field, and the selected constructs will be based on gathered information about existing objects.

Five important characteristics of item generations are considered to ensure the quality of construct measurement (Fowler, 1995). (1) items should be constantly explained; (2) items should be constantly administered to respondents; (3) have consistent communication of what constitutes an adequate answer; (4) ensure that all respondents can access to the information needed to answer the question accurately; and (5) the willingness for respondents to provide the correct questionnaire answers.

Drawing on the above characteristics of item generations, the measurement items for each construct are developed. In details, the measurement items of GPCI includes (1) design of products for reduce consumption of material/energy during the full life cycle (Chen et al., 2006; Li et al., 2016); (2) design of products for reduce waste generation during the full life cycle (Chen et al., 2006; Li et al., 2016); (3) using less or non-polluting/toxic materials. (Using environmentally friendly material) (Chen et al., 2006; Chan et al., 2016); (4) improving and designing environmentally friendly packaging (e.g.: less paper and plastic material used) for existing and new products (Chan et al., 2016); (5) design for disassembly, reusability, recyclables and recovery (Chen et al., 2006; Chan et al., 2016); (6) using eco-labelling, environment management system and ISO 14000 (Tseng et al., 2013); (7) degree of new green product competitiveness understand customer needs (Tseng et al., 2013); (8) designing at least one produce line that is designed to have positive effects on the environment or which is environmentally labelled and marketed; (9) designing product features and applications that will promote responsible, efficient, cost-effective and environmentally preferable use. The first seven measurement items were adopted from the previous survey research on GPDI, and they are evaluated through the criteria for reliable measurement items. It is worth mention that the eighth and nineth measurement items of GPDI are new developed and they sourced by Asset 4 database. These two measurement items are used in the reliable database to measure the degree of GPDI in companies, while not included in the quantitative research, moreover, these two measurement items fit the characteristics of item generations, especially constantly explained and allow participants to understand the question and answer them accurately, therefore, including these two items make the measurement more accurate.

There are 9 measurement items for GPCI, and the measurement items are generated from the existing quantitative research in the field of GPDI. The measurement items including (1) sources from suppliers who comply with environmental regulations (Tseng et al., 2013); (2) low cost green provider: unit cost versus competitors' unit cost (Tseng et al., 2013); (3) Consumption low energy (such as water, electricity, gas and petrol) during production/use/disposal (Chen et al., 2006; Chiou et al., 2011); (4) use of cleaner technology to make savings and prevent pollution (Chen et al., 2006; Chiou et al., 2011); (5) recycle, reuse and remanufacture of materials internal to the company (Chen et al., 2006; Chiou et al., 2011);

(6) controls operations process to reduce waste from all sources (Wong et al., 2020); (7) sending in-house auditor to appraise environmental performance of supplier (Tseng et al., 2013); (8) updates manufacturing processes to meet standards of environmental law (Tseng et al., 2013); (9) utilizes cleaner transportation modes (Wong et al., 2020). Majority of GPCI's measurement items are traced from the same papers as GPDI. The reason for that is these papers (including Tseng et al., 2013; Chen et al., 2016; Chiou et al, 2011) are the pioneer study of GI in the context of China and both GPDI and GPCI are included as two types of GI in their study, which is consistent with this study. Nevertheless, two measurement items from Wong et al (2020) are included in this study due to the reason that includes two important aspects of GPCI, i.e., controls operations and transportation modes, which are not included in the rest of studies, the measurement items of Wong et al. (2020) are allows respondence to relevant to their working experience and access to information needed to answer the question accurately.

The measurement items for exploitation and exploration can be traced from the same a few papers due to the reason that majority of papers discussion exploitation and exploration as two aspects of ambidexterity. Exploitation has 9 measurement items in the measurement pool, including (1) introduction of new generations of products (Patel et al., 2013); (2) improvement of product quality (Cao et al., 2009); (3) improvement of product flexibility (Cao et al., 2009); (4) improving efficiency (Azadegan and Dooley, 2010); (5) reduction of production cost (Cao et al., 2009); (6) enhancement of existing markets (Cao et al., 2009); (7) upgraded current knowledge and skills for familiar products and technologies (Wang and Rafiq, 2014); (8) enhanced staff skills (Wang and Rafiq, 2014); (9) frequently adjust procedures, rules, and policies to make things work better (Cao et al., 2009). While the exploration has 8 measurement items including (1) extension of product range (Cao et al., 2009); (2) opening up new markets (Cao et al., 2009); (3) acquired technologies and skills entirely new to the business unit (Wang and Rafiq, 2014); (4) frequently experiment with significant new ideas or ways of doing things (Azadegan and Dooley, 2010); (5) employees frequently come up with creative ideas that challenge conventional ones (Azadegan and Dooley, 2010); (6) acquire product development skills and processes which are entirely new to the industry (Wang and Rafiq, 2014); (7) acquired entirely new managerial and organizational skills (Wang and Rafiq, 2014); (8) compared to the competition, a high percentage of our sales come from new products launched in the past three years (Azadegan and Dooley, 2010). Although there are many quantitative papers that study ambidexterity and they have provided a large number of measurement items for exploitation and exploration, some of them are limited in certain settings and are not suitable in this study, therefore, more generalised items are chosen so that they can fit our context for this study. Additionally, since the concept of exploitation and exploration could be difficult to understand by respondents, only the measurement items that described in details of what activities associated with exploitation and exploration are selected, thus they allow respondents to understand the information related to questionnaire and enhance the accuracy of the answer.

The measurement items for BDAI, BDAM and BDAP are collected from Kim et al. (2012); Wamba et al. (2017) and Raut et al. (2021). Since the mainstream of BDAC research can be traced back to the study of IT capability and many measurement items for BDAC have evolved from IT capability, this study also starts with an understanding of IT capability and its measurement items. Kim et al. (2012) explores the value of IT capability research through the theoretical lens of sociomaterialism. To this end, we extend the metaphor of interconnectedness introduced in a previous study to explain the formation and evolution of a firm's IT capability from the sociomaterialist perspective. Then, this study also relates to the measurement items from the studies of Wamba et al. (2017) and Raut et al. (2021), which focus more on the specific activities that represent BDAC. By following the trends of how measurement items develop, questionaire items can be constantly explained and can access the information needed to answer the question accurately. In terms of the information on the measurement items of BDAI, BDAM and BDAP, the measurement items of BDAI includes (1) system is capable to handle semi-structured and unstructured data (Raut et al., 2021); (2) compared to rivals within our industry, our organization has good infrastructure and facilities (Raut et al., 2021); (3) compared to rivals within our industry, our organization has the foremost available analytics systems (Kim et al., 2012; Wamba et al., 2017); (4) all other (e.g., remote, branch, and mobile) offices are connected to the central office for sharing analytics insights (Kim et al., 2012; Wamba et al., 2017); (5) our organization utilizes open systems network mechanisms to boost analytics connectivity (Kim et al., 2012; Wamba et al., 2017); (6) there are no identifiable communications bottlenecks within our organization for sharing analytics insights (Kim et al., 2012; Wamba et al., 2017); (7) software applications can be easily used across multiple analytics platforms (Kim et al., 2012; Wamba et al., 2017); (8) analytics-driven information is shared seamlessly across our organization, regardless of the location (Kim et al., 2012; Wamba et al., 2017); applications can be adapted to meet a variety of needs during analytics tasks (Kim et al., 2012; Wamba et al., 2017). The measurement items of BDAM includes (1) we continuously examine innovative opportunities for the strategic use of business analytics (Kim et al., 2012; Wamba et al., 2017); (2) we frequently adjust business analytics plans to better adapt to changing conditions (Kim et al., 2012; Wamba et al., 2017); (3) when we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work (Kim et al., 2012; Wamba et al., 2017); (4) when we make business analytics investment decisions, we project how much these options will help end-users make quicker decisions (Kim et al., 2012; Wamba et al., 2017); (5) in our organization, the responsibility for analytics development is clear (Kim et al., 2012; Wamba et al., 2017); (6) in our organization, business analysts and line people coordinate their efforts harmoniously (Kim et al., 2012; Wamba et al., 2017); (7) real-time assess of data and information has helped organization in better decision making (Kim et al., 2012; Wamba et al., 2017); (8) we constantly monitor the performance of the analytics function (Kim et al., 2012; Wamba et al., 2017); (9) our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process (Kim et al., 2012; Wamba et al., 2017); (10) our company is better than competitors in bringing detailed information into a business process (Kim et al., 2012; Wamba et al., 2017). The measurement items for BDAP includes (1) our analytics personnel is capable of parallel computing to address voluminous data (Raut et al., 2021); (2) our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE tools, etc.) (Kim et al., 2012; Wamba et al., 2017); (3) our analytics personnel are very capable in the areas of data management and maintenance (Kim et al., 2012; Wamba et al., 2017); (4) our analytics personnel are very capable in decision support systems (Kim et al., 2012; Wamba et al., 2017); (5) our analytics personnel show superior understanding of technological trends (Kim et al., 2012; Wamba et al., 2017); (6) our analytics personnel show superior ability to learn new technologies (Kim et al., 2012; Wamba et al., 2017); (7) our analytics personnel are very knowledgeable about the critical factors for the success of our organization (Kim et al., 2012; Wamba et al., 2017); (8) our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions (Kim et al., 2012; Wamba et al., 2017); (9) our analytics personnel are very knowledgeable about the business environment (Kim et al., 2012; Wamba et al., 2017); (10) our analytics personnel are very capable in terms of managing projects (Kim et al., 2012; Wamba et al., 2017).

Regarding the measurement of the triple bottom line of companies, the measures for EP, FP and SP come from different sources, including one source that studies the triple bottom line (i.e., de Giovanni, 2012) and other sources that understand a specific performance (e.g., Liu et al., 2020; Gualandris and Kalchschmidt, 2016) The reason for this is that few studies examine these three performances simultaneously; most studies focus on only one performance. By evaluating different studies, items are developed that give a better idea of what constitutes an appropriate response and allow respondents to answer the question accurately. The measurement items for EP includes (1) significant improvement in its overall environmental situation (Zailani et al., 2012; Zhu and Sarkis, 2007); (2) significant improvement in its compliance to environmental standards (Zailani et al., 2012); (3) significant reduction in emission of air pollutants (de Giovanni, 2012; Zailani et al., 2012); (4) significant reduction in energy consumption de Giovanni, 2012; Zailani et al., 2012); (5) significant reduction in wastewater (Zhu and Sarkis, 2007); (6) significant reduction the consumption for hazardous/harmful/toxic materials (Zailani et al., 2012; Zhu and Sarkis, 2007); improve a company's environmental situation Zhu and Sarkis, 2007); (8) significant reduction in environmental resource impact controversies. It is worth noting that measurement item 8 is a freshly constructed item obtained from the Asset 4 database. This study is able to deliver a more accurate response for EP by producing a new measurement item from a credible database. Besides, the measurement items for FP includes (1) growth of sales (Cao and Zhang, 2011); (2) growth in return on investment (Cao and Zhang, 2011); (3) return of assets (de Giovanni, 2012); (4) profit margin (Cao and Zhang, 2011; de Giovanni, 2012); (5) increase in market share (de Giovanni, 2012); (6) acquisition of new customers de Giovanni, 2012); (7)decrease in cost of materials purchasing per unit of product (Liu et al., 2020); (8) decrease in cost for energy consumption per unit of product (Liu et al., 2020). Meanwhile, the measurement items of SP includes (1) using social performance indicators (Sancha et al., 2016); (2) employees' health and safety (de Giovanni, 2012; Gualandris and Kalchschmidt, 2016); (3) incentives and engagement for local employment (de Giovanni, 2012); (4) improvement of community health and safety (de Giovanni, 2012); (5) development of economic activities (de Giovanni, 2012); (6) employee satisfaction (Gualandris and Kalchschmidt, 2016); (7) improvement in human right compliance (Gualandris and Kalchschmidt, 2016); (8) improvement in labour safety and labour conditions in our facilities (Sancha et al., 2016); reduction of number of industrial accidents Sancha et al.,, 2016). The measurement items for each construct are also listed in Appendix 1.

With regards to the types of responses to the questions, the Likert-type response scale is used, and the points on the scale reflect the measurement continuum. Responses are presented in an ordinal manner, that is, all the points are in an ascending order without any overlap, and each point on the response scale has its own meaning and can be interpreted the same way by each participant to ensure data quality (Rattray and Jones, 2007). Due to the reason that Likert-type response with just two or three points have lower reliability than the response with five to seven points, and the gain levels off after seven points. Seven response items are chosen in this study.

5.2.3 Purify and pre-test items

The next step is purifying and pre-testing items. This process needs to receive judges from expert, since they are high knowledgeable about the research area and scale development. This process is suggested to include both target-population judges and expert judges, therefore, the content validity test was evaluated by two directors from Chinese manufacturing companies and three academics in the field of operations management (OM) in the University in UK. They were asked to evaluate the appropriateness of items for the key concepts in the study. The methodologies for content validity proposed by Rungtusanatham et al. (1998) are used in this study. A content validity task is represented in Table 5.2.

Table 5.2 Example of content validity task

	TASK A	**TASK B**						
Measurement items	Dimension	Adequacy						
		1	2	3	4	5	6	7
12. Consumption low energy (such as water, electricity, gas and petrol) during production/use/disposal.	**2**						**X**	

To begin with, we gave each judge a score sheet which contained the operational definition of GPDI, GPCI, exploitation, exploration, BDAI, BDAM, BDAP, EP, FP, SP, and a random listing of 89 measurement items. In the Task A, the judges were introduced to use the operational definitions to categorize the measurement items into no more than one dimension. The result of task A was used to compute the Cohen's kappa (κ) value. Cohen's Kappa value is an indication of beyond–chance agreement among the judges on the overall task and corrects for rate agreement due to chance (Cohen et al., 2003; Rungtusanatham et al., 1998).

Table 5.3 shows the content validity results. The results show that all the items reaching the minimum cut-off point (60%) in "the percent of judges assigning the item to the correct dimension", except from GPDI8, GPCI7, SP5. Thus, these three items are removed from the item pool. After dropping these three items, the Cohen's kappa value is 0.743, which meet inter-judge agreement. The standard deviation for Cohen's kappa (κ) was 0.071, yielding a 95 percent confidence interval for the kappa in the interval [0.62, 0.90].

In Task B, the judges were requested to rate the item's adequacy based on a 7-point scale. Task B aims to test how adequately each measurement item measures the dimension. The 7-point response scale ranges from "1" as barely adequate to "7" as almost perfect. After collecting the data in Task B, the average adequacy score and standard deviation of adequacy of each measurement item are computed and evaluated. As shown in Table 5.3, majority of items score quite good average adequacy scores (>5.0), except for GPDI8, GPCI4, GPCI7, EXPLORAT1. The standard deviation of items EXPLORAT1 and SP5 are 1.140 and 1.483 respectively. These values are higher than the acceptable standard deviation (≤ 1.00)

(Rungtusanatham et al., 1998), and it was decided to delete both items. Finally, considering both "the percent of judges assigning the item to the correct dimension" and the "standard deviation", GPDI8, GPCI4, GPCI7, EXPLORAT1, BDAM5, EP7, SP5 needs to be removed from the content validity test.

Table 5.3 Content/Face Validity Assessment Result

Proposed constructs	**Proposed measurement items**	**Average Adequacy Score**	**Sample Standard**	**% of judges assign the item to the correct dimensions**
Green Product Innovation (GPDI)	GPDI1	6.20	0.837	100%
	GPDI2	6.20	0.447	80%
	GPDI3	5.20	0.447	60%
	GPDI4	6.60	0.548	100%
	GPDI5	5.00	0.707	80%
	GPDI6	5.20	0.837	60%
	GPDI7	4.80	0.447	80%
	GPDI8	6.60	0.837	20%
	GPDI9	6.20	0.548	80%
Green Process Innovation (GPCI)	GPCI1	5.00	0.707	100%
	GPCI2	5.80	0.447	80%
	GPCI3	5.80	0.837	100%
	GPCI4	3.40	0.548	60%
	GPCI5	5.20	0.837	100%
	GPCI6	6.80	0.447	100%
	GPCI7	2.60	0.548	40%
	GPCI8	6.40	0.548	60%
	GPCI9	5.00	0.707	80%
Exploitation (EXPLOIT)	EXPLOIT1	7.00	0.000	100%
	EXPLOIT2	6.40	0.548	100%
	EXPLOIT3	6.80	0.447	80%
	EXPLOIT4	6.60	0.548	100%
	EXPLOIT5	7.00	0.000	100%
	EXPLOIT6	6.60	0.548	80%
	EXPLOIT7	6.60	0.548	100%
	EXPLOIT8	6.80	0.447	100%
Exploration (EXPLORAT)	EXPLORAT1	4.40	1.140	60%
	EXPLORAT2	5.20	0.837	100%
	EXPLORAT3	6.80	0.447	100%
	EXPLORAT4	6.60	0.548	80%
	EXPLORAT5	6.40	0.548	80%

Proposed constructs	Proposed measurement items	Average Adequacy Score	Sample Standard	% of judges assign the item to the correct dimensions
	EXPLORAT6	5.20	0.837	60%
	EXPLORAT7	7.00	0.000	100%
	EXPLORAT8	6.60	0.548	80%
	EXPLORAT9	5.60	0.548	80%
Big Data Analytics Infrastructure Capability (BDAI)	BDAI1	6.20	0.447	100%
	BDAI2	7.00	0.000	100%
	BDAI3	6.40	0.548	80%
	BDAI4	6.60	0.707	100%
	BDAI5	6.00	0.548	100%
	BDAI6	5.20	0.837	60%
	BDAI7	6.00	0.707	100%
	BDAI8	6.80	0.447	100%
	BDAI9	6.20	0.837	80%
Big Data Analytics Management Capability (BDAM)	BDAM1	5.80	0.837	60%
	BDAM2	6.20	0.447	80%
	BDAM3	6.80	0.447	100%
	BDAM4	6.60	0.548	60%
	BDAM5	7.00	0.000	80%
	BDAM6	5.00	0.707	80%
	BDAM7	6.00	0.707	100%
	BDAM8	5.00	0.707	60%
	BDAM9	5.60	0.548	100%
	BDAM10	6.00	0.707	80%
Big Data Analytics Personnel Capability (BDAP)	BDAP1	7.00	0.000	100%
	BDAP2	6.80	0.447	100%
	BDAP3	7.00	0.000	100%
	BDAP4	6.20	0.837	100%
	BDAP5	6.40	0.894	100%
	BDAP6	6.80	0.447	100%
	BDAP7	6.40	0.548	80%
	BDAP8	6.80	0.447	100%
	BDAP9	7.00	0.000	100%
	BDAP10	6.80	0.447	100%
Environmental Performance (EP)	EP1	6.80	0.447	100%
	EP2	7.00	0.000	100%
	EP3	6.40	0.548	80%
	EP4	7.00	0.000	100%
	EP5	6.80	0.447	100%
	EP6	6.20	0.837	80%
	EP7	6.60	0.548	100%
	EP8	6.80	0.447	80%
Financial Performance (FP)	FP1	7.00	0.000	100%
	FP2	7.00	0.000	100%

Proposed constructs	**Proposed measurement items**	**Average Adequacy Score**	**Sample Standard**	**% of judges assign the item to the correct dimensions**
	FP3	6.80	0.447	80%
	FP4	6.80	0.447	100%
	FP5	7.00	0.000	100%
	FP6	6.00	0.707	80%
	FP7	6.00	0.707	80%
	FP8	6.60	0.548	80%
Social Performance (SP)	SP1	6.00	0.707	100%
	SP2	6.80	0.447	100%
	SP3	6.00	0.707	100%
	SP4	6.20	0.837	80%
	SP5	5.20	1.483	20%
	SP6	6.40	0.548	80%
	SP7	6.60	0.548	100%
	SP8	7.00	0.000	100%
	SP9	6.20	0.837	80%

5.2.4 Questionnaire development

5.2.4.1 Questionnaire format

After finalizing the measurement items, there are 8 items for green product innovation (GPDI), 7 items for green process innovation (GPCI), 8 items for exploitation (EXPLOIT), 8 items for exploration (EXPLORAT), 9 items for BDAI, 9 items for BDAM, 10 items for BDPI, 7 items for environmental performance (EP), 8 items for financial performance (FP), 8 items for social performance (SP). According to Hinkin (1995), three items are the minimal number for each construct for ensure the reliability of the measurement, and the measurement scale within sufficient items would cause problems such as decrease in content validity, construct validity, and internal consistency. Furthermore, the construct will be “under identified” if the variables’ number is less than three (Hair et al., 2019), therefore, it is vital to have no less than three measurement items for each concept.

5.2.4.2 *Translation of questionnaire*

As the target respondents for this research were working in Chinses firms, both forward and backward translated versions are required (Hinkin, 1998). Firstly, the English-language validated questionnaire needed to be translated into Chinses. Two scholars in China are consulted to check if the measurement items in Chinese correctly reflected the organizational context that Chinese firms experience. Then the Chinese questionnaire was then translated back into English by a third-party translator to ensure that the measurement items accurately reflected the original meanings. The original English questionnaire and later re-translated questionnaire were thoroughly reviewed, and no significant change in the English wording were found. Both the finalised English and Chinese questionnaires are provided in Appendix.

5.2.4.3 *Pilot study*

In the pilot study, the same three academics and two industrialists who assisted with item purification and pre-testing were invited to review and refine the questionnaire since they are not only experienced in the research topics, but are familiar with this study and can identify if the suggestions they raised for the measurement items earlier in the questionnaire have been corrected. Firstly, they were invited to evaluate the readability of the representative measurement items. Then face-to-face discussions were held to get their feedback on how to enhance the readability of questionnaire items. One of the academics pointed out that some concepts in the question items may be unfamiliar to some respondents and suggested to give explicit examples to help respondents understand these items. Some of the items were modified based on this comment, such as the examples of expert systems, artificial intelligence, data warehousing, mining, marts were provided to specifically explain the techniques used in decision support systems in BDAP 4. In the second round, the question items were further evaluated by panel of staff members of *Product Development and Management Association (PDAM)* in China. Face-to-face discussions were conducted to ensure that there were no misunderstandings of items and to obtain their recommendations for amendments. Only a few words in the question items were modified due to the English Chinese translation issues.

5.2.5 Data collection

5.2.5.1 Data collection and questionnaire administration procedure

This study focuses on in single firms with the adoption of GI, thus, this research targeted the respondents as practitioners with related knowledge and experience to obtain practical insights of GI. The firms are selected from the database “China Business Council for Sustainable Development (CBCSD)” to identify the green practice of the firm. The purpose of CBCSD is to help companies improve understanding and performance in environmental and social responsibility, and to push forward the course of sustainable development by common efforts, so all the firms in this database dedicate to integrate green ideas in businesses and fit in our requirement for research objects. The firms in CBCSD database are most likely large corporates and the number of involved companies are limited, in order to cover all sides of firms as possible, this research also looked at other firms who work on converting their business into a model that are ecologically and socially. More firms from "the China Yellow Pages" were reviewed, particularly regarding of their participation in green practises. Since firms often highlight their ecological missions and the advantages of their products, services, and company, their official webpages and documentation were reviewed to check if firms fit this research or not.

The survey was developed by adopting Qualtrics, a software that will enable access to the questionnaire through a web link. In order to improve the response rate of this research, the data collection followed (Frohlich, 2002)'s recommendations. Firstly, contact target firms as early as possible with explanation of academic purpose and prove of confidentiality. We sent the questionnaire along with the information sheet and consent form, to make sure that the participants were informed about the voluntary nature of their participation to the research, which means they would not receive any payments or incentives from filling in the questionnaire. Since this research is endorsed by an associations, *Centre of Product Innovation and Management (CPIM)*, the email carried with the CPIM endorsement letter (see Appendix 4). Secondly, questionnaires were sent to the key informants, at the same time, contact details of researcher was provided to facilitate communication with respondents. Thirdly, multiple follow up emails were sent to the key informants to remind respondents to complete the questionnaire in time. The survey questionnaires were sent via email over 12 weeks (12/2019 – 03/2020). A merged contact list containing contact information of 1620 firms was used in this research. A total of 431 survey questionnaires were received and the response rate was approximately 26.6 %, which was at a reasonable level comparing with other research using similar data collection methods (Ateş et al., 2012).

The dataset is filtered as following steps. Firstly, this research adopts the complete case analysis, which is described as a statistical analysis that only includes participants for which we have no missing data on the variables of interest, therefore the questionnaires with missing data on any variable were eliminated, and 12 survey questionnaires were deleted, and 431 questionnaires left. Secondly, the filter questions are designed to filter out invalid data. We administrate the questionnaire before asking the filtering questions (a. Do you adopt GI in your firm? b. Do you adopt big data analytics technology in your firm?) at the outset of the questionnaire. In this way, we can make sure that all firms belonging to the sample are suitable for this study. If respondents select "no" in any of the filter questions, their company do not adopt GI and/or big data technology and it is inappropriate to include their answer in the analysis, 39 questionnaires are deleted and 392 questionnaires are left in this process. In addition, we process different data caring to identify the cases with abnormal data. For instance, the engagement of respondents is checked by calculating the standard deviation of the answers in each questionnaire. When the standard deviation value equals to zero, it represents that the answers to each question in the case are the same, and unengaged responses are deleted accordingly. Individual answers are checked manually in order to ensure the quality of dataset, the questionnaires with more than ten same answers in a row were deleted. Therefore, 375 copies of questionnaire were valid, and 56 responses were deleted. Table 5.4 shows the information of the respondents.

Table 5.4 Sample descriptive (N=375)

Classification	**Number**	**First-wave frequency (n=185)**	**Second-wave frequency (n=190)**	**Chi-square test for non-response bias**	**Total Percentage (%)**
Industry					

Manufacturing	155	78	77	X^2=5.402	41.3
Building industry	39	19	20	df=7	10.4
Processes for natural resources	31	17	14	p=0.611	8.3
Biological engineering, pharmacy	18	5	13		4.8
Agriculture, food product	41	22	19		10.9
Service, consultancy	57	25	32		15.2
Chemicals	5	3	2		1.3
Other	29	16	13		7.7
Number of employees					
Less than 50	33	13	20	X^2=6.315	8.8
Between 51 and 100	64	30	34	df=4	17.1
Between 101 and 200	69	35	34	p=0.177	18.4
Between 201 and 500	79	33	46		21.1
Above 500	130	74	56		34.7
Organization annual revenue					
(yuan)	11	6	5	X^2=4.184	2.9
Less than 10 million	34	12	22	df=4	9.1
Between 10 million and 50 million	58	27	31	p=0.382	15.5
Between 50 million and 100 million	64	30	34		17.1
Between 100 million and 200 million	208	110	98		55.5
Above 200 million RMB					
Ownership structure					
State owned or state holding company	81	44	37	X^2=3.094	21.6
Joint venture				df=4	
Private company	57	32	25	p=0.542	15.2
Wholly foreign owned company	223	103	120		59.5
Other	10	4	6		2.7
	4	2	2		1.1
Title of respondent					
Vice president or above	4	1	3	X^2=4.093	1.1
President's assistant	6	1	5	df=5	1.6
Department manager	150	75	75	p=0.536	40.0
Senior manager	56	26	30		14.9
Operator	121	63	58		32.3
Others	38	19	19		10.1

5.2.5.2 Non-response bias

Non-response bias indicates the bias caused by the potential respondents who are not answering the questionnaire. There are usually two reasons that respondents refuse to answer, one is the sensitive content included in the questionnaire, which leads to systematic bias of study, another reason is some respondents forget to answer the questionnaire, which causing the random bias in the data. Non-response bias is usually evaluated using two methods (Swafford et al., 2006). The first method is testing the significant differences between the respondents and the non-respondents from the mail list. By adopting *t*-Test using annual sales and number of employees data, no non-responses bias can be confirmed if there are no statistical differences. Since the mail list did not provide non-respondents' annual sales and number of employees, this method is not application for this research.

The second method is testing the significant differences between early respondents and late respondents, as the late respondents are considered as the surrogate for non-respondents. Researchers can conduct *t*-Test to examine whether the early respondents and later respondents share the same distribution of measurement items at $p<0.05$. We followed the method suggested by Zhang et al. (2018) to divide the responses into first wave (185 questionnaires) and second-wave respondents (190 received questionnaire). Then the X^2 difference test is performed to assess the difference between two groups in terms of industry, number of employees, organization annual revenue, ownership structure and title of respondents. As shown in the table 5.4, non-significant results of the X^2 difference test indicate that non-response bias was not a threat to our sample.

5.2.5.3 Common method bias

Common method bias refers to the spurious variance among variables due to the adoption of a single source or method in data collection, it is essential to examine common method biases since it would have potentially serious effects on research findings (Podsakoff et al., 2003). The dominant bias in survey data is that a single informant answers all questions, and it is necessary to take measures ad hot in questionnaire design and examine common method biases. In details, different constructs (ambidexterity activities, GI activities, big data analytics capability dimensions and firm performances) are distinguished from each other in questionnaire, the independent and dependent variables are separated into different sections with the explanations of variables' concepts in order to moderate respondents' consistent tendency. In addition, Harman's one factor analysis was employed to examine whether one common factor could explain most of the variance. In EFA, all items were added with only one factor to extract, and the result showed ten factors whose eigenvalues exceeded 1.0 explained 67.051% of the variance, with a single factor is extracting 21.30% of total variance. Since the single factor extraction is far less than 50%, there is no threat of common method bias. Similarly, the common latent factor by CFA was checked in Amos by add regression lines to every observed item to determine the common variance among them. The fit indices were not acceptable (χ^2=3469.139, d.f.=629, χ^2/d.f.=5.515, RMSEA=0.110, NFI=0.394, CFI=0.443). Therefore, one factor was not sufficient to explain the variance, which also proves that common method bias was not a serious problem in this study.

5.2.6 Confirmatory analysis

Reliability and validity are two concepts to evaluate the quality of the research. They indicate how well a method, technique, or test measure something. Reliability refers to the overall consistency of a measure. Reliability test is an important indicator to assess the quality of the data. According to (Narasimhan and Jayaram, 1998), a two-step method has been suggested to test the reliability of the construct: firstly, the unidimensionality of the measurement items need to be assessed using EFA; secondly, the internal consistency of the measurement items should be examined by calculating Cronbach's alpha.

Specifically, the importance of unidimensionality has been stated by (Hattie, 1985) that a set of items forming an instrument, and all measure are describing one thing in common is the most critical and basic assumption of measurement theory, unidimensionality is therefore regarded as an important process before conducting structural model testing. The unidimensionality of the key constructs of this study is addressed by using EFA, as shown in Table 5.5. The varimax method is used to simplify the expression of a particular sub-space in terms of just a few major items each, and it is adopted in EFA. The Kaiser-Meyer-Olkin test (KMO) is run for measuring how suited the data is for factor analysis. The test measure sampling adequacy for each variable in the model and for the complete model. The KMO measure of sampling adequacy of this study is 0.858, which is much greater than the suggested criteria 0.60 (Worthington and Whittaker, 2006b). The Eigenvalues for all ten constructs are greater than 1.0, which indicate the sample is adequate for running EFA. In terms of the measurement items, the percentage of variance of the GPDI4, GPDI5, GPDI6, GPDI8, GPCI1, GPCI4, GPCI6, GPCI7, EXPLOIT2, EXPLOIT5, EXPLOIT6, EXPLOIT7, EXPLOIT8, EXPLORAT1, EXPLORAT3, EXPLORAT4, EXPLORAT5, BDAI1, BDAI2, BDAI3, BDAI6, BDAI8, BDAI9, BDAM1, BDAM2, BDAM7, BDAM8, BDAM9, BDAP1, BDAP3, BDAP5, BDAP6, BDAP9, EP1, EP2, EP3, EP5, FP5, FP6, FP7, FP8, SP1, SP2, SP4, SP6, SP8 are extracted in communality are smaller than 0.50, which shows that they have a low proportion of variance that is shared with other items. In summary, the unidimensionality of each dimension is supported. There are 36 items retained after EFA analysis and each factor has more than three measurement items, which meet the suggestions of (Shah and Goldstein, 2006b) that a ratio of fewer than three measurement items per latent variable is of concern since the model is statistically unidentified in the absence of additional constraints. Additionally, Cronbach's alpha is assessed to measure internal consistency between items in a scale, in other word, it indicates how a participant is responding across all items. In this study, all items in each constructs fulfil the criteria of reliability required by Cronbach's alpha greater than 0.7, indicating a high level of internal consistency (Hair et al., 2019).

Table 5.5 Exploratory Factor Analysis

Factor loadings										
	Big data analytics personnel capability	Exploration	Financial performance	Big data analytics management capability	Green product innovation	Green process innovation	Exploitation	Big data analytics infrastructure capability	Social performance	Environmental performance
GPDI1	.095	.132	.076	.058	**.759**	.132	-.055	.029	-.046	.101
GPDI2	.026	.122	.144	.058	**.718**	.072	.153	-.071	.133	.098
GPDI3	.111	.017	.018	.004	**.708**	.140	.022	.160	.113	.088
GPDI7	.010	.091	.068	.060	**.713**	-.047	.178	.173	.015	.008
GPCI2	.137	.064	.113	.052	.111	**.766**	.067	.110	.095	.175
GPCI3	.042	.073	.122	.129	.106	**.844**	.003	-.013	.073	.022
GPCI5	.039	.001	.008	.105	.068	**.872**	.069	.060	.060	.076
EXPLOIT1	.210	.058	.097	.017	.003	.057	**.708**	.194	.185	-.047
EXPLOIT3	.030	.083	.019	.034	.120	.015	**.778**	-.065	.061	.159
EXPLOIT4	.063	.079	.067	.029	.131	.067	**.860**	.012	-.013	.042
EXPLORAT2	.079	**.888**	.073	.084	.099	.071	.089	.076	.086	.080
EXPLORAT6	.122	**.799**	.056	.091	.141	.030	.029	.092	.069	.034
EXPLORAT7	.033	**.798**	.104	.161	.100	.028	.092	.065	.066	.032
EXPLORAT8	.140	**.822**	.015	.030	.029	.020	.036	.095	.031	.094
BDAI4	.154	.119	.077	.215	.102	.032	.073	**.715**	.010	.202
BDAI5	.113	.099	.166	.084	.110	.076	.071	**.749**	.142	-.006
BDAI7	.124	.116	.035	.168	.088	.051	-.028	**.832**	.034	.073
BDAM3	.110	.096	.127	**.729**	.058	.085	-.065	.050	.055	.054
BDAM4	.159	.115	.104	**.687**	.059	.061	.051	.092	.162	.140
BDAM5	.111	.092	.156	**.822**	.067	.119	.081	.107	.134	-.006
BDAM6	.076	.063	.129	**.717**	.001	.047	.039	.203	.056	.043
BDAP2	**.684**	.057	.096	.159	.048	.009	.120	.122	.096	.159
BDAP4	**.765**	.176	.140	.035	.096	.066	.011	.007	.002	.107
BDAP7	**.672**	.062	.051	.146	.085	.038	.078	.094	.191	.127
BDAP8	**.830**	.053	.099	.008	.018	.074	.103	.112	.119	.086
BDAP10	**.742**	.063	.023	.148	.064	.058	.013	.087	.147	.041

EP4	.216	.126	.031	.098	.009	.094	.086	.104	.177	**.761**
EP6	.108	.054	.254	.007	.180	.091	.215	.077	.001	**.668**
EP7	.189	.073	.059	.125	.149	.115	-.074	.078	.145	**.741**
FP1	.100	.118	**.697**	.112	.104	.094	.123	.072	.210	.118
FP2	.099	.012	**.714**	.186	.093	.066	.045	.047	.086	.022
FP3	.117	.140	**.716**	.071	.026	.051	.048	.087	.189	.096
FP4	.060	-.005	**.851**	.149	.087	.046	-.010	.077	.026	.064
SP3	.214	.108	.188	.138	.077	.074	.113	.019	**.655**	.114
SP5	.201	.049	.155	.165	.087	.086	-.032	.126	**.793**	.094
SP7	.136	.100	.167	.111	.054	.094	.152	.053	**.749**	.114
Eigenvalue	8.438	2.438	2.226	2.150	1.868	1.689	1.585	1.327	1.243	1.174
Total variance explained					67.051%					

5.2.7 Item and scale refinement

5.2.7.1 Assessing model fitness by comparing with competing models

CFA is a statistical procedure commonly used to test the fit of data to measurement models. (Graham, Guthrie and Thompson, 2003) pointed out three main reasons that CFA is important in measurement study, first, CFA allows different rival models to be fit to data, and the measure can only be deemed credible when underlying construct model has survived in the confirmation efforts. Second, CFA forces researchers to be precise in defining the constructs. Third, CFA models can be evaluated so as to reward parsimony because more parsimonious results are more likely to be replicable. It has suggested that in an SEM context, the initial phase of analysis should include an examination via CFA of the measurement models. If the measurement models are not adequate, the interpretation of structural model results would be less interesting.

Two measurement models are analysed to check the model fitness of this study by using CFA, i.e., Harman's single factor model, and six-correlated factor models. Firstly, Harman's single factor model are conducted in SPSS. We perform a factor analysis with the variables left from EFA test and constrain the number of factors extracted where only one determining factor in the model. If the factor explains more than 50% of the variance, the test would as the majority of variance is explained by a single factor. Our result passes the test with the factor explains 23.619% of variants. Then another factor model conceptualized six factors that are freely correlated with each other. The fit indices of factor model match the acceptable model fit recommended by (Shah and Ward, 2007b) (see Table 5.6). In addition, the correlated model is superior to the single factor model, which indicates that the factors significantly and positively correlating with each other's practices and the model has a strong fit to sample data.

Table 5.6 Measurement fit for the calibration and validation samples

Measures of fit	**Statistic measure**	**Whole sample (n = 262)**	**Recommended value for close for acceptable fit**
Absolute	$\chi2$-Test statistic (d.f.)	161.302 (120)	NA
	Root mean square error of approximation (RMSEA)	0.036	≤0.08
	RMSEA, 90% confidence interval	(0.020, 0.050)	(0.00;0.08)
	Standardized root mean square residual (RMR)	0.052	≤0.10
Incremental	Non-normed fit index (NNFI)	0.944	≥0.90
	Comparative fit index (CFI)	0.956	≥0.90
	Incremental fit index (IFI)	0.957	≥0.90
Parsimonious	Normed $\chi2$ ($\chi2$/d.f.)	1.344	≤3.0
	Parsimony normed fit index (PNFI)	0.784	≥0.70

5.2.7.2 Convergent validity

Validity means the accuracy of items to the constructs, and it assess the degree to which the items measure what it is expected to measure. Validity can be divided into content validity and construct validity. The two main measures of construct validity are convergent validity and discriminant validity, in which convergent validity refers to the convergence of the items under the same constructs, while discriminant validity is the measure of the distinct constructs, ensuring the uniqueness of each construct (Hair et al., 2019). When examining the convergent validity of the items, CFA suggested by O'Leary-Kelly and J. Vokurka (1998) is employed in this study. As shown in Figure 5.1 and Table 5.7, all the items had factor loadings greater than 0.50, and t values were significant ($p<0.001$). The model fit indices were $\chi^2=742.737$, d.f.=549, χ^2/d.f.=1.353, RMSEA=0.031, NFI=0.870 IFI=0.963, TLI=0.956, CFI=0.962, which indicating a high level of convergent validity. Besides, the calculation of average variance extracted (AVE) and composite reliability have also been applied to test for the convergent validity of the constructs. The AVE refers to the average amount of variance that a construct explains in its indicator variables relative to the overall variance of its indicator (Flynn et al., 2010), and the composite reliability is also taken as the measure of internal consistency in scale items (Netemeyer et al., 2003). The value of AVE for GPCI, EXPLOIT, EXPLORAT, BDAI, BDAM, BDAP, FP and SP exceeded 0.5, which indicating satisfactory convergent validity, as it means that the latent construct accounts for more than 50% of the variance in the observed variables. The value of AVE is greater than 0.4 is still acceptable, and when AVE is less than 0.5, if the composite reliability is higher than 0.6, the convergent validity is also eligible (Hair et al., 2019). The composite reliability for all constructs is higher than 0.7, indicating a good convergent validity.

5.2.7.3 Discriminant validity

For achieving high discriminant validity, it is essential to explain how much the construct correlated with other constructs in the model and how distinctly the measurement items only represent this single construct rather than other constructs. Firstly, Fornell-Lacker Criterion is used to assess discriminant validity (Fornell and Larcker, 1981). It requires that all the indicators loaded much higher on their hypothesized factor than on other factors. Meanwhile, the squared roots of AVEs on the diagonal are higher than the value of the inter-construct on the same columns and rows, which means constructs' own loading are higher than cross loadings. Besides, this study also tested the square root of the AVE against the inter-correlations of the construct with the other constructs in the model to examine the discriminant square root of the AVE exceeded the validity, and all the correlations with other variables(Hair et al., 2019), please see as Table 5.8.

Since the Fornell-Lacker Criterion approach does not reliably detect the lack of discriminant validity in common research situation, we also adopted the heterotrait-monotrait ratio of correlations (HTMT) introduced by Henseler et al. (2015) to assess the discriminant validity. HTMT is an estimator of disattenuated (perfectly reliable) construct correlation, such as R_{XY}, therefore a convenient alternative test of discriminant validity (Franke and Sarstedt, 2019). In line with Radomir and Moisescu (2019), the criterion can be described in mateix from with R_{XX} being a matrix of the correlations between each item x_i and x_j of contract X, and R_{YY} being the corresponding correlations of construct Y, with R_{XY} being the matrix of the correlations between each x_i and y_j. As the geometric mean of two number is the square root of their product, HTMT is calculated by:

HTMT = mean (R_{xy}) / (mean [R_{xx}] mean [R_{yy}])$^{\cdot}$

High HTMT values indicate a lack of discriminant validity, and we adopted the threshold value of 0.90 and recommend a cutoff value of 0.85 when the constructs are conceptually more distinct (Henseler et al., 2015). Table 5.9 presents all the values that fulfilled the criterion of HTMT 0.85, showing that the model that has established reliability and validity. Moreover, the results of HTMT inference also indicated that the confidence interval does not show a value of 1 on any of the constructs. Therefore, the measurement model in this study was measured satisfactory with confirmation of adequate reliability, convergent validity, and discriminant valid.

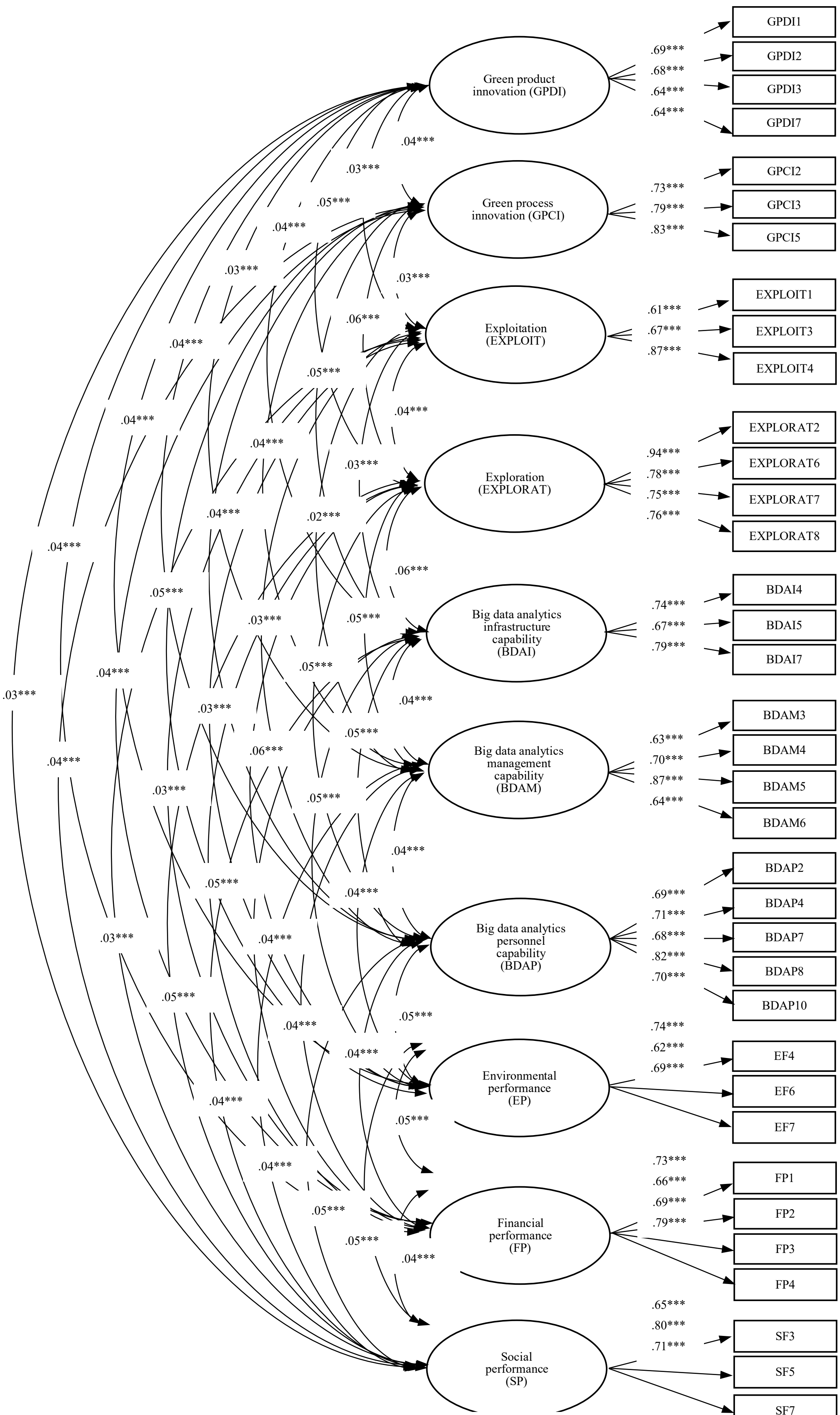


Figure 5.1 Measurement model

Table 5.7 Result of Confirmatory Factor Analysis

Confirmatory Factor Analysis (N=375)	**Standardized Factor Loading λ (standard error)**	**t-value**	**Composite Reliability**
GPDI1: Design of products for reduce consumption of material/energy during the full life-cycle	0.688 (0.469)	--	0.752
GPDI2: Design of products for reduce waste generation during the full life-cycle	0.678 (0.473)	10.129	
GPDI3: Using less or non-polluting/toxic materials. (Using environmentally friendly material)	0.639 (0.648)	9.738	
GPDI7: Degree of new green product competitiveness understand customer needs	0.619 (0.613)	9.515	
GPCI2: Low cost green provider: unit cost versus competitors' unit cost	0.733 (0.632)	--	0.826
GPCI3: Consumption low energy (such as water, electricity, gas and petrol) during production/use/disposal	0.789 (0.404)	13.398	
GPCI5: Controls operations process to reduce waste from all sources	0.826 (0.400)	13.591	
EXPLOIT1: Improvement of product quality	0.608 (0.545)		0.765
EXPLOIT3: We place strong emphasis on improving efficiency	0.673 (0.486)	9.912	
EXPLOIT4: Reduction of production cost	0.869 (0.251)	9.782	
EXPLORAT2: Opening up new markets	0.937 (0.155)	--	0.883
EXPLORAT6: Learned product development skills and processes entirely new to the industry (e.g. product design, prototyping new products, timing of new product introductions and customizing products for local markets)	0.781 (0.440)	19.219	
EXPLORAT7: Acquired entirely new managerial and organizational skills that are important for innovation (e.g. forecasting technological and customer trends; identifying emerging markets and technologies; integrating R&D, marketing, manufacturing and other functions; managing the product development process)	0.746 (0.536)	17.859	
EXPLORAT8: Compared to the competition, a high percentage of our sales come from new products launched in the past three years.	0.760 (0.556)	18.401	
BDAI4: All other (e.g., remote, branch, and mobile) offices are connected to the central office for sharing analytics insights	0.746 (0.553)	--	0.779

BDAI5: Our organization utilizes open systems network mechanisms to boost analytics connectivity	0.670 (0.615)	11.159	
BDAI7: Software applications can be easily used across multiple analytics platforms	0.790 (0.446)	12.140	
BDAM3: When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work	0.634 (0.651)	--	0.809
BDAM4: When we make business analytics investment decisions, we project how much these options will help end-users make quicker decisions	0.704 (0.526)	11.050	
BDAM5: In our organization, business analysts and line people coordinate their efforts harmoniously	0.874 (0.258)	12.314	
BDAM6: Real-time assess of data and information has helped organization in better decision making.	0.642 (0.698)	10.295	
BDAP2: Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE tools, etc.)	0.690 (0.654)	--	0.844
BDAP4: Our analytics personnel are very capable in decision support systems (e.g., expert systems, artificial intelligence, data warehousing, mining, marts, etc.)	0.714 (0.617)	12.150	
BDAP7: Our analytics personnel are very knowledgeable about the critical factors for the success of our organization	0.679 (0.586)	11.623	
BDAP8: Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions	0.820 (0.417)	13.564	
BDAP10: Our analytics personnel are very capable in terms of managing projects	0.697 (0.728)	11.904	
EP4: Significant reduction in energy consumption	0.737 (0.549)	--	0.722
EP6: Significant reduction the consumption for hazardous/harmful/toxic materials	0.616 (0.647)	9.682	
EP7: Significant reduction in environmental resource impact controversies	0.687 (0.524)	10.396	
FP1: Growth of sales	0.734 (0.492)	--	0.809
FP2: Growth in return on investment	0.659 (0.600)	11.421	
FP3: Return of assets	0.689 (0.593)	11.894	
FP4: Profit margin	0.785 (0.411)	13.157	
SP3: Incentives and engagement for local employment	0.653 (0.679)	--	0.766
SP5: Employee satisfaction	0.797 (0.469)	11.329	
SP7: Improvement in labour safety and labour conditions in our facilities	0.714 (0.563)	10.786	

Table 5.8 Validity Analysis

	CR	AVE	MSV	MaxR(H)	GPDI	GPCI	EXPLOIT	EXPLORAT	BDAI	BDAM	BDAP	EP	FP	SP
GPDI	0.752	0.431	0.166	0.754	**0.657**									
GPCI	0.826	0.614	0.135	0.832	0.320***	**0.784**								
EXPLOIT	0.765	0.526	0.098	0.818	0.313***	0.182***	**0.725**							
EXPLORAT	0.883	0.656	0.108	0.919	0.329***	0.183***	0.236***	**0.810**						
BDAI	0.779	0.541	0.212	0.787	0.344***	0.233***	0.170***	0.326***	**0.736**					
BDAM	0.809	0.518	0.225	0.848	0.253***	0.322***	0.162***	0.296***	0.460***	**0.720**				
BDAP	0.844	0.521	0.275	0.853	0.258***	0.240***	0.259***	0.287***	0.404***	0.366***	**0.722**			
EP	0.722	0.465	0.274	0.729	0.408***	0.367***	0.266***	0.323***	0.408***	0.337***	0.523***	**0.682**		
FP	0.809	0.516	0.275	0.816	0.335***	0.276***	0.222***	0.249***	0.341***	0.455***	0.347***	0.399***	**0.718**	
SP	0.766	0.524	0.275	0.779	0.316***	0.326***	0.242***	0.302***	0.356***	0.475***	0.525***	0.509***	0.524***	**0.724**

Note: Diagonal entries (in bold) are average variances extracted; entries below the diagonal are correlations.

* Significant at 0.001 level;

α indicates Cronbach's alpha.

Table 5.9 Discriminant validity – the HTMT test

Construct	GPDI	GPCI	EXPLOIT	EXPLORAT	BDAI	BDAM	BDAP	EP	FP	SP
GPDI										
GPCI	0.327 [0.108, 0.468]									
EXPLOIT	0.330 [0.133, 0.455]	0.201 [0.019, 0.331]								
EXPLORAT	0.336 [0.167, 0.463]	0.185 [0.005, 0.337]	0.256 [0.084, 0.396]							
BDAI	0.362 [0.189, 0.485]	0.253 [0.089, 0.380]	0.230 [0.032, 0.377]	0.352 [0.187, 0.473]						
BDAM	0.256 [0.032, 0.402]	0.329 [0.152, 0.460]	0.178 [0.000, 0.333]	0.333 [0.168, 0.464]	0.497 [0.357, 0.610]					
BDAP	0.276 [0.049, 0.412]	0.260 [0.091, 0.398]	0.317 [0.133, 0.451]	0.316 [0.152, 0.443]	0.421 [0.261, 0.533]	0.411 [0.249, 0.525]				
EP	0.430 [0.242, 0.550]	0.391 [0.211, 0.513]	0.323 [0.105, 0.477]	0.326 [0.164, 0.459]	0.415 [0.246, 0.545]	0.372 [0.203, 0.497]	0.534 [0.384, 0.632]			
FP	0.337 [0.150, 0.456]	0.297 [0.121, 0.435]	0.265 [0.076, 0.402]	0.266 [0.101, 0.394]	0.364 [0.197, 0.496]	0.480 [0.327, 0.582]	0.366 [0.177, 0.502]	0.427 [0.258, 0.558]		
SP	0.325 [0.103, 0.454]	0.348 [0.177, 0.469]	0.346 [0.147, 0.469]	0.319 [0.169, 0.437]	0.370 [0.181, 0.508]	0.498 [0.353, 0.591]	0.547 [0.414, 0.642]	0.518 [0.365, 0.635]	0.557 [0.422, 0.662]	

5.3 SEM RESULTS

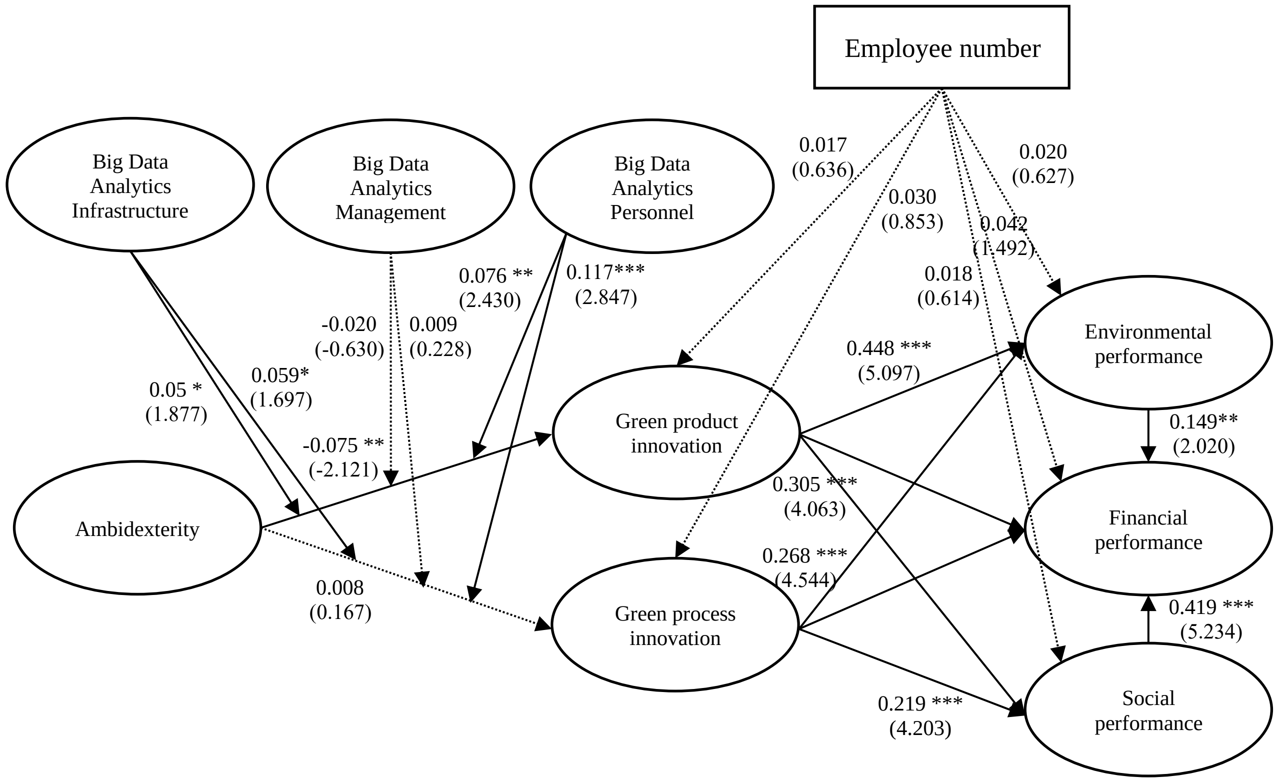


Figure 5.2 SEM results

SEM technique was then adopted to test the theoretical model (see as Figure 5.2). The good model fit indices for SEM fit are obtained (X2 = 312.931, df = 183, X2/df = 1.710, CFI = 0.942, IFI = 0.943, GFI = 0.929 and RMSEA = 0.044). In H1a and H1b, the hypotheses that ambidexterity is positively associated with GPDI and GPCI are made. However, the result indicates that ambidexterity is negatively associated with GPDI ($\beta = -0.075$, $p < 0.05$) and the positive impact of ambidexterity on GPCI is not significant ($p = 0.868 > 0.1$). Therefore, H1a and H1b are not supported. In terms of the hypotheses relating to the moderator role of BDAC, H2a and H2b predicted that BDAI would act as a moderator in the relationship between ambidexterity and two types of GI. H2a and H2b are supported with results show that the interaction term of ambidexterity and BDAI are positively impact GPDI ($\beta = 0.050$, $p < 0.01$) and GPCI ($\beta = 0.059$, $p < 0.1$). The results indicates that the negative relationship between ambidexterity and GPDI becomes weaker when develops BDAI, and the concurrent adoption of BDAI with ambidexterity brings a positive impact on GPCI. In H3a and H3b, the hypotheses are BDAM positively moderates the relationship between ambidexterity and GI. However, the results shows that the positive interaction of BDAM and ambidexterity on GPDI ($p = 0.529 > 0.1$) and GPICI ($p = 0.820 > 0.1$) are not significant. Therefore, H3a and H3b are rejected. In The moderator role of BDAP are also considered in H4a and H4b, the effect of the interaction term of BADP are positive and significant on both GPDI ($\beta = 0.076$, $p < 0.5$) and GPCI ($\beta = 0.117$, $p < 0.01$), therefore H4a and H4b are supported. Similar to BDAI, these results indicate that the development of BDAP reduce the negative relationship between ambidexterity and GPDI, while working on BDAP and ambidexterity simultaneously brings a positive impact on GPCI.

The hypotheses H5a and H5b are GPDI and GPCI positively associated with EP. The positive effects of GPDI on EP ($\beta = 0.059$, $p < 0.01$) and GPCI on EP ($\beta = 0.059$, $p < 0.01$) are both significant, therefore H5a and H5b are supported. The hypotheses H6a and H6b are GPDI and GPCI positively associated with SP. The positive effects of GPDI on SP ($\beta = 0.305$, $p < 0.01$) and GPCI on SP ($\beta = 0.219$, $p < 0.01$) are both significant, therefore H6a and H6b are supported. In terms of the relationships among the performance variables, the hypotheses of EP and SP have positive impacts on FP can be found in H7 and H8. As expected, both EP ($\beta = 0.149$, $p < 0.01$) and SP ($\beta = 0.41$, $p < 0.01$) are positively and significantly associated with FP. All the SEM results of hypotheses can be found in Table 5.10.

Table 5.10 Results of hypotheses

Path	***β***	***t*-value**	***p*-value**
Control effect			
Employee number → GPDI	0.017	0.636	0.525
Employee number → GPCI	0.030	0.853	0.394
Employee number → EP	0.018	0.614	0.531
Employee number → FP	0.042	1.492	0.136
Employee number → SP	0.020	0.627	0.539

Main effect			
H1a: Ambidexterity → GPDI	-0.075	-2.121	0.034**
H1b: Ambidexterity → GPCI	0.008	0.167	0.868
H5a: GPDI → EP	0.448	5.097	***
H5b: GPCI → EP	0.268	4.544	***
H6a: GPDI → SP	0.305	4.063	***
H6b: GPCI → SP	0.219	4.203	***
H7: EP → FP	0.149	2.020	0.043**
H8: SP → FP	0.419	5.234	***
Interaction effect			
H2a: Ambidexterity x BDAI → GPDI	0.050	1.877	0.060*
H2b: Ambidexterity x BDAI → GPCI	0.059	1.697	0.090*
H3a: Ambidexterity x BDAM → GPDI	-0.020	-0.630	0.529
H3b: Ambidexterity x BDAM → GPCI	0.009	0.228	0.820
H4a: Ambidexterity x BDAP → GPDI	0.076	2.430	0.015**
H4b: Ambidexterity x BDAP → GPCI	0.117	2.847	0.005***

* Significant at 0.1 level; ** Significant at 0.05 level; *** Significant at 0.01 level.

5.4 MEDIATION RESULTS

In order to test the moderator role of EP and SP in the relationship between GI and FP, the Bootstrapping has been employed to conduct the mediation analysis (Rungtusanatham et al., 1998). In this method, the procedure of 95 percentile bias-corrected confidence intervals with 2000 samples with replacement was applied to represent the sampling distribution of the indirect effect (Zhang et al., 2021). The Bootstrapping method can analysis both direct and indirect effect of the independent variable on the dependent variable and show whether the effects are significant or not is regarded as the key indicator of mediator's significance. The total effect can be understood in two parts: the direct and indirect effect.

The direct effect is the effect of exposure on the outcome absent the mediator. The indirect pathway is the effect of exposure on the outcome that works through the mediator. The results show that total effect between GPDI and FP is 0.290 ($p < 0.01$), and the direct and indirect effect paths are positive and significant at 0.01 level (Table 5.9). These results show that EP and SP jointly mediates the relationship between GPDI and FP. Meanwhile, a separate analysis has adopted to examine the mediator role of EP and SP in the relationship between

GPCI and FP. The results indicate that the total effect between GPCI and FP is 0.210 ($p < 0.01$), and both direct effect and indirect effect are positive and significant (Table 5.10). The results suggest that SP and EP can also jointly mediates the relationship between GPCI and FP. Therefore, H9a, H9b, H10a, and H10b are confirmed. As suggested in the theoretical model, EP and SP can be views as the parallel mediator in the relationship between GI and FP. The indirect effect between GPDI and FP, and GPCI and FP can be represented by four different paths as follow:

Path 1: GPDI → EP → FP

Path 2: GPCI → EP → FP

Path 3: GPDI → SP → FP

Path 4: GPCI → SP → FP

According to (Rungtusanatham et al., 2014), mixed findings may be derived for the structural model with parallel mediators, which means that there could have more than one mediator in an indirect relationship. This is due to the fact that the total indirect impact does not reveal the influence of a given path. One of the constituent pathways may be responsible for the majority of the total indirect effect. As a result, in order to further investigate H9a, H9b, H10a, and H10b, it is necessary to specifically evaluate the specific indirect effect (Ledermann et al., 2011). The PROGRESS macro for SPSS is used in this research to investigate the specific indirect effect (Hayes, 2015). More specifically, the PROGRESS macro only includes the variables in the parent model and direct effect that are required for describing the individual indirect effect as a total effect, as shown in Table 5.11 and Table 5.12. The estimations of the specific indirect effect and 95% confidence interval bootstrapping are reported in Table 5.13. Individual bootstrapping mediation analysis employs 2000 bootstrap samples again. Since the confidence interval for the indirect effect of both path 1 ad Path 2 does not include zero, the hypothesis of significant mediation effects of both EP and SP in the relationship between GPDI and FP further support H9. Also, the confidence interval for the indirect impacts of path 3 and path 4 do not cover zero, and the strong mediation roles of both EP and SP in the association between GPDI and FP justify H10. Furthermore, the magnitude of the effects can be distinguished from individual indirect effect, and the results show that the mediation effect of SP (path 2 and path 4) is higher than that of EP (path 1 and path 3).

Table 5.11 Mediation results of GPDI on FP

Effect path	**Estimate**	**95% Confidence interval**	**Two-tailed significance**
Total effect	0.290	[0.181, 0.400]	0.000 ***
Direct effect	0.143	[0.037, 0.249]	0.008 ***
Indirect effect path	0.146	[0.090, 0.216]	0.003 ***

* Significant at 0.1 level; ** Significant at 0.05 level; *** Significant at 0.01 level.

Table 5.12 Mediation results of GPCI on FP

Effect path	**Estimate**	**95% Confidence interval**	**Two-tailed significance**
Total effect	0.210	[0.124, 0.296]	0.000 ***
Direct effect	0.084	[0.001, 0.168]	0.040 **
Indirect effect path	0.126	[0.076, 0.180]	0.001 ***

* Significant at 0.1 level; ** Significant at 0.05 level; *** Significant at 0.01 level.

Table 5.13 The estimated specific effects and 95% confidence intervals for testing H9a, H9b, H10a, and H10b.

Path	**Indirect effect**	**Bootstrapped Standard error**	**95% CI based on bootstrapping**	
			Lower bound	**Upper bound**
Path 1 GPDI → EP → FP	0.053	0.023	0.090	0.216
Path 2 GPDI → SP → FP	0.095	0.027	0.046	0.150
Path 3 GPCI → EP → FP	0.043	0.017	0.012	0.078
Path 4 GPCI → SP → FP	0.083	0.024	0.041	0.134

5.5 CHAPTER SUMMARY

This chapter initially described the scale development procedure that used produce new instruments for assessing the latent constructs in this study, which included specifying the theoretical domain and operational definition of constructs, item generation, item purification, and pilot testing. Throughout the process, all suggested items are subjected to rigorous empirical testing, such as EFA and CFA, to assess the construct reliability, convergent validity, and dimensionality of the scales. The model fit indices demonstrate a good fit for the measurement model. Furthermore, the assessment method ensures that the correct latent variables for each construct may truly operate the implementation of its components.

Moreover, the main concerns of the theoretical model have been examined in a large scale sample , including i), the direct effect of ambidexterity on GPDI/GPCI, ii), the moderator role of BDAI, BDAM and BDAP in the relationship between ambidexterity and GPDI/GPCI, iii), the direct association of two types of GI with EP and SP, and iv), the mediator role of EP and SP in the relationship between GI and FP. SEM technique was adopted in order to evaluate the measurement of latent variables, and also test relationships between latent variables. The SEM approach was used to assess the measurement of latent variables as well as to investigate correlations between latent variables. SEM takes numerous equations into account at the same time, and this study used this technique to establish direct relationships and moderator effects in the same model. The results of SEM indicate that ambidexterity is adversely related with GPDI while has no effect on GPCI. Also, BDAI and BDAP positively moderate the association between ambidexterity and GI, while BDAM does not have any effect on the relationship between ambidexterity and GI. GPDI and GPCI also positively and significantly influence firm's EP and SP. Additionally, in order to test how GPDI and GPCI influence FP, this study use Bootstrapping approach to conduct the mediation analysis. With the Bootstrapping method, both direct effect and indirect effect of the independent variables (i.e., GPDI and GPCI) on the dependent variable (i.e., FP) are evaluated. The results show that EP and SP can be seen as the parallel mediators for the relationship between GI and FP. More in-depth discussion and explanation of theoretical model results will be provided in the Section 7.

CHAPTER 6 FUZZY-SET QUALITATIVE COMPARATIVE ANALYSI

6.1 INTRODUCTION

In this study, fuzzy-set qualitative comparative analysis (fsQCA) is employed to determine which combinations of exploitation, exploration, big data analytics (BDA) resources and firm size are important to achieve GI for firms operating in different contexts. Unlike other statistical methods, fsQCA supports equifinality. Equifinality means that a given outcome, i.e., a high level of green product innovation (GPDI) and green process innovation (GPCI) can be caused by different combinations of elements, and these combinations of elements may differ depending on the context (Schmitt et al., 2017). FsQCA is particularly applicable in big data analytics capability (BDAC) research because, depending on the domains targeted for evidence generation, the factors that form the core contribution to GI can vary considerably (Abbasi et al., 2016). Therefore, it is crucial to identify the factors and conditions that enable organisations to achieve high levels. FsQCA follows such a paradigm, as it aims to reduce the elements for each pattern to the basic necessary and sufficient conditions, Furthermore, fsQCA supports the presence of causal asymmetry, which states that the presence or absence of a causal condition depends on how it is combined with one or more other causal conditions for an event to occur (Fiss, 2011).

Since cases are composed of combinations of theoretically relevant attributes, the relationships between these attributes and the outcome of interest can be understood by examining the subset relationships (Ragin, 2013, 2009). For example, exploitation and exploration are used as two individual elements in the configuration. Therefore, the configuration results can be used to determine whether they should be used as substitutes or complements. If both Exploitation and Exploration are present in a configuration, this means that they are complementary and ambidexterity is a necessary condition for this solution. However, if only one of the two elements appears in a configuration, then they act as substitutes in that solution. These results complement the findings of SEM, as the theoretical model only explores the complementary relationship between exploitation and exploration.

As this study aims to investigate the modelling of asymmetric relationships between variables, fsQCA is beneficial to the study in several ways (Wang et al., 2019). This study is consistent with the focus of this method on the quantitative method used previously. The main advantages of using fsQCA in survey research arise in comparison to typical regression-based analysis and the limitations the latter has. Specifically, survey methods examine variables in a competitive environment as they calculate the net effect between variables in a modal, whereas fsQCA focuses on the complex and asymmetric relationships between the outcome of interest and its antecedents.

Moreover, fsQCA could be the best approach to deal with multi-way interactions and examine how variables systemically combine to create outcomes (Schmitt et al., 2017). Compared to traditional analysis techniques, fsQCA uses both qualitative and quantitative assessments to determine the degree to which a case belongs to a group, thus enabling a bridge between qualitative and quantitative methods (Ragin, 2000). FsQCA is a method that follows the principles of complexity theories within the configurational approach, which examines the interactions that develop between elements of a chaotic and nonlinear nature (Fiss, 2011; Mikalef et al., 2019). Furthermore, the FsQCA uses calibrated measurements after transforming the data into the range [0, 1]. Calibration is common in the natural sciences, but less so in the social sciences. It can help qualitative researchers to assess significant and irrelevant variances and quantitative researchers to relate examples accurately (Ragin, 2008).

The survey is limited to two- or three-way interaction effects, such as studying the direct effect of ambidexterity on GPDI and GPCI, while cluster analysis (fsQCA) can find homogeneous patterns without controlling for the outcome (Fiss, 2011), sThis is particular crucial in this research due to the reason that firms are highly likely to apply more than one type of BDAC in order to achieve better GI. Instead of investigating the moderator role of each type of BDAC, fsQCA enables the researchers to uncover how to combine different types of BDAC with exploitation and exploration in order to attain high level performance of GPDI and GPCI. Since this study aims to design systems that take into account all the different requirements to achieve a high GI, fsQCA allows the computation of multiple solutions for multiple types of practitioners rather than just the vast majority explained by the best solution of a Regression analysis. This study benefits from using both the survey and fsQCA methods, even though the same data are used. The different methods solve different research questions and enhance the research opportunities within the study, the use of different methods provides an opportunity to find answers to all research questions. Thus, it is possible to perform standard statistical analyses for studies with limited numbers of cases. For these reasons, fsQCA is an appropriate research method to complement SEM in this study.

6.2 OVERVIEW OF FUZZY-SET QUALITATIVE COMPARATIVE ANALYSIS

According to the developer Prof. Charles C. Ragin (2008), fsQCA is a configurational comparative method that based on set theory and fuzzy logic. Mendel and Korjani, (2012) provide an exhaustive explanation regarding the theoretical aspects of fsQCA. In their study, fsQCA is a methodology that obtains linguistic summarizations from data that are associated with cases. As shown in Figure 6.1, the methodology can be summaries in 9 steps in total (Mendel and Korjani, 2012), and Table 6.1 explicitly explained the 9 steps and detailed how these steps are applied in this study.

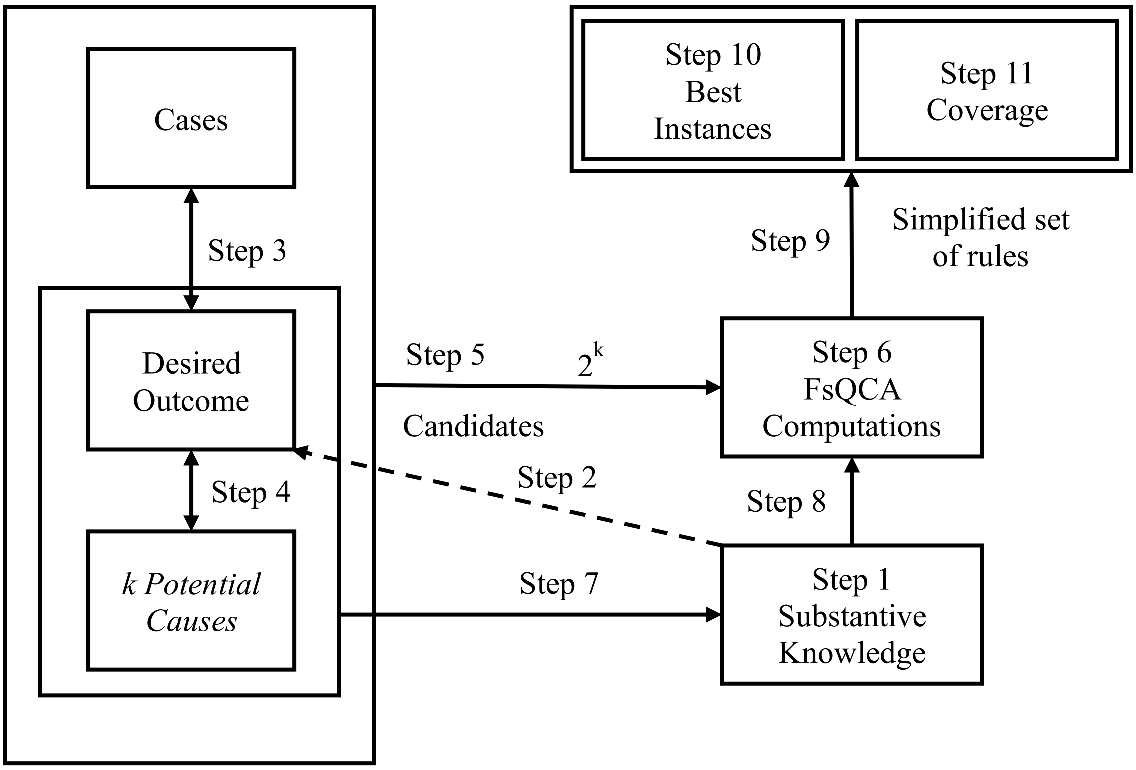


Figure 6.1 FsQCA summarized (Mendel and Korjani, 2012)

Table 6.1 Application of fsQCA

Number	Summaries in each step	Application in this study
Step 1	Collect substantive knowledge about a research problem	In this study, fsQCA is utilized to address the research question 3: Under what conditions, can exploitation, exploration and BDAC help to achieve high level of GI? The necessary context is provided in 2 LITERATURE REVIEW and 3 HYPOTHESES DEVELOPMENT.
Step 2	Specify one or above desired outcomes, separate fsQCA need be run for each outcome.	Accoring to the research question, the desired outcomes for fsQCA are GPDI and GPCI respectively.
Step 3	Choose the cases depending on the specific knowledge about the potential causes for the outcomes.	The sample for fsQCA is the same as the survey data, which comprises 375 individuals from Chinese companies with experience in GI activities and BDA operations.
Step 4	Postulate a set of *k* potential causes that lead to the desired outcome. The potential causes can be either	By operate the truth table, it computes all possible configurations (or combinations) that may occur,

	individually or in variable combinations. 2^k possible causal combinations are used in fsQCA with the logic that "if this causal combination, then the desired outcome".	providing 2 *k* rows, with *k* representing the number of outcome predictors, and each row representing every possible combination.
Step 5	Show each causal combination includes *k* terms connected to each other by AND, while all 2^k candidate rules are for the same desired outcome and are therefore connected by the work OR.	In order to check all the possible combinations, this study choose individual causes rather than variable combinations, therefore, there is no setting that a certain combination must appear or must not appear when running fsQCA.
Step 6	Uses the case-based data to reduce the 2^k candidate rules to a smaller number of rules. The reason for having fewer rules is the rules with the same desired outcome are logically combined using set theory reduction techniques, and some causal conditions are absorbed and disappear from the final causal combination.	For samples larger than 150 cases the frequency threshold may be set at 3 (or higher), while for smaller samples the threshold may be set at 2 (Fiss, 2011; Ragin, 2008). As our sample is 375, the threshold is set at 3, and all combinations with smaller frequency are removed from further analysis.
Step 7	If there is limited diversity, which mean not enough cases to provide evidence about all 2^k candidate causal combinations, some substantive knowledge needs to be obtained from domain experts about whether a causal condition could lead to a desired outcome	Not applicable in this study.
Step 8	Incorporate into additional substantive knowledge for further fsQCA computations.	No additional operation required
Step 9	Present a small collection of simplified if-then rules, which shows at least one simplified causal combination for desired outcomes. In the last two steps, the best instances are connected to each rule, and the coverage of cases by each rule is computed.	The fsQCA findings will be displayed in a table that shows all combinations. Please see "Table 6.2 Configurations that lead to high level of GPDI" and "Table 6.3 Configurations that lead to high level of GPCI".

The fundamental goal of fsQCA is to establish which combination of factors is minimally necessary and/or to achieve a certain outcome, as well as to determine which groups of cases share a specific combination of conditions (Llopis-Albert et al., 2019). A configuration is made up of positive, negative or absent conditions or factors. A condition is necessary when a certain outcome cannot be achieved in the absence of it, while a condition is sufficient when the condition can lead to the outcome without the assistance of any other conditions (Ragin and Fiss, 2008). FsQCA assumes complex causality and symmetric relationship that presents different pathways that are sufficient to result in a certain outcome. In all cases studies, there are sufficient or necessary conditions, while conditions could be sufficient and necessary when combined with other conditions or may represent merely one alternative among others, which shown in some cases but not to others, therefore, fsQCA implies that several configurations could lead to the same outcome.

FsQCA overcomes the constrain of only working on binary variables, instead, it enables the researchers to examine the different levels of belongingness of cases to a certain set (Llopis-Albert et al., 2019). In order to do so, the outcome and causal conditions need to be defined as fuzzy sets, where requires the establishment of membership functions. The first stage of is to undertake a calibration technique in which all data are converted into measure of set membership using theoretical or substantial knowledge external to the empirical data, therefore classifying meaningful groups of cases (Ragin and Fiss, 2008). Fuzzy values refer to the degrees of membership in a certain set, and it ranges from full membership (1) to non-membership (0), whereas the crossover point (0.5) representing neither in nor out of the set.

The second stage is to create a truth table, which is a 2^k row matrix where k represents the number of configurations, and each column represents an antecedent condition. The reason to select number 2 is that both the causal condition and its complement are considered (Llopis-Albert et al., 2019). The truth table illustrates all logically feasible combinations of causal conditions and classifies the cases based on the logical combinations. Each empirical example corresponds to a certain configuration, depending on which antecedent conditions the case meets (Fiss, 2011). The third stage is to reduce the rows' number in the truth table. In this stage, the Quine-McCluskey algorithm is used (Quine, 1952). The algorithm uses Boolean algebra to conducts a counterfactual analysis of causal conditions, and each of which is minimally sufficient to produce the outcome. It analyzes set relationships by detecting causal conditions combinations that consistently bring to an outcome, and then removing the causal conditions that only occasionally lead to the outcome, indicating that these causal conditions are not essential elements of a sufficient configuration for the outcome (Mohsen and Eng, 2016). The final analysis reports information on two important measures in fsQCA: consistency and coverage (Ragin and Fiss, 2008). Consistency is that membership score on the outcome is consistently higher that the membership score of the causal combination, which can be weighted by the relevance of each case, while solution coverage refers to a proportionate measure of how well the solution describes the outcome.

6.3 FSQCA IN GREEN INNOVATION RESEARCH

The number of contextual studies undertaken within comparative research has increased during the previous few decades. The qualitative comparative analysis approach is derived from political science and sociology. This approach is characterized by causal asymmetry and the applicability of small sample sizes since causative circumstances and their combinations that may lead to an equifinal outcome are recognized (Kraus et al., 2017; Ragin, 2000). In recent years, new comparison techniques based on set-theoretical logics have emerged as a significant trend. Fuzzy-set qualitative comparative analysis (fsQCA) is a well-known methodology that stems from quantitative comparative analysis and is rapidly being used in business and management research (Tho and Trang, 2015). This technique has been applied to solve complex qualitative comparative problems in many research areas in the management study (e.g., Schmitt et al., 2017; Tho and Trang, 2015; Xiong and Sun, 2022). By applying fsQCA, researchers aim to determine which combinations of factors is minimally necessary and/or sufficient to achieve a specific outcome and can also identify the groups of cases that shar a certain combination of conditions (Llopis-Albert et al., 2019).

FsQCA was generally unknown to researchers in this field prior to 2013, but it has becoming increasingly commonly employed in green management studies in the last five years (Kraus et al., 2017). The fsQCA technique can be used alone or in combination with other methodologies in research. The paper written by Stekelorum et al. (2021) is an example of only using faQCA in research. The work examines the extent to which different combinations of internal and external green supply chain management practices impact third-party logistics providers' operational and financial performance. While many papers use fsQCA in conjunction with other methodologies. Among these methodologies, fsQCA is most typically applied with SEM. For instance, Kawai et al. (2018) combine SEM and fsQCA approaches to explore how stakeholder pressures in host countries push multinational corporate subsidiaries to develop green product and process innovations. The study of Shahzad et al. (2021) fills a gap in the literature about the influence of the knowledge management process on corporate GI. Using partial least squares structural equation modelling and fsQCA on 393 respondents in Pakistani manufacturing corporations, the results show that investing in and adopting cutting-edge technologies and green practices is beneficial for long-term success and soft concerns in today's knowledge-based economy. Meanwhile, fsQCA is also applied with other methodologies, such as like case study, panel data etc. Scarpellini et al. (2017) explore the impact of human capital on companies in the context of eco-innovative entrepreneurship. Eight case studies and fsQCA demonstrate how the existing relationships of current resources with the economy and financial resources, as well as other corporate capabilities, are formed. Beside. Xiong and Sun (2022) evaluate the influence of green money on environmental deterioration using panel data from 34 countries. FsQCA is used to examine the combined influence of green finance (for example, green investment, GI, green insurance, and industrial structure) on CO_2 emissions.

The combination of SEM and fsQCA is the most typically used in studies of green management. SEM is useful for research that allow for the estimate of numerous causal links between one or more independent variables and one or more decent variables at the same time (Hair et al., 2011). In practice, multiple combinations of factors may be able to generate the same result. Compare with more quantitative methods, like SEM, which are based on correlation, fsQCA analysis, on the other hand, adheres to the configuration theory paradigm, which allows for the evaluation of comprehensive interplays between elements of a messy and non-linear character (Fiss, 2007). Moreover, fsQCA seeks to establish logical connections between combinations of causal conditions and an outcome, and fsQCA results summarize the sufficiency between subsets of all the possible combinations of the causal conditions or their complements and the outcomes (Mendel and Korjani, 2012). Unlike earlier qualitative comparative analyses, fsQCA allows for the outcome and predictor variables to be on a fuzzy scale rather of a binary scale. Rather to just discovering correlations between independent and dependent variables, FsQCA completes SEM by investigating distinct patterns of components that contribute to a certain conclusion. Furthermore, fsQCA allows for element reduction for each pattern and only contains essential and adequate requirements. As a result, fsQCA is recognized as a complementary methodology for unravelling the complicated relationships that emerge between independent and dependent variables (Mikalef and Pateli, 2017).

6.4 COMPLEXITY THEORY AND COMPLEMENTATY THEORY

In the operations management literature, the employment of fsQCA were built upon prior organizational theories such as contingency theory (Lexutt, 2020), resource dependence theory (Lee et al., 2019), institutional theory (Miska et al., 2016), transaction cost economics (Basu et al., 2021) and resource-based view (Tseng and Chiang, 2016) as well as its extension, including dynamic capabilities view (Ciampi et al., 2021), natural resource-based view (Stekelorum et al., 2021) and resource orchestration theory (Hughes et al., 2018). While the theoretical developments of these research were grounded, the emphasis was on contexts rather than fsQCA. As a result, the theoretical lens applied in this research may not give adequate reasons for the selection of fsQCA. Among fsQCA studies, a number of research stress that the reason of using fsQCA from a configurational perspective. From this perspective, two important theories are widely used to develop research propositions: complexity theory (Acquah et al., 2021; Gounaris et al., 2016; Mikalef et al., 2019) and configurational theory (Ambroise et al., 2018; da Silva et al., 2020; Sjödin et al., 2019). Both theories emphasize on systems thinking for analysing situations where causality is complex and configurational.

The emergence of order in a complex system with various interacting components is the focus of complexity theory (Gounaris et al., 2016). Because complexity theory incorporates the principle of equifinality, which states that multiple paths can occur when they lead to the same outcome (Woodside, 2014), the theory believes that the outcome of interest can be equally described by various sets of causal conditions that combine in sufficient configuration for outcome, and the occurrences of any feature may not be required for achieving a specific outcome (Fiss, 2011). The interaction of components in a complex system is non-linear, which means that a change in one component might have a negligible or significant impact on the system. Moreover, complexity theory explains the emergence of causal asymmetry. Causal asymmetry occurs when the presence or absence of a causal condition depends on how this causal condition interacts with other causal conditions in order to achieve a certain outcome (Woodside, 2014). As a result, the system cannot be comprehended by evaluating individual system components but rather by examining the system as a whole.

Configurational theory emerged from organisational research and strategic management (Fiss, 2007). This theory posits that a set of the same variables can be achieve a specific outcome in various ways depending on how these variables are combines (Ordanini et al., 2014). Mohsen and Eng (2016) listed three principles in configuration theory, (1) there is no single factor that can lead to an outcome of interest; (2) causal factors do not operate in isolation; and (3) the same causal factor can have various impacts on the outcome depending on the context. The concept of "equifinality" is also used to explain why the same outcome can be achieved by different configurations of the causal factors (Ragin, 2000). However, some confusion persists concerning the label for the theory, whether to appropriately use the term configurational theory or configuration theory. Yet, both terms explicitly shift attention from individual causal conditions to the combination of causal conditions. In this study, configuration theory explains how organizations can create GI from BDAC by exploring complex patterns and combinations of interconnected elements (Wang et al., 2019). Since the business value generation of BDAC is a complex process resulting from multi-way interactions among multiple elements, we asset that configuration theory provides an excellent anchor to explain the creation of BDA's business value on GI and explore the configurational effects of BDAC and organizational elements on improving GI.

Both complexity theory and configurational theory hold three main tenets that coincide well with fsQCA: conjunction, causal asymmetry and equifinality. First, it is the joint presence or absence of a set of variables that leads to the outcome of interest (i.e., conjunction). As fsQCA focuses on testing combinatory patterns of conditions that lead to the outcome of interest, it is a suitable analysis method to incorporate the principle of conjunction. Unlike traditional symmetric methods that examine each factor individually, fsQCA can address the interactions among factors (Schmitt et al., 2017). Second, the configurations leading to the negative outcome are not the mirror opposites of configurations leading to the positive outcome (i.e., causal asymmetry) (Ambroise et al., 2018; Gounaris et al., 2016). This principle reveals that traditional symmetric methods are not applicable in understanding a complex system because they focus on identifying determinants that explain high levels of the outcome and, most importantly, assume that the exact opposite will lead to low levels of the outcome. On the other hand, fsQCA offers an asymmetrical test that makes no predictive claims for how an outcome relates to the antecedent conditions. Third, the outcome of interest can be equally explained by alternative sets of causal conditions that combine in sufficient configurations for the outcome (i.e., equifinality) (Fiss, 2011; Ragin, 2009). Many fsQCA studies successfully identified multiple alternative equifinal configurations of conditions that lead to the same outcome of interest, supporting the proposition of equifinality held by complexity theory and configurational theory.

6.5 APPLICATION OF FUZZY-SET QUALITATIVE COMPARATIVE ANALYSIS

6.5.1 Calibration

FsQCA aims to find out all the combinations of causal conditions that potentially lead to a certain outcome. The first step of the fsQCA analysis is to calibrate dependent and independent variables into crisp or fuzzy sets. Two types of GI are set as the dependent variable of our study, i.e., GPDI and GPCI, while the independent variables that are used include exploitation, exploration, big data analytics infrastructure (BDAI), big data analytics management (BDAM), big data analytics personnel (BDAP) as well as elements of the external environment, i.e., the size-class which firms belongs to. Crisp sets are more appropriate in categorical variables that have two, and only two options such as a firm's size-class which is dichotomized into large firms with 250 or more employees and Small-Medium Enterprises (SMEs) with < 250 employees. Fuzzy sets on the other hand, may range anywhere on the continuous scale from 0, which denotes an absence of set membership, to 1, which indicates full set membership. Fuzzy sets are best suited in converting continuous values such as all other constructs that are on a 7-point Likert scale. To calibrate continuous variables into fuzzy sets we followed the method proposed by Mikalef et al. (2019) and Ragin (2009). According to the procedure, the degree of set membership is based on three anchor values. These represent a full set membership threshold value (fuzzy score = 0.95), a full non-membership value (fuzzy score = 0.05), and the crossover point (fuzzy score = 0.50) (Woodside, 2013b). Since this study uses a 7-point Likert scale to measure constructs, the suggestions put forth by Ordanini et al. (2014)

are followed to calibrate them into fuzzy sets. Following these guidelines, and based on prior empirical research (Fiss, 2011; Ragin, 2009), we computed percentiles so that the upper 25 percentiles serve as the threshold for full membership; the lower 25 percentiles for full non-membership; and the 50 percentiles represent the cross-over point. Table 6.1 shows the thresholds for the variables included in this study and the anchor values for each.

Table 6.2 Fuzzy set calibration

Variable	**Means (S.D.)**	**Percentiles**			**Thresholds**		
		25%	50%	75%	Full membership	Cross-over membership	Full non-membership
GPDI	5.86 (0.74)	5.50	6.00	6.50	6.75	6.00	4.50
GPCI	5.48 (0.95)	5.00	5.67	6.00	7.00	5.67	4.00
Exploitation	5.85 (0.79)	5.33	6.00	6.33	7.00	6.00	4.33
Exploration	5.64 (0.95)	5.25	5.75	6.25	7.00	5.75	3.75
BDAI	5.49 (0.90)	5.00	5.67	6.00	6.67	5.67	3.93
DBAM	5.50 (0.83)	5.00	5.50	6.00	6.75	5.50	4.00
BDAP	5.47 (0.88)	5.00	5.60	6.20	6.80	5.60	4.00

6.5.2 Truth table analysis

After calibration, sets can be subjected to fuzzy truth table analysis to examine the relationship between the configuration conditions and the outcome. Scholars have recommended testing the conditions that might be necessary to achieve the desired outcome before analysing sufficiency (Ragin, 2009; Tho and Trang, 2015), where a ‘necessary’ condition is defined as a condition such that the outcome would not have occurred in its absence. After the necessary conditions analysis, we then ran the truth table algorithm, choosing the outcome and conditions, and applying the standard analysis procedure on fsQCA. Frequency and consistency cut-off points were specified in this step. Here, the minimum acceptable frequency of cases for solutions was set at 1 and the lowest acceptable consistency cut-off at 0.75, which meets the recommended minimum threshold of 0.75 (Ragin and Fiss, 2008). This process clarifies any relationships between combinations of potentially causal or descriptive characteristics and the outcome of interest. The output of a fuzzy-set truth table analysis consists of one or more combinations of characteristics associated with an outcome. The results are presented in the following section.

6.6 CONFIGURATION ANALYSIS

For the analysis of configurations leading to high GPDI and GPCI outcomes we relied on the software fsQCA 3.0 (Ragin, 2009). By applying the fsQCA algorithm a truth table of 2k rows is produced, where k is the number of predictor elements, and each row indicates a possible combination. FsQCA then sorts all the 375 observations into each of these rows based on their degree of membership of all the causal conditions. Consequently, some truth table rows may contain many cases and others just a few or even none. At this stage it is necessary to reduce the number of rows according to two conditions: (1) a row must contain a minimum number of cases, this value was set to a frequency threshold of 5 cases (Ragin and Fiss, 2008); and (2) selected rows must achieve a minimum consistency level of 0.80. FsQCA analysis causal conditions and configurations of causal conditions by the metrics of consistency and coverage. Consistency measures the degree to which a subset relation has been approximated (Ragin and Fiss, 2008). It is similar to the concept of significance in statistical models (Schneider and Wagemann, 2010), therefore a consistency score of less than 0.75 or even 0.8 would be significant in consistency. As a result, solutions that do not meet this criterion are excluded from the analysis. Solution coverage is used to evaluate the relative relevance of a causative combination and functions similarly to variance explained in a regression study. Because consistency and coverage are antagonistic, a high consistency may have a poor coverage and vice versa.

6.7 FUZZY-SET QUALITATIVE COMPARATIVE ANALYSIS OUTCOME

In the final procedure, fsQCA evaluate which configurations of variables are the sufficient conditions that are necessary to yield high GPDI and GPCI outcomes. This procedure necessitates cross-case analysis of membership between the causal sets and the outcome set (Mohsen and Eng, 2016). The fsQCA analysis yields three types of solutions: complex, parsimonious, and intermediate (Ragin and Fiss, 2008). Each solution derives a set of pathways that are predictive of a high membership score in the outcome condition. The parsimonious solution uses all simplifying assumptions regardless of whether they are based on easy or difficult counterfactuals, therefore, the parsimonious solution should only be used when the assumptions for using the remainders are fully justifiable. The intermediate solution distinguishes between easy and difficult assumptions and takes into account simplifying assumptions based on easy counterfactuals. Finally, the complex solution is unconcerned with simplifying assumptions and is typically employed as the final solution when there is no justification for simplifying the solution.

To obtain results we use the method proposed by (Ragin and Fiss, 2008), which identifying core conditions that are part of both parsimonious and intermediate solutions, and peripheral conditions are those that are eliminated in the parsimonious solution and only appear in the intermediate solution (Fiss, 2011). The black circles (•) denote the presence of a condition, while the crossed-out circles (⊗) indicate the absence of it (Ragin and Fiss, 2008; Woodside, 2014). Core elements of a configuration are marked with large circles (prime implicants which are produced by the parsimonious and intermediate solution of fsQCA), peripheral elements with small ones (implicants that are present in intermediate solutions but not in the parsimonious solutions), and blank spaces are an indication of a don't care situation in which the causal condition may be either present or absent. In the solutions of the present study no peripheral elements exist.

Table 6.3 Configurations that lead to high level of GPDI

Configuration	**Solution for high level of GPDI**						
	SME				Large firm		
	1	2	3	4	5	6	7
Exploitation	●		●	●	●	●	

Exploration		⊗		●	●	●	●
BDAI	●	⊗	⊗		●		●
BDAM	●	⊗	⊗	●	●	●	●
BDAP		⊗	⊗	●		●	●
Consistency	0.960	0.859	0.913	0.967	0.969	0.967	0.969
Raw coverage	0.480	0.060	0.072	0.478	0.303	0.307	0.295
Unique coverage	0.032	0.001	0.003	0.031	0.012	0.016	0.003
Overall consistency	0.850579						
Overall coverage	0.94996						

Table 6.4 Configurations that lead to high level of GPCI

Configuration	Solution for high level of GPCI						
	SME				Large firm		
	1	2	3	4	5	6	7
Exploitation	●		●	●	●	●	
Exploration		⊗		●	●	●	●
BDAI	●	⊗	⊗		●		●
BDAM	●	⊗	⊗	●	●	●	●
BDAP		⊗	⊗	●		●	●
Consistency	0.954	0.896	0.943	0.958	0.947	0.945	0.948
Raw coverage	0.500	0.066	0.078	0.495	0.310	0.314	0.302
Unique coverage	0.031	0.002	0.003	0.027	0.012	0.016	0.004
Overall consistency	0.876633						
Overall coverage	0.935433						

The configurations shown in the Table 6.2 and Table 6.3 represents the alternative combination of conditions that associate to the respective outcomes, in this case, GPDI and GPCI respectively. Each solution represents a cluster of firms that share common configurations of elements or antecedents that lead to high level of outcomes. Surprisingly, the results show the same configurations that lead to high level of GPDI and GPCI, which indicates that GPDI and GPCI can be achieved at the same time by the adoption of certain combinations of BDAC, exploitation and exploration in the China context. And following explanations present the configurations that lead to high level of GPDI and GPCI.

The fsQCA analysis produced 7 configuration solutions (pathways) that leading to high level of GPDI. The overall consistency and overall coverage for GPDI are 0.860579 and 0.94996. The consistency values are above 0.75 and coverage values are above 0.25, indicating that a substantial proportion of the outcome is covered by the seven configurations. Solution 1 to 4 are appropriate for SMEs, while solution 5 to 7 are suitable for large firms. Solution 1 (consistency = .0.960, raw coverage = .480, unique coverage = 0.032) demonstrates that a high degree of exploitation, BDAI and BDAM, provides the highest unique coverage for GPDI. High unique coverage means that, as compared to all other solutions, this combination mostly contributes to high level of GI. Solution 2 (consistency = .0.869, raw coverage = .060, unique coverage = 0.001) describes the absent of exploration, BDAI, BDAM and BDAP are sufficient to achieve high levels of GPDI for SMEs. Solution 3 (consistency = .0.913, raw coverage = .072, unique coverage = 0.003) is another solution that show the absent of all three types of BDAC, indicating that high level of exploitation and the absent of BDAI, BDAM and BDAP are also sufficient to achieve high level of GPDII. Solution 4 (consistency = .0.967, raw coverage = .478, unique coverage = 0.031) is the last solution for SMEs, and the only solutions that show the present of both exploitation and exploration in SMEs, indicating the combination of high levels of exploitation, exploration, BDAM and BDAP. Regarding to the solutions that applied for large firm to achieve high level of GPDI, solution 5 (consistency = .0.969, raw coverage = .303, unique coverage = 0.012) shows that high level of exploitation, exploration, BDAI and BDAM are sufficient to achieve high level of GI. Solution 6 (consistency = .0.967, raw coverage = .307, unique coverage = 0.016) shows the same configuration as solution 4, which indicates that the combination of high level of exploitation, exploration, BDAM and BDAP can achieve high level of GPDI for firms in different sizes. The last solution (consistency = .0.969, raw coverage = .295, unique coverage = 0.003) is the only solution that including all types of BDAC, and they work with high level of exploration are sufficient for achieving high level of GPDI for large firms.

Similarly, the configuration solutions for GPCI indicate 7 solutions statements with overall solution coverage of 0.876633 and a consistency of 0.935433, which indicates that a good proportion of the outcome is covered by these configurations. Solution 1 (consistency = .0.954, raw coverage = .500, unique coverage = 0.031) demonstrates that a high degree of exploitation, BDAI and BDAM, provides the highest unique coverage for GPCI. High unique coverage means that, as compared to all other solutions, this combination mostly contributes to high level of GPCI. Solution 2 (consistency = .0.869, raw coverage = .066, unique coverage = 0.002) describes the the absent of exploration, BDAI, BDAM and BDAP are sufficient to achieve high levels of GPCI for SMEs. Solution 3 (consistency = .0.943, raw coverage = .078, unique coverage = 0.003) is another solution that show the absent of all three types of BDAC, indicating that high level of exploitation and the absent of BDAI, BDAM and BDAP are also sufficient to achieve high level of GPCI. Solution 4 (consistency = .0.958, raw coverage = .495, unique coverage = 0.027) combines the present of both exploitation and exploration in SMEs, the results show that the combination of high levels of exploitation, exploration, BDAM and BDAP, has the highest consistency for GPCI. In terms of the solutions for large firm to achieve high level of GPCI, solution 5 (consistency = .0.947, raw coverage = .310, unique coverage = 0.012) describes the combination of exploitation, exploration, BDAI and BDAM are sufficient to achieve high level of GI. Solution 6 (consistency = .0.945, raw coverage = .314, unique coverage = 0.016) is same configuration as solution 4, which indicates that the combination of high level of exploitation, exploration, BDAM and BDAP can achieve high level of GPCI for both SMEs and large firms. The last solution (consistency = .0.948, raw coverage = .302, unique coverage = 0.004) is the only solution that combines the presence of BDAI, BDAM and BDAP, and the combination of BDAC and exploration are sufficient for achieving high level of GPCI for large firms.

To test the robustness of these findings, this work used the methods proposed by Ciampi et al. (2021) and verified the robustness over three alternative calibration choices. For the robustness check, the calibration procedure described by Ordanini et al. (2014) is used. All full membership requirements have been changed to value 6, crossover points to 4.5, and full non-membership scores to 3. The rationale for establishing full non-membership at 3 rather than 2 is because the distribution of values, which was based on respondents responding that they strongly agreed, was incorrect (Mikalef et al., 2019). Because all three tests yield the same results regardless of the calibration method used, the robustness of the findings can be confirmed.

6.8 PREDICTIVE VALIDITY

Testing our solutions (models) for predictive validity is important. Predictive validity shows how well the model predicts the dependent variable in additional samples (Woodside, 2013). Predictive validity is important because achieving only good model fit does not necessarily mean that the model offers good predictions. We present here how to perform predictive validity testing in fsQCA (Mikalef et al., 2020). To test for predictive validity, the first step is to split the sample into two equal sub-samples through random selection, e.g., modelling sub-samples for GPDI and GPCI as sub-sample 1 and sub-sample 2; modelling holdout samples for GPDI and GPCI as holdout sample 1 and holdout sample 2 (Ali et al., 2016; Mikalef et al., 2019). Testing for predictive validity including hold-out samples is always possible and doing so substantially increases the added value for both empirical positivistic and interpretative case studies (Woodside, 2014). An fsQCA analysis was run for the modelling sub-sample using the same observation number and consistency criteria as in the original analysis. The solution of the analysis for the modelling sub-sample for GPDI and GPCI are presented in Table 6.4 and Table 6.5 respectively and show the patterns of complex combination of conditions were causally consistent indicators of high levels of GPDI and GPCI. Moreover, the models produced by the modelling sub-sample were tested on the data of the holdout sample. The new variable is plotted against the outcome of interest using the holdout sample. Plotting each model on its respective outcome variable produced highly consistent models with high coverage.

Figure 6.2 and Figure 6.3 illustrates how data from the holdout sample plot produced by the modelling sub-sample for GPDI and GPCI. Consistency and coverage values are presented here, which should not contradict the consistency and coverage of the solution. The numbers below the “Plot” button show set-theoretic consistency scores (Ragin, 2018). If one of these two numbers indicates high consistency, the other can be interpreted as a coverage score. In this study, separate predictive analysis is conducted for GPDI and GPCI respectively. In the case of GPDI, 0.847269 indicates high consistency, while 0.972029 indicates the coverage. These calculations show that the data are largely consistent (85%) with the argument that Figure 6.2 is a subset of developing high level of GPDI and its coverage of the development of GPDI is 97%. This means that Figure 6.2 accounts for 85% of the sum of memberships in the development of a high level of GPDI. In the case of GPCI, 0.867396 indicates high consistency, while 0.952186 indicates the coverage. These calculations show that the data are largely consistent (87%) with the argument that Figure 6.3 is a subset of developing high level of GPCI and its coverage of the development of GPCI is 95%. This means that Figure 6.4 accounts for

87% of the sum of memberships in the development of a high level of GPCI.

Table 6.5 Solution analysis for the modelling sub-sample for GPDI

GPDI			
	Raw coverage	Unique coverage	Consistency
Exploitation * Exploration * BDAI * BDAM * SMEs * ~ Large firm	0.477	0.023	0.983
Exploitation * Exploration * BDAM * BDAP * SMEs * ~ Large firm	0.484	0.031	0.987
Exploitation * Exploration * BDAI * BDAM * ~ SMEs * Large firm	0.307	0.014	0.959
Exploitation * Exploration * BDAM * BDAP * ~ SMEs * Large firm	0.312	0.018	0.956
Exploitation * Exploration * ~BDAI * ~BDAM * ~BDAP * SMEs * ~ Large firm	0.069	0.009	0.990
Solution coverage: 0.847269			
Solution consistency: 0.972029			

Table 6.6 Solution analysis for the modelling sub-sample for GPCI

GPCI			
	Raw coverage	Unique coverage	Consistency
Exploitation * Exploration * BDAI * BDAM * SMEs * ~ Large firm	0.489	0.019	0.963
Exploitation * Exploration * BDAM * BDAP * SMEs * ~ Large firm	0.498	0.029	0.971
Exploitation * Exploration * BDAI * BDAM * ~ SMEs * Large firm	0.319	0.014	0.952
Exploitation * Exploration * BDAM * BDAP * ~ SMEs * Large firm	0.322	0.018	0.946
Exploitation * Exploration * ~BDAI * ~BDAM * ~BDAP * SMEs * ~ Large firm	0.072	0.009	0.984
Solution coverage: 0.867396			
Solution consistency: 0.952186			

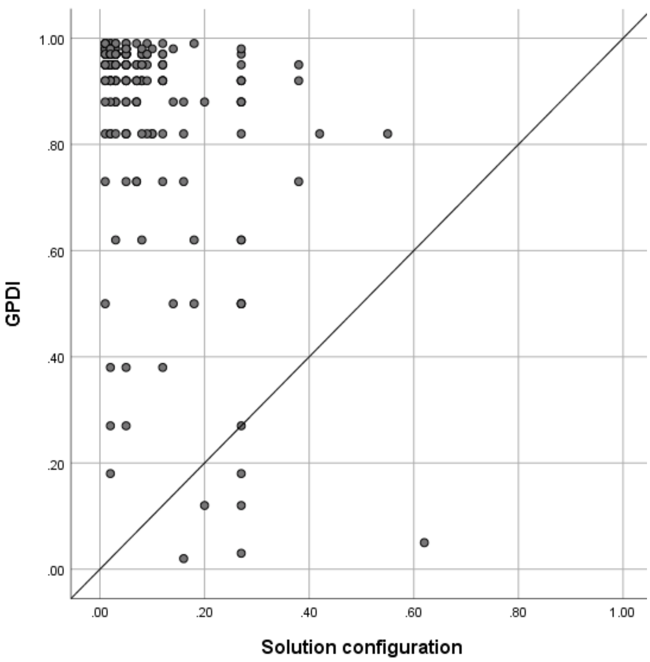


Figure 6.2 Test of the solution from the modelling GPDI sub-sample using data from GPDI holdout sample

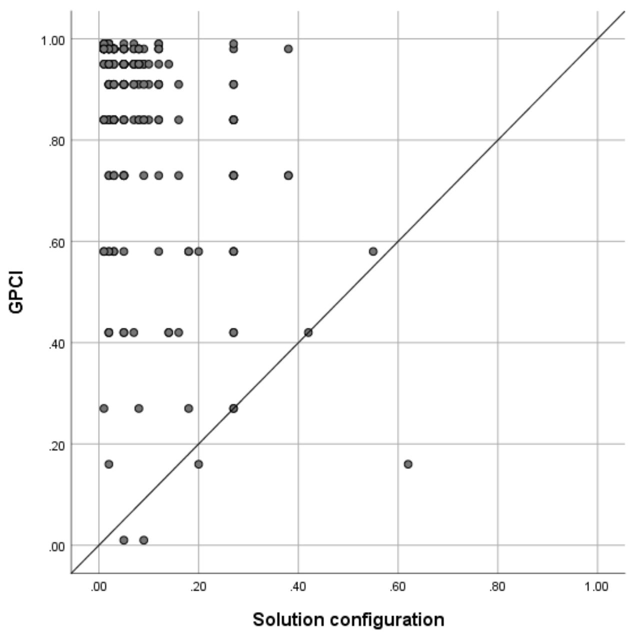


Figure 6.3 Test of the solution from the modelling GPCI sub-sample using data from GPCI holdout sample

6.9 CHAPTER SUMMARY

This chapter explains the fsQCA methodology, then performs it and presents the research results. First and foremost, this chapter discusses the use of fsQCA in green management research. It has been discovered that the use of this method has been more prevalent in the last five years. Also, explain why fsQCA and SEM can be properly combined to increase the study's reliability and robustness. Then drawing on the complexity and complementary theory, this chapter present how fsQCA methodology incorporates perspectives of conjunction, causal asymmetry and equifinality to analyze the different configurational pathways to GPDI and GPCI. Before running the analysis, an overview of the 11 steps of fsQCA is provided. The approach is then used to gain a better understanding of the complex, non-linear and synergistic effects of exploiation and exploration in conditioning the effect of BDAC on GPDI and GPCI. The results of FsQCA complement the general tendency in SEM by uncovers the multiple reliaties that exist in terms of achieving a desired outcome.

By appling fsQCA methodology, the confluence of exploiration, exploration, three types of BDAC, and firm size is studied, and patterns of conditions that facilitate GPDI and GPCI emerge. Seven diffrernt configurations emerged to stimulate the cpprdination, with 85% of cross-functional corrdination for GPDI and 87% of cross-functional corrdination for GPCI. In this study, the configuration solutions for GPDI and GPCI are the same, meanwhile, the outcomes of fsQCA provide interesting results that refine the outcoms from SEM. In cougruence with the moderator role of BDAC in reationship between ambidexteriy and GI (i.e., H2, H3 and H4), fsQCA solution 4,5 and 6 suggest that two types of BDAC are needed in achieving GI. An interesting finding of fsQCA that is different from the main findings in SEM is that BDAM can not moderate the influence of ambidexterity on GI in SEM, while in fsQCA 4,5 and 6, which apply ambidexterity, BDAM is always presents. Therefore, the fsQCA outcomes serve to empirically validate arguments that suggested that BDAC can be of great value in a number of conditions (Mikalef and Pateli, 2017).

CHAPTER 7 DISCUSSION

7.1 INTRODUCTION

This chapter discusses the study findings and summarizes the theoretical and practical implications. The research objectives of this study are to examine the implementation and impact of GI. By using two methodologies, i.e., survey and fuzzy-set qualitative comparative analysis (fsQCA), the objectives are met with the fining presented in Chapters 5 and 6. Specifically, Chapter 5 presents the results of structural equation modelling (SEM) analysis and phantom model approach, which show empirical evidence about how ambidexterity can be used to achieve better green innovation (GI), the moderator role of big data analytics capability (BDAC) in the relationship between ambidexterity and GI, as well we the impact of GI on firm's triple bottom line. Second, Chapter 6 consider the asymmetric relationship between variables and multiple combinations of variables may exists to achieve on outcome, fsQCA is conducted as a complement methodology to reveal the multi-way interactions among variables, and the way to achieve high green product innovation (GPDI) and green process innovation (GPCI).

Therefore, this chapter begins from the discussion of the findings identified in Chapters 5 to 6 in section 7.2. Drawing from these discussions, the contributions of the thesis from both theoretical and practical aspects are presented in section 7.3. Lastly, the summary of this chapter will be provided in section 7.4.

7.2 DISCUSSION OF FINDINGS

7.2.1 Discussion of structural equation modeling findings

The conventional view of GI emphasizes the importance of the implementation of efficient management practices to deal with environmental concerns in product and process innovation ((Chiou et al., 2011; Dangelico, 2016; Tseng et al., 2013). More recent literature in the field highlights the necessity of discovering the practices that drives a better GI (Peters and

Buijs, 2021; Wang et al., 2020). In order to address this question, this study adopted survey study to investigate (1) how ambidexterity acts as the antecedent to influence GI in the context of china, (2) how the firm's BDAC moderates the relationship between ambidexterity and GI, and (3) how GI promotes different types of firms' performance. By presenting the inconsistent arguments in the existing literature, this study provided a more accurate exposition as to how the interplay of exploitation and exploration can contribute to GI, and how big data analytics infrastructure (BDAI), big data analytics management (BDAM) and big data analytics personnel (BDAP) may strengthen the influence of ambidexterity on GI, moreover, the impact of GI on firms' environmental, financial, and social performance is also identifies. From the perspective of resource based theory (RBT), Knowledge based view (KBV) and information processing view (IPV), this study has developed a theoretical framework to link these importance concepts together. Following are the discussion of empirical findings according to the SEM results in Chapter 5.3 SEM RESULTS.

7.2.1.1 Ambidexterity and GI

Surprisingly, according to table 5.10, the relationship between ambidexterity and GI reveals a negative and significant result for H1a and an insignificant result for H1b, which contradicts our hypothesis. One possible explanation is that China is still in a period of fast economic expansion (D. Zhang et al., 2019). In terms of exploitation, there's not much previous green experience to draw on for learning and improvement in many Chinese firms, or the employees are not capable in terms of using programming or developing appropriate technical solutions to identify incremental improvement ideas, therefore the outcomes of exploitation may not be able to enhance GI. Besides, some firms execute exploration in GI only with the purpose of avoiding penalties of environmental contamination, instead of aiming to integrate environmental protection into firm culture (Bansal and Roth, 2000; Chiou et al., 2011). Such exploration may only lower the amount of hazardous materials/gas/water created during manufacturing to the level needed by the government, without doing all possible to limit the generation of harmful substances to a minimum. Ineffective exploitation and restrained exploration may negatively impact the operational excellence and efficiency (O'Reilly III and Tushman, 2013). Therefore, despite these efforts, firms may still struggle to promote GPDI.

Furthermore, the development of ambidexterity in pursuit of GPDI take into account for both cost effectiveness and environmental efficiency, while overlook the specific customer demand for green products. For instance, firms may fail to produce some of the most important product characteristics for customers, such as reusability, recycling, and recovery. As a result, firms that focus solely on the potential environmental benefit of the product, while disregarding consumer demands, will be seeing their GPDI decline. This finding is consistent with Arranz et al. (2019) that ambidexterity as an impediment to the firm's GI activities.

Likewise, the study of Peters and Buijs (2021) offers another perspective, specifically that when choosing between a high risk and uncertainty approach and a more conservative and less green strategy, firms often prefer the latter one. The reason for this is that exploration not only takes a lot of time and effort, but it may also not yield the expected results, and this approach is not suitable for firms hoping for short-term outcomes. Using existing expertise and knowledge, on the other hand, can swiftly deliver an incremental solution based on the previous product or process. Due to this selective tendency, an imbalance of the development between exploitation and exploration develops, leading to a lack of cross-fertilization within and across organization functions (Hansen et al., 2019).

Previous research has shown that focusing on one side of ambidexterity has detrimental consequences; in this situation, if firms primarily focus on exploitation, it will be difficult to adapt to changes in the external environment and service in a long term (Ahuja and Curba Morris Lampert, 2001). Since GPCI requires maintain environmental compliance and minimize energy consumption during production, and changes in the external environment have relatively low influence on GPCI (Chiou et al., 2011), ambidexterity that focuses on exploitation then has few impacts on GPCI. Meanwhile, the external environment may have a significant impact on green products, particularly considering customer demands for green products are continuously changing. If radical innovations cannot be generated, it is highly possible that customer requirements will not be satisfied and the successes of the GPDI will be reduced.

7.2.1.2 The moderator role of BDAC

In addition, this study provides empirical evidence to understand whether the development of different types of BDAC can strengthen the impact of ambidexterity and GI in the context of China. Regarding the moderator role of BDAC in the relationship between ambidexterity and GI, explanation will be provided from the perspective of BDAI, BDAM and BDAP based on the results shown in table 5.10.

First of all, the moderating effect of BDAI can be found in the results of H2a and H2b, which both show significant and positive interaction on GPDI/GPCI. Regarding the result of moderator role of BDAI on the relationship between ambidexterity and GPDI, the main effect is negative, and the interaction effect is positive. The results indicate that although the development of ambidexterity leads to less GPDI, and the negative relationship between ambidexterity and GPDI becomes weaker when BDAI increases. It can be explained that BDAI enables access to high volume, variety and velocity of data, and also acquisition, extraction and analysis of information derived from multiple sources (Raut et al., 2021). Besides, BDAI brings superior equipment and software applications for business, and provide essential conditions for recording diversified and fast-moving data from many platforms (Akter et al., 2016; Kim et al., 2012). Firms would struggle to acquire knowledge and create knowledge from big data without development of the data analytics infrastructure. Specifically, by obtaining information from existing green activities and stakeholders, the extracted knowledge not only gives an accurate grasp of consumer demands and expectations, but it also provides an understanding of customers' perceptions about the current green produce.

Through the development of BADI, firms use the internal resources and potentially obtain more information from external resources, allowing them to analyse the larger amount of data(Fosso Wamba et al., 2015). By improving the efficiency and accuracy of information generation, BDAI helps to improve the efficiency of exploitation. The creation of knowledge may lead to numerous radical ideas, thereby increasing the possibilities of creating new green products that meet customer needs (Öhman et al., 2021).

At the same time, the result of H2b demonstrates that, whereas ambidexterity has no influence on GPCI, the concurrent development of BDAI with ambidexterity can have a positive impact on GPCI. If there is no BDAI, firms may consume a significant amount of people and time to enhance the green process based on the firms' prior experience, or they may collect radical ideas about process innovation from the employees in different departments of the company. This is the inefficiency of ambidexterity that results from firms failing to provide a system for gathering ideas and exchanging information, while BDAI brings fundamental infrastructure and facilities to help firms not only collect sufficient information from different platform, but also share knowledge seamlessly across the organization, regardless of the location(Akter et al., 2016). Yet, once a firm establishes BDAI, it may interact with ambidexterity to positively improve GPCI.

Secondly, the moderator role of BDAM can be observed in the results of H3a and H3b. The results demonstrate that BDAM has no impact on the association between ambidexterity and GI, which rejects the hypothesis. As BDAM represents the management team's capability to improve data governance, data scope definition, identifying organisational structure, policy and standard creation, and stakeholder selection. Prior studies indicating that the governance rules, procedures, and standards are produced by BDAM, and high BDAM assures the availability, integrity, consistency, and security of Big Data (Kim et al., 2012). That is, BDAM is at the level of data administration and delivering high-quality data to technical staff, however, the management-level assistance does not engage in the usage of superior data analysis methods and technologies to extract useable information from data. Firms that seek to enhance existing green goods or processes, as well as come up with original GI solutions, must do so through big data analysis, rather than management-level operations.

On the other hand, current research contends that BDAM enables the creation of a data-driven culture since the top management team emphasises and implements data-driven decisions. Once a data-driven culture is established, employees will consider data as the primary resource for leveraging insight and ideas, hence enhancing ambidexterity (Awan et al., 2021; LaValle et al., 2011). This reasoning is based on the pre-existing data culture; however, the development of big data analysis is still in its early stages in China, especially among managers, their comprehension of big data and ability to deploying valuable big data may be restrained. Managers may set regulations and governance linked to big data analysis, but the relevance of big data analysis may not be ingrained in business culture, and it leads to the difficulties to diminish workers' dependence on intuition, as well as to foster cross-departmental cooperation. As a result, BDAM has little influence on the impact of ambidexterity on GI.

Thirdly, H4a and H4b reveal that BDAP positively moderates the association between ambidexterity and GI. Similar to the results of BDAI, BDAP development can mitigate the negative impact of ambidexterity on GPDI. As previously stated, one of the reasons why exploitation cannot promote GI is a lack of analytics personnel. Analytics personnel are one of a company's most valuable assets. They not only utilise BDA to better information collecting by computing to address massive data, but they also have a superior awareness of technical trends, allowing them to stay up with the fast-growing BDA technologies (Gupta and George, 2016; Kwon et al., 2014). If the wrong judgement is made about the demands of the users, or if the product's environmental protection is not effectively monitored and regulated, ambidexterity will have a detrimental influence on GPDI. While the development of BDAP can very well fix this problem. Professional technicians can employ programming skills to process the acquired data and appropriately offer customers' desires as well as product areas that require improvement. This knowledge may be used in both exploitative and exploratory actions, enhancing the likelihood of successful GPDI.

Besides, while ambidexterity has no direct impact on GPCI, the development of BDAP can interact with ambidexterity to positively affect process innovation. The reason why ambidexterity does not affect GPCI might be an imbalance between exploitation and exploration. That is, exploitation will utilise more resources than research in enhancing the green process, allowing exploitative activities to benefit from more resources (Andriopoulos and Lewis, 2009). The findings indicate that the interplay of BDAC and ambidexterity might significantly enhance GPCI, most likely through improving the synergy of exploitation and exploration (Cao et al., 2009). Personnel analysts can employ computing and programming techniques to transform data into knowledge, which might be a recap of previous experience or a prediction of future product process improvement. Also, these acquired resources are interoperable, which means they may be used for both exploitation and exploration, implying that ambidexterity can substantially increase GPCI.

7.2.2 Discussion of mediation analysis findings

The SEM results for H5a, H5b, H6a, and H6b are also included in table 5.10, which demonstrate that both GPDI and GPCI have a positive effect on EP and SP, supporting the study of Chiou et al. (2011) that GI development is critical for a firm's competitive advantage. Although both academics and practitioners have emphasized the importance of environmental management in developing nations, this study delves deeper into the environmental and social values of GI in the context of China. This study provides evidence that GPDI and GPCI improve EP (H5a and H5b), which is consistent with the findings of (Rehman et al., 2021b), who state that GI strategies significantly reduce the impact on the environment by improving existing products and processes in a more environmentally friendly manner, as well as introducing new products and processes that may radically transform the existing methods of operations.

The H6a and H6b results show that GI also results in a high level of SP. This conclusion reinforces up the findings of (Zailani et al., 2015), who argue that GI initiatives such as GPDI and GPCI enable firms attain higher SP. By making more green-related organizational decisions, firms are better addressing stakeholder concerns, environmental agency pressures, and growing social consciousness among employees, consumers, and communities (Zailani et al., 2015). The results of H5a, H5b, H6a and H6b show that woking on GI allows Chinese firms to better improve EP and SP, that’s being said, taking environmental issues into account when innovating new products and processes allows firms maintaining competitiveness and achieve sustainable development (Zhang et al., 2021).

Meanwhile, the SEM results in table 5.10 show that both EP (H7) and SP (H8) have a beneficial influence on FP. These findings are consistent with the sustainability studies that emphasize the significance of realizing the triple bottom line (Feng et al., 2018; Zailani et al., 2012; Zhang et al., 2021). More importantly, this study builds on prior research to better understand the indirect effects of GPDI and GPCI on FP. As shown in table 5.11 and table 5.12, both EP and SP significantly and positively mediate the relationship between two types of GI and FP. These findings support the argument of Chan et al. (2016) that GI can enhance FP when environmental protection and social benefit are considered. The empirical evidence in this study also refutes the argument that GI brings to additional cost and financial burden for firm (Li et al., 2014), or that GI has no association with FP (Gilley et al., 2000). Instead, the expenditure of GI could be offset by lowering penalties and boosting corporate social behaviour, and it could even lead to economic growth by attracting extra investment and long-term firm sustainability (Rehman et al., 2021b). As a consequence, this study extends the environment management literature by using empirical evidence to demonstrate how GI positively improves triple bottom lines, and it also provides a constructive viewpoint on the role of GI in improving firm performance in the context of China.

7.2.3 Discussion of fuzzy-set qualitative comparative analysis findings

The fsQCA results in tables 6.2 and table 6.3 of Chapter 6 show that the same configurations are employed to obtain high levels of GPDI and GPCI. The possible explanation could be (1) both GPDI and GPCI share some common norms, like the use of eco-labelling systems, environment management systems and ISO 14000 (Tseng and Chiang, 2016); (2) these two types of innovation naturally interact with each other (Wang et al., 2021; Xie et al., 2019), for instance, firms needs to design at least one produce line that is designed to positively effects on the environment for produce environmentally labelled products; (3) both GPDI and GPCI share similar ultimate goals, such as reduce consumption of water, material and energy during the full life cycle (Wang et al., 2021). Due to the above reasons, same solutions for achieving both GPDI and GPCI are justified. The discussion of each fsQCA solutions will be explained in detail.

Solutions 1 to 4 correspond to Small-Medium Enterprises (SME's) as configurations that lead to a high level of GPDI and GPCI, such industries may include processes for natural resource, food product, as well as those in the consultancy sectors. In the solution 1, exploitation, BDAI and BDAM are marked as necessary in improving GI, while exploration and BDAP are found to be the non-important elements. The result shows that, compared with pursuing radical GI, small companies are more suitable for incremental innovation, such as improving product quality, enhance production process efficiency, and reducing pollutions generated during production. This can be explained by the fact that radical innovation frequently necessitates a large investment of personnel and capital, which is difficult for small companies to afford. When developing exploitation, it is important to identify existing problems and improve solutions, therefore, firms require strong big data infrastructure and facilities to collect and process a large amount of data extracted from existing green products and processes (Kaisler et al., 2013). At the same time, it is critical to have leaders who can manage BDA effectively and allocate resources reasonably (Mikalef et al., 2018). In this case, even if there is no particularly strong technical talent in the firm, GI can still be leveragef through bid data analytics facilities and management, thus forming an incremental GI.

Solution 2 and solution 3 are the only two solutions that show the absent of three types of BDAC in realizing advanced GI. These two solutions demonstrate that, in many cases, BDAC are not necessary in achieving better GI for SMEs', in fact, SMEs may realize green targets without the deployment of BDAC. Since big data analysis relies heavily on relevant facilities, managers' capacity to facilitate BDA, as well as technology-related talents, all of which take a significant amount of people and material resources to develop, which is very difficult for some SMEs (Mikalef et al., 2018). The observed difference between solution 2 and solution 3 are the adoption of exploitation and exploration. In the solution 2, the absent of exploration can be found, and application of exploitation is not prioritized, while in the solution 3, exploitation is the core aspects in improving GI, and GI exploration is not required. When SMEs need to choose between exploitation and exploration. It appears that developing exploitation is a preferable option. This might be due to the fact that SMEs are more adapted to generating incremental GI, since continual learning and internal knowledge from experience provide firms with short-term gains (Raisch and Birkinshaw, 2008), and it is difficult for them to devote significant time and resources in seeking radical innovation.

Solution 4 is the only solution for SMEs that has developed BDAP. Technical talents possess professional knowledge and skills, allowing them to apply big data to a variety of tasks (Mikalef et al., 2020). When there are exceptional technical professionals who can analyze data through advanced programming or tools, they can process the data to extract valuable resources or knowledge that cannot be duplicated by others (Shamim et al., 2020). Firms that do not have such resources are relatively less competitive in the market. At the same time, management capabilities are also developed in this solution, emphasizing the necessity of a manager or CEO who knows the importance of BDA and have the capability to allocate resources and use the technology to make the best decisions. Besides, ambidexterity can be leveraged when SMEs develop BDAM and BDAP at the same time. This may be attributed in significant part to highly skillful technological personnel. In SMEs, unlike large companies, the technical talent can handle a wide range of tasks, moreover, they pay close attention to the details in data from various sources in order to understand the problems and customers' needs, and to effectively improve existing products and processes. They can also tackle complex technological difficulties with the support of managers, so as to come up with revolutionary GI ideas through a long period of research.

Solution 5 to solution 7 correspond to conditions of large corporates. Such industries usually include for manufacturing, as well as those in the biological engineering and pharmacy sectors. Specifically, solution 5 and solution 6 presents core elements for firms that operate under conditions of ambidexterity, which emphasis the importance of applying exploitation and exploration simultaneously. In additional, BDAM is a necessary condition in both solutions. This can be justified by the fact that in the large firm, managerial capable of solve business problems through data analytics is an essential for facilitate ambidexterity. Firms use ambidexterity to refine and extend existing processes and product, as well as build new linkages for competences, technologies and products in order to discover how to make their products and process better, cheaper and greener. Surprisingly, this result is contradicted those of the survey study, which found that BDAM is not the moderator of the relationship between ambidexterity and GI. As the fsQCA results show that BDAM has to work with another type of BDAC for achieving ambidexterity, indicating that ambidexterity or GI cannot be achieved without the infrastructure or people, no matter how good the managers are at coordinating infrastructure and people harmoniously.

Solution 7 is the only solution that shows three types of BDAC as the necessary conditions, and exploration is found to be critical components of high GI. This solution denotes that only large companies can develop all of these three BDAC capabilities when exploring new GI opportunities. This can be explained by the fact that large firms have more resources which allows them to develop their big data analysis capabilities in different aspects. The three BDACs can promote and coordinate with each other to improve the success of exploring new solutions. Some radical large companies can achieve GI by only investing in exploring new green products and processes.

The findings provide support for the idea that different combinations of antecedents, i.e., exploitation, exploration, different types of BDAC play a greater or lesser importance depending on the contexts of application and the conditions that characterize them. Our results show that different combinations of strategies are found to be significant contributors to firm's GI depending on the size-class of the focal firm. Results show that value-creating configurations can be equifinal, and that the link between firm's capability and level of GI is not always linear.

7.3 RESEARCH IMPLICATIONS

7.3.1 Theoretical implications

Based on the findings, this study offers some useful insight regarding the theoretical and managerial. Firstly, new knowledge has been generated in terms of the way combined exploration and exploration can influence GI. Previous studies of ambidexterity mainly believed that ambidexterity plays an essential role to pursuing innovation and improving firms' competitive advantage (Andriopoulos and Lewis, 2009; O'Reilly III and Tushman, 2013). The findings of this study are differed from those studies which assume that the joint effect of exploitation and exploration would automatically benefit GPDI and GPCI.

The GI literature is enriched by demonstrating that the combined ambidexterity created through an interaction of exploitation and exploration not only hampers the development of product design and product features to minimize its negative impact on environment, but also has no impact on the change or adjustment within the manufacturing process that contribute to environment during the whole production stages. The findings are aligned with Peters and Buijs, (2021) that ambidexterity often leads to a failed GI as a result of multiple uncertainties that firms face in GI. This finding could be explained by the fact that the Chinese companies have not fully developed green related technologies and resources, the negative association between ambidexterity an GPDI might be caused by limited experience can be raw for learning and improvement, and not enough analytics personnel support for radical innovation. While the reason ambidexterity shows no impact on GPCI might be due to the slow progress of the development of process as well as the one-side focus on ambidexterity (Ahuja and Curba Morris Lampert, 2001; Peters and Buijs, 2021). Hence this study does not suggest that exploitation and exploration should be implemented simultaneously to facilitate better GI.

Secondly, with more firms use BDA techniques in their operations, new knowledge of BDAC literature has been generated in terms of the way it influences the GI of firms. Previous BDAC studies in business and management focus on its business value to pursuing competitive advantage or financial outcome (Kaisler et al., 2013; LaValle et al., 2011; McAfee and Brynjolfsson, 2012a). While despite the important role of BDAC as enablers of boost performance, limited research has empirically examined how different forms of BDAC can be leverage in pursing environmental sustainability and GI. The SEM findings from this study indicates that BDAI and BDAP positively moderate the relationship between ambidexterity and GPDI and GPCI respectively, while BDAM does not have moderation impact. That is to say, by developing BDAI and BDAP, the negative impact of ambidexterity on GPDI can be decrease, and their interaction with ambidexterity brings a positive influence on GPCI.

The results show that BDAC can lead to enhanced GI by affecting the underlying processes ambidexterity. Drawing on RBT, KBV and IPV, this study articulates how developing BDAC can be translated into valuable knowledge and resources that help firm maintain their competitiveness and pursuing green goals in produce and process innovation. This study demonstrates that creating a strong BDAC increases the speed of insight extraction, makes sense of complicated and past-paced environmental management, creates real-time monitoring information on consumers and rivals, and identifies operational inefficiencies and bottlenecks (Mikalef et al., 2019). BDAC supplements the green information required by ambidexterity, facilitates green knowledge generation and knowledge sharing, and improves the firm's capacity to adapt to changing environments. Therefore, demonstrate that BDAC can lead to innovation in terms of new green product and process under certain circusmtances.

Thirdly, this study contributes to the debate regarding the impact of GI on firm performance. The findings from this study complement existing knowledge by evaluating how the adoption of two types of GI can be translated into relevant financial, environmental and social benefits (Chiou et al., 2011; Wang et al., 2021; Xie et al., 2019). When implementing GPDI and GPCI, the firms consider both environmental regulations and laws, and the societal norms, therefore, the environmental disruption and damage during the product manufacturing and process can be greatly reduced.

Moreover, previous studies provide inconsistent conclusions about the impact of GI on FP (Y. S. Chen et al., 2006; Xie et al., 2019; Zhang and Walton, 2017). Therefore, by showing that EP and SP positively mediated FP, the research suggest that nevertheless the potential high expenditure of developing GPDI and GPCI, the investment on GI will benefit the firm by preventing environmental penalty and attracting external investment, and eventually brings better financial income to firm (Zhang et al., 2021). That is, not only does GI meet the stakeholders' expectation form minimum pollution, but the new knowledge and technologies used in GI will help forms to performance better in the market. As a result, this study adds to the body of literature on environmental management by empirically demonstrating that GI can positively boost triple bottom lines, as well as providing a valuable viewpoint on the role of GI in firm performance in China.

From a methodological standpoint, one type of research method, mostly survey, is commonly adopted in the field of GI (Abu Seman et al., 2019; Chiou et al., 2011; Wang et al., 2021; Zhang and Walton, 2017). In order to reduce the potential bias that a single method could bring, this study contributes by providing another research, i.e., fsQCA, method with SEM. The SEM methodology is appropriate in examining the causal paths, such as the influence of ambidexterity on firm's GI, and moderator role of BDAC, while fsQCA provides a deeper understanding of the complex, non-linear and synergistic effects of exploitation, exploration, and BDAC practices on a specific GI practice. Overall, the results of SEM demonstrate the general tendency, fsQCA exhibits the multiple realities that exist in terms of achieving a desired state (Mikalef et al., 2019)

7.3.2 Practical implications

This study also provides some interesting insights for firm managers with regard to the adoption of ambidexterity, BDAI and GI. Firstly, it is essential for managers to consider environmental regulations and rules, and society expectation on environmental protection (Chiou et al., 2011). When the environmental awareness is raised in the firm, managers are more likely to be more engage in appropriate and meaningful green behaviours. More specifically, the economic concerns would be integrated into firm's product innovation and progress innovation (Sun et al., 2020). By behaving in this manner, businesses may establish a green image, which can fulfil the needs of diverse stakeholders for minimising environmental impact, as well as provide new chances and investment.

Secondly, although previous studies have emphasized that ambidexterity is an important strategy for firms to achieving innovation (Andriopoulos and Lewis, 2009; O'Reilly III and Tushman, 2013), giving that both exploitation and exploration play important roles in Chinese business, firms should pay attention to the way to adopt them in order to achieving high level of GI. In this paper, the results show that simultaneously employ exploitation and exploration does not guarantee a better GI in China. Indeed, for firms who do not have much experience in green product development and green process operations have limited knowledge and experience in GI, and it leads to a relatively ineffective exploitation, meanwhile, many firm, especially SMEs would have financial burden in continuously conduct experimentation and discovery new ideas in GI, even for some firms that recently start to explore the radical ways of GI, it may take longer time to get good results.

Thirdly, for firms who are or will be integrate BDAC in their business process, the knowledge that generate from having big data infrastructure and analytics personnel can be effectively deployed for developing GPDI and GPCI. More specifically, the presence of good infrastructure and facilities make it possible to handle a variety of simi-structured and unstructured data, therefore, the firms can make use of more accurate and timely information to improve the effectiveness of ambidexterity (Raut et al., 2021). Moreover, when firms utilize open systems network mechanisms, the analytics connectivity would be boosted, therefore, the analytics- driven information can be seamlessly shared across the organizations, regardless the locations (Kim et al., 2012; Wamba et al., 2017).

Fourthly, this study offers practitioners a more in-depth explanation of the relationship between GI and performance. Only with a clear understanding of the importance of GI, firms are more likely to adopt and implement the practice, and then benefit from it. The benefit of GI brings so the triple bottom line suggests that the firm's efforts of not only focus on economic targets but concerning about environmental and social impacts. When firms develop the greenness of its product and process, customers are more likely to buy those products that contribute to environmental and social issues, so that other competitors in the market must adjust existing strategies or build new strategies to achieve non-economic target. Moreover, except from facilitate the adoption of GI on the focal firm and its competitors, it is also considered to improve the environmental and social responsibility in supply chain (de Giovanni, 2012). When organizations internalizing the corporate environmental responsibility and corporate social responsibility paradigm, they engage a series of activities with stakeholders such as employees, consumers and governments (Maloni and Brown, 2006).

More importantly, by incorporate environmental and social bottom line, firms would incorporate corporate environmental responsibility and corporate social responsibility paradigm into firm's goals and strategies, therefore, the potential economic opportunities of GI initiatives can be realised. By intensifying production processes, firms lessen environmental pollution while lowering the costs of resources and waste disposal (Bansal and Roth, 2000). Firms can improve revenue through green marketing, the sales of green products, and outsourcing corporate environmental expertise. Moreover, rent-earning firm-based resources, like corporate reputation, learning capabilities, and product quality, can be improved through green corporate activities.

Last but not least, the result of fsQCA brings about the opportunities for companies to nurture BDAC by specifically investing in the basic resources on which these capabilities are based, such as the BDAI, BDAM and BDAP (Ciampi et al., 2021; Gupta and George, 2016). The different combination of BDAC creates different resources that allows firms to extract new valuable knowledge from raw data which enable firms to always aware of the current and potential transformations happening in the competitive context (Mikalef and Pateli, 2017). Besides, when trained staff who have the ability to use data analytics technics to solve problems, and also able to treat the importance of data analytics as a way to obtain valuable sources of business information, together with the widespread diffusion of an organization's data-driven culture and knowledge management systems capable of collecting, storing, sharing and utilizing the obtained information, allows firms to have the opportunities to implement new value creation activities through which green value propositions can be shaped and green value can be introduced and improved (Ciampi et al., 2021; Teece, 2007).

Although the SEM results suggest that ambidexterity cannot increase companies' GI, the fsQCA findings further discover their relationship by demonstrating that the development of BDAC may reduce the negative impact of ambidexterity on GPDI, and that working with ambidexterity may even have a positive effect on GPCI. As a result, when firms seek to build exploitation and exploration to pursue GI, this study suggests investing resources in developing BDAC at the same time. In practice, firms may develop and concentrate different types of BDAC at the same time to seek the best solution to facilitate GI. The methodology of the fsQCA study complements the results of SEM. FsQCA considers exploitation and exploration as two individual elements, so that they can appear either alone (as substitutes) or simultaneously (complements). For example, solution 1,3,7 appear either exploitation or exploration, while solution 4,5,6 appears exploitation and exploration at the same time, that means ambidexterity is used with other BDAC elements in achieving high GI. Moreover, the results of fsQCA give SMEs or large companies different solutions to improve GI, so firms can choose to implement a certain solution according to their actual situation. It is worth mentioning that although the results of SMEs show that the effects of ambidexterity on GPDI and GPCI are not the same, the results of fsQCA show the same configurations in achieving them. The different results provide new evidence to show that synergy between ambidexterity and BDAC can promote GPDI and GPCI at the same time.

7.4 CHAPTER SUMMARY

The discussion of findings and the implications of this research are thoroughly described in this chapter. The discussion section started with explaining the SEM results. It begins with a rationale for why ambidexterity does not enhance GI. Considering China is in the early stages of economic growth, many firms priorities economic advantages above green management and GI, and firms may lack the resources and knowledge to promote the development of ambidexterity (Q. Zhang et al., 2019). Despite the company's attempts to investigate and utilize green produce and processes, the ultimate outcome will be poor operational efficiency and excellence. This outcome may also be explained by the fact that, due to the constraints on firm development, exploitation is the favored alternative for the majority of enterprises (Peters and Buijs, 2021). This one-sided empathy will also prevent firms from adapting to changing environments and client wants, hampering the growth of GI.

In terms of BDAC's moderator role, BDAI and BDAP positively moderate the relationship between ambidexterity and GI, highlighting the relevance of BDAI and personnel in terms of their effect on knowledge acquisition, knowledge sharing, and knowledge creation (Nonaka et al., 1995; Öhman et al., 2021). BDAI provides the necessary conditions for recording diverse and fast-moving data, and personnel use analytics techniques to turn required data into valuable resources, and they both significantly improve the knowledge and resources for ambidexterity, and also increase operational efficiency. However, the fact that BDAM does not regulate the relationship between ambidexterity and GI might be attributed to a lack of knowledge in big data management and green business.

Besides that, the findings that GPDI and GPCI have a positive influence on EP and SP are consistent with the results of (Chiou et al., 2011), and the findings can be explained by GI significantly reducing environmental pollution by improving existing products and processes as well as introducing radical products and processes that transform existing operations. Also, GI have a greater grasp of stakeholders' concerns, thus they take environmental issues into account in order to seek sustainable growth (Zhang et al., 2021). More crucially, the mediation analysis results show that the influence of GI on FP is mediated by EP and SP, resolving the literature's discrepancy by demonstrating that GI spending can have an effect by decreasing penalties and promoting enterprises' social behavior.

Furthermore, the discussion of fsQCA findings provides constructive suggestions for how SMEs or big enterprises might improve GI by combining various elements of exploitation, exploration, and BDAC practices. According to the fsQCA conclusions, exploitation is more vital than exploration for SMEs, whereas exploration is required for all large firms. This may be explained by the fact that SMEs choose to pursue short-term success through exploitation, whereas large enterprises are concerned with long-term competitiveness through exploration (Cao et al., 2009; Raisch and Birkinshaw, 2008). The fsQCA results supplement the SEM results, suggesting that exploitation and exploration may be used individually to achieve GI. Furthermore, the creation of BDAC is required for large firms but not for SMEs. This may be interpreted to imply that large corporations require big data infrastructure and analytics professionals to deal with massive amounts of data and use the valuable knowledge to uncover green-related innovation prospects. While the growth of BDAC may impose additional financial burdens on SMEs, a minor investment in ambidexterity does not aid the development of GI. Furthermore, fsQCA results demonstrate that BDAM is a required component for any business that has implemented BDAC in order to achieve GI. This finding provided a reasonable explanation for the SEM results, which reveal that BDAC does not attenuate the influence of ambidexterity on GI, implying that BDAM must collaborate with other types of BDAC to improve GI.

In terms of the research implications of this study, both theoretical and practical implications are explained in depth. The development of new knowledge in the role of ambidexterity in GI, the integration of BDAC in business processes, the impact of GI on firm performance, and the methodology that combines SEM and fsQCA are all theoretical implications. While the practical implications focus on what practitioners may learn from this study. To begin, managers must evaluate environmental norms and guidelines, as well as society's expectations for environmental preservation (Chiou et al., 2011). The SEM results reveal that firms with little GI experience are inclined to inefficient ambidexterity, which leads to unsatisfactory GI outcomes. Although the findings do not support a beneficial relationship between ambidexterity and GI, the use of BDAC might provide more accurate and fast information, improving the effectiveness of ambidexterity. More significantly, depending on the circumstance, practitioners can choose an acceptable strategy to pursue GI from fsQCA solutions.

CHAPTER 8 CONCLUSION

8.1 INTRODUCTION

Given the environmental impact of green management, firms recognise the importance of green innovation (GI) in company success. Despite the fact that the relevance of GI is well understood, few studies have been conducted to study its determinants (Tang et al., 2018; Zhang et al., 2021). As a result, professionals and practitioners encourage researchers to concentrate on approaches that could enhance GI. The operation of a specific antecedent, ambidexterity, is investigated in this research. Furthermore, as big data-related technologies have become the most significant information technology (IT) innovation in recent decades, there is a rising need to get a comprehensive understanding of BDAC from large-scale corporate data that goes beyond the existing level of knowledge about big data utilisation (Wang and Byrd, 2017). resource based theory (RBT), Knowledge based view (KBV) and information processing view (IPV) are used to uncover the value of big data analytics capability (BDAC). The primary goals of this study are to improve knowledge of how ambidexterity and BDAC enable GI, as well as how to experience greater firm performance through the environmental and social benefits afforded by GI. The following are the study's research questions:

RQ1: Does ambidexterity as an underlying antecedent positively influence GI?

RQ2: Does BDAC moderate the relation between ambidexterity and GI?

RQ3: Under what conditions, can exploitation, exploration and BDAC help to achieve high levels of GI?

RQ4: Does GI bring a firm better performance in the context of China?

To address the proposed questions, this study isolates the practices of ambidexterity (i.e., exploitation and exploration) and BDAC including big data analytics infrastructure (BDAI), big data analytics management (BDAM) and big data analytics personnel (BDAP) and argue that they are necessary for firms to realize green value. This research is grounded on a mixed-method approach. (1) Survey was used to experimentally verify the newly developed theoretical model. This study collected 375 valid data from Chinese firms. SEM and phantom model approach were used to test the hypotheses. (2) fuzzy-set qualitative comparative analysis (FsQCA) was applied to demonstrate that that there are seven main clusters for firms that represent different combinations of corer elements in their attainment of GI gains from ambidexterity and BDAC. The difference solutions are considered to be the result of the different contexts in which these firms operate, showing that there is equifinality in achieving GI.

8.2 SUMMARY OF EACH CHAPTER

Each chapter describes the study's significant contributions and relates back to the research questions. Table 8.1 has an overview of each chapter.

Table 8.1 Summary of contribution of each chapter

	Significant contribution	**Provide answer to research questions**
Chapter 1	• Research background and general statements are provided to outline the significance of the topic. • Research area is defined by presenting the overview of research gap, research questions, and scope of research. • The importance of the research is highlighted and the value this research delivers is discussed.	• This chapter outline the research questions and the problems that will be addressed in this study.
Chapter 2	• A review of literature is conducted to discuss the current knowledge and present research gaps in GI, ambidexterity, and BDAC. • The concepts of key constructs are clarified. • Relevant theories, i.e., RBT, KBV, IPV, are described.	• The study's fundamental supports are provided for identifying research gaps in the study. • The identifies gaps are linked to all the research questions.

Chapter 3	• Several hypotheses that address different aspects of research question are provided. • The hypotheses state the predictions about what the research will discover.	• This chapter proposed a theoretical model to investigate the antecedence and consequences of GI. • It provides tentative answers to the research question that have not yet been tested.
Chapter 4	• Survey research is thoroughly discussed, including the details of the analysis technique, and 7-steps scale development.	• This chapter described research design and quantitative techniques to answer the research questions. • Scale development is introduced to demonstrate how to perform a reliable and valid construct measurement.
Chapter 5	• The potential measurement items of each construct are examined by using a series of scale development processes. • The SEM technique is adopted to test the relationship between ambidexterity and GI, the moderator role of BDAC, and the impact of GI on EP and SP.	• This chapter empirically investigate the antecedents and consequences of GI in order to answer RQ1, RQ2, and RQ 4.
Chapter 6	• The method of fsQCA is introduce in this chapter • FsQCA is used to examine the complex, non-linear and synergistic effects of different elements in achieving high level of GI.	• This chapter presents seven different configurations leading to high of GI, and the fsQCA results answer RQ 3.
Chapter 7	• The results of both survey research and fsQCA are analysis and compared with previous studies. • Both theoretical implication and practical implications are explicitly presented.	• This chapter provides constructive justifications and explanations for each research questions.

8.3 KEY FINDINGS OF THIS STUDY

8.3.1 Findings from empirical study

Regarding the impact of the research findings on the problem that inspire the idea of this thesis, the empirical evidence obtained for this study supports four key findings. Firstly, the negative and significant result for the direct effects of ambidexterity on GPDI implies that simultaneously applying exploitation and exploration hinders the innovation in green product, whereas the non-significant result for the direct effect of ambidexterity on GPCI implies that conducting exploitation and exploration at the same time have no effect on innovation in green process. The possible explanations would be the lack of experience and knowledge in undertaking exploitation and exploration, which resulting in inefficient ambidexterity. Also, it commonly takes a long time to realise the benefit of ambidexterity on reaching GI, and it might bring negative impact (i.e., financial burden, resource waste) before success. These results add values to the GI study by identifying that in the context of China, where many firms are in the start-up stage or have relatively small size, GI cannot achieve a high degree of operational excellence and efficiency from deploying ambidexterity.

Secondly, consistent with the dynamic capabilities view, which contends that the effectiveness of BDAC contributes to firms' competitive advantage (Teece, 2018), this study further investigates the moderator role of three key categories of BDAC, namely, BDAI, BDAM and BDAP, in the relationship between ambidexterity and GI. The results of moderating SEM demonstrate that the interaction effect of ambidexterity and BDAI, as well as ambidexterity and BDAP on GI, are both significant and positive, while the interaction effect of ambidexterity and BDAM on GI is insignificant. The results indicate that when firms simultaneously applying exploitation and exploration, developing BDAI or BDAM could offset the negative impact of ambidexterity on GPDI, and even boost GPCI. The moderator role of BDAC provides a mechanism by which BDAC can contribute to GI practices.

Thirdly, in responding the call of Berrone et al. (2013) for more sophisticated theorising and empirical test in the field of operations management. The results shows that GI has a significant and positive impact on EP and SP, and they considerably support the claim that GI can help improve firm's EP and SP. This finding is in line with prior studies that emphasised the necessity of considering environmental issues and societal expectation when innovating new products and product, by doing so, firms can maintain competitive advantage and achieve sustainable growth (Chiou et al., 2011; Xie et al., 2019).

Fourthly, this study also finds that both EP and SP have significant and positive indirect impacts on the GP, that is, the relationship between GI and FP is mediated by EP and SP. The results imply that firms are likely to develop GI to improve FP if they facilitate the performance in environmental and social perspective (Zhang et al., 2021). Therefore, this study provides details on how GPDI and GPCI can be translated into relevant environmental, social and financial benefits. The research suggests that despite the potentially costly of developing GI, that investment will benefit the firm by demonstrating its willingness to deal with institutional pressure and stakeholder expectation, and by helping it to achieve better performance.

8.3.2 Findings from fuzzy-set qualitative comparative analysis

As shown above, the use of structural equation modelling (SEM) techniques provides explicit causal interpretations to regression equations based on direct and indirect effects of observed variables, nevertheless, the interplays between different elements cannot be determined. According to complexity theory and configurational theory, the multiple paths can occur when they lead to the same outcome (Woodside, 2014), and the same of variables can be achieve a specific outcome in various ways depending on the way these variable combine (Ordanini et al., 2014). FsQCA was employed to complement the SEM results and uncover how to combine different types of BDAC with exploitation and exploration in order to attain high level performance of GPDI and GPCI. The results of fsQCA for this study also supports for four key findings.

Firstly, fsQCA results show that the configurations to achieve both high level of GPDI and GPCI are the same, it can be explained that GPDI and GPCI have certain shared standard and ultimate goals, and these two activities naturally interact with each other (Wang et al., 2021; Xie et al., 2019). Therefore, the combined effect of these resources that will enable a firm to achieve GPDI and GPCI at the same time. This also means that a multitude of processes need to be put into practice, which suggests top management commitment to have a clear plan for firm-wide exploitation, exploration, and BDA adoption and diffusion (Mikalef et al., 2019).

Secondly, the interplay of exploitation and exploration in reaching GI differs across SMEs and large firms. According to the results that only show the present of either exploitation or exploration in the solution, exploitation is found to be more important for small and medium enterprises (SMEs), whereas exploration is a necessary variable for large firms. It could be explained that SMEs are more likely to pursue short-term success that enable them to remain profitable, however, large firms are more concerned with pursuing long term competitive advantage, so they need to make extra efforts to create the radical green solutions for product and process (Cao et al., 2009). The results also complement the SEM results that exploitation and exploration could be applied separately in achieving GI.

Thirdly, the results show that the development of BDAC is necessary for large firms to achieving high level of GI, while SMEs may pursue GI without the adoption of any practice of BDAC. However, for firms that are eager to develop BDAC, BDAM is the necessary element for achieving GI, in the meanwhile, BDAI or/and BDAP should be used in conjunction BDAM. FsQCA results provide a possible explanation of the SEM results that BDAM does not moderate the impact of ambidexterity on GI, that is, BDAM needs to work with other type of BDAC to influence GI rather than being adopted individually. Indeed, only when a firm develops a certain level of big data infrastructure and facilities, or have analytics personnel to address voluminous data, can it pursue green related innovative opportunities for the strategic use of business analytics.

Last but not least, fsQCA results complement the results of SEM, indicating that combining ambidexterity with BDAC could lead to high level of GI (as shown in fsQCA solution 4,5,6). Particularly, the adoption of ambidexterity, BDAM and BDAP is the general solutions for all types of firms in pursuing GI. The findings of fsQCA differ significantly form

SEM results and show that only working on ambidexterity does not positively influence GI.

8.4 LIMITATION AND AVENUES FOR FUTURE RESEARCH

Despite the contributions of the present study, it is constrained by a number of limitations that future research could strive to solve. In terms of the limitations in research objective, ambidexterity is understood as the combined dimension of ambidexterity, which posit that exploitation and exploration are not necessarily in a competition. The reason of choosing combined ambidexterity is based on Teece (2007)'s assertation that two processes are taking place in a complementary domain that do not necessarily compete, especially in the high-tech industry. The research of Burgelman and Grove (2007) also reported a rhythmic pacing to shift between exploration and exploitation in a longitudinal study of Intel. Since this study focus on the firms adopt high-tech, i.e., BDAC, and we believe that exploitation and exploration can be supportive for each other and argue that they can help leverage the effects of the other. However, balanced ambidexterity, which focus on the balanced dimension of ambidexterity, is also used by many studies to explore how a better match in the relative magnitude of exploitation and exploration improves firm performance by allowing for more structured control of performance risk (Cao et al., 2009). Therefore, future studies are suggested to look at examine both the "balanced" and "combined" ambidexterity in developing green management.

Meanwhile, although this study investigates the impact of resources related to ambidexterity and BDA on GI, we leave out some significant contextual factors. It is rather likely that the benefit of coordinating ambidexterity and big data initiatives will be more beneficial in certain circumstances than others or may be dependent on the timeframe since they were introduced (Mikalef et al., 2019). This is an area that future research should focus on, and it has greater practical relevance, especially given the expense of adopting BDA. It is critical to understand how ambidexterity and BDAC generate value in each industry, as well as the methods through which they do so, and how that value may be harvested.

Additionally, there are some limitations of the research method. The boundary condition for the study is the generalizability of the findings beyond the populations from which our sample firms are drawn. This SMEs studies collected data from a single country, i.e., China, where is based in a transitional ecology. The research results could be distinguished if the data is collected in other countries. In this regard, even though the sample of Chines-based firms provided a good basis for the identification and examination of various activities linking to the activities like GI, ambidexterity, BDAC and firm performance, there is a need for future study to improve the generalizability of the findings in other contexts.

Moreover, this research also suffers from a potential weakness to quantitative studies, in that is examine the GPDI and GPCI using cross-sectional survey data rather than longitudinal data (Zhang et al., 2021). In the dynamic process of implementing GI, the implementation of GPDI and GPCI could change accord to different situation. Therefore, qualitative studies, such as longitudinal studies, are needed to better understand how the GPDI and GPCI evolve and/or coevolve over time, as well as the impact that these patterns have on organizational survival rates and short- and long-term firm performance. Longitudinal research can also draw stronger conclusions on the causality of the links between ambidexterity dimensions and GI.

Finally, as stated by previous research, self-reported data is utilised to assess research hypotheses. Despite the measurement items we adopt have been widely tested in previous literature, and 7-step scale development has been made to validate data quality, the potential bias cannot be excluded. The quality of the data, along with a study design that relies on a single key informant, and it implies bias and that factual facts may not correspond with respondents' impressions (Mikalef et al., 2019). Despite this, using top management respondents as key informants is an effective strategy to reduce bias because they often have high expertise on a variety of related topics. Future research might take a multi-informant approach by sampling many respondents inside a single business, which would be a good method to establish inter-rater validity and increase internal validity.

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APPENDIX 1 DESCRIPTION OF MEASUREMENT ITEMS

GREEN PRODUCT INNOVATION

Table A 1.1 Measurement items of Green Product Innovation

Item	Measurement items	Reference
GPDI1	Design of products for reduce consumption of material/energy during the full life cycle.	Chen et al., 2006; Li et al., 2016.
GPDI2	Design of products for reduce waste generation during the full life cycle.	Chen et al., 2006; Li et al., 2016.
GPDI3	Using less or non-polluting/toxic materials. (Using environmentally friendly material).	Chen et al., 2006; Chan et al., 2016.
GPDI4	Improving and designing environmentally friendly packaging (e.g.: less paper and plastic material used) for existing and new products.	Chan et al., 2016
GPDI5	Design for disassembly, reusability, recyclables and recovery	Chen et al., 2006; Chan et al., 2016.
GPDI6	Using eco-labelling, environment management system and ISO 14000	Tseng et al., 2013
GPDI7	Degree of new green product competitiveness understand customer needs	Tseng et al., 2013
GPDI8	Designing at least one produce line that is designed to have positive effects on the environment or which is environmentally labelled and marketed	New developed (sourced by Asset 4 database)
GPDI9	Designing product features and applications that will promote responsible, efficient, cost-effective and environmentally preferable use	New developed (sourced by Asset 4 database)

GREEN PROCESS INNOVATION

Table A 1.2 Measurement items of Green Process Innovation

Item	Measurement items	Reference
GPCI1	Sources from suppliers who comply with environmental regulations	Tseng et al., 2013
GPCI2	Low cost green provider: unit cost versus competitors' unit cost	Tseng et al., 2013
GPCI3	Consumption low energy (such as water, electricity, gas and petrol) during production/use/disposal.	Chen et al., 2006; Chiou et al., 2011
GPCI4	Use of cleaner technology to make savings and	Chen et al., 2006; Chiou

	prevent pollution	et al., 2011
GPCI5	Recycle, reuse and remanufacture of materials internal to the company	Chen et al., 2006; Chiou et al., 2011
GPCI6	Controls operations process to reduce waste from all sources	Wong et al., 2020
GPCI7	Sending in-house auditor to appraise environmental performance of supplier	Tseng et al., 2013
GPCI8	Updates manufacturing processes to meet standards of environmental law	Tseng et al., 2013
GPCI9	Utilizes cleaner transportation modes	Wong et al., 2020

EXPLOITATION

Table A 1.3 Measurement items of Exploitation

Item	Measurement items	Reference
EXPLOIT1	Introduction of new generations of products.	Patel et al., 2013
EXPLOIT2	Improvement of product quality	Cao et al., 2009
EXPLOIT3	Improvement of product flexibility	Cao et al., 2009
EXPLOIT4	Improving efficiency	Azadegan and Dooley, 2010
EXPLOIT5	Reduction of production cost	Cao et al., 2009
EXPLOIT6	Enhancement of existing markets	Cao et al., 2009
EXPLOIT7	Upgraded current knowledge and skills for familiar products and technologies.	Wang and Rafiq, 2014
EXPLOIT8	Enhanced staff skills	Wang and Rafiq, 2014
EXPLOIT9	Frequently adjust procedures, rules, and policies to make things work better	Cao et al., 2009

EXPLORATION

Table A 1.4 Measurement items of Exploration

Item	Measurement items	Reference
EXPLORAT1	Extension of product range	Cao et al., 2009

EXPLORAT2	Opening up new markets	Cao et al., 2009
EXPLORAT3	Acquired technologies and skills entirely new to the business unit	Wang and Rafiq (2014)
EXPLORAT4	Frequently experiment with significant new ideas or ways of doing things.	Azadegan and Dooley, 2010
EXPLORAT5	Employees frequently come up with creative ideas that challenge conventional ones.	Azadegan and Dooley, 2010
EXPLORAT6	Acquire product development skills and processes which are entirely new to the industry.	Wang and Rafiq, 2014
EXPLORAT7	Acquired entirely new managerial and organizational skills.	Wang and Rafiq, 2014
EXPLORAT8	Compared to the competition, a high percentage of our sales come from new products launched in the past three years.	Azadegan and Dooley, 2010

BIG DATA ANALYTICS INFRASTRUCTURE CAPABILITY

Table A 1.5 Measurement items of Big Data Analytics Infrastructure Capability

Item	**Measurement items**	**Reference**
BDAI1	System is capable to handle semi-structured and unstructured data.	Raut et al., 2021
BDAI 2	Compared to rivals within our industry, our organization has good infrastructure and facilities.	Raut et al., 2021
BDAI 3	Compared to rivals within our industry, our organization has the foremost available analytics systems	Kim et al., 2012; Wamba et al., 2017
BDAI 4	All other (e.g., remote, branch, and mobile) offices are connected to the central office for sharing analytics insights	Kim et al., 2012; Wamba et al., 2017
BDAI 5	Our organization utilizes open systems network mechanisms to boost analytics connectivity	Kim et al., 2012; Wamba et al., 2017
BDAI 6	There are no identifiable communications bottlenecks within our organization for sharing analytics insights	Kim et al., 2012; Wamba et al., 2017
BDAI 7	Software applications can be easily used across multiple analytics platforms	Kim et al., 2012; Wamba et al., 2017
BDAI 8	Analytics-driven information is shared	Kim et al., 2012;

	seamlessly across our organization, regardless of the location	Wamba et al., 2017
BDAI 9	Applications can be adapted to meet a variety of needs during analytics tasks	Kim et al., 2012; Wamba et al., 2017

BIG DATA ANALYTICS MANAGEMENT CAPABILITY

Table A 1.6 Measurement items of Big Data Analytics Management Capability

Item	**Measurement items**	**Reference**
BDAM1	We continuously examine innovative opportunities for the strategic use of business analytics	Kim et al., 2012; Wamba et al., 2017
BDAM 2	We frequently adjust business analytics plans to better adapt to changing conditions	Kim et al., 2012; Wamba et al., 2017
BDAM 3	When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work	Kim et al., 2012; Wamba et al., 2017
BDAM 4	When we make business analytics investment decisions, we project how much these options will help end-users make quicker decisions	Kim et al., 2012; Wamba et al., 2017
BDAM 5	In our organization, the responsibility for analytics development is clear.	Kim et al., 2012; Wamba et al., 2017
BDAM 6	In our organization, business analysts and line people coordinate their efforts harmoniously.	Kim et al., 2012; Wamba et al., 2017
BDAM 7	Real-time assess of data and information has helped organization in better decision making.	Kim et al., 2012; Wamba et al., 2017
BDAM 8	We constantly monitor the performance of the analytics function	Kim et al., 2012; Wamba et al., 2017
BDAM 9	Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process	Kim et al., 2012; Wamba et al., 2017
BDAM 10	Our company is better than competitors in bringing detailed information into a business process	Kim et al., 2012; Wamba et al., 2017

BIG DATA ANALYTICS PERSONNEL CAPABILITY

Table A 1.7 Measurement items of Big Data Analytics Personnel Capability

Item	Measurement items	Reference
BDAP1	Our analytics personnel is capable of parallel computing to address voluminous data	Raut et al., 2021
BDAP 2	Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE tools, etc.)	Kim et al., 2012; Wamba et al., 2017
BDAP 3	Our analytics personnel are very capable in the areas of data management and maintenance	Kim et al., 2012; Wamba et al., 2017
BDAP 4	Our analytics personnel are very capable in decision support systems.	Kim et al., 2012; Wamba et al., 2017
BDAP 5	Our analytics personnel show superior understanding of technological trends	Kim et al., 2012; Wamba et al., 2017
BDAP 6	Our analytics personnel show superior ability to learn new technologies	Kim et al., 2012; Wamba et al., 2017
BDAP 7	Our analytics personnel are very knowledgeable about the critical factors for the success of our organization	Kim et al., 2012; Wamba et al., 2017
BDAP 8	Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions	Kim et al., 2012; Wamba et al., 2017
BDAP 9	Our analytics personnel are very knowledgeable about the business environment	Kim et al., 2012; Wamba et al., 2017
BDAP 10	Our analytics personnel are very capable in terms of managing projects	Kim et al., 2012; Wamba et al., 2017

ENVIRONMENTAL PERFORMANCE

Table A 1.8 Measurement items of Environmental Performance

Item	Measurement items	Reference
EP1	Significant improvement in its overall environmental situation	Zailani et al., 2012; Zhu and Sarkis, 2007
EP2	Significant improvement in its compliance to environmental standards	Zailani et al., 2012
EP3	Significant reduction in emission of air pollutants	de Giovanni, 2012; Zailani et al., 2012
EP4	Significant reduction in energy consumption	de Giovanni, 2012;

		Zailani et al., 2012
EP5	Significant reduction in wastewater	Zhu and Sarkis, 2007
EP6	Significant reduction the consumption for hazardous/harmful/toxic materials	Zailani et al., 2012; Zhu and Sarkis, 2007
EP7	Improve a company's environmental situation	Zhu and Sarkis, 2007
EP8	Significant reduction in environmental resource impact controversies	New developed (sourced by Asset 4 database)

FINANCIAL PERFORMANCE

Table A 1.9 Measurement items of Financial Performance

Item	Measurement items	Reference
FP1	Growth of sales	Cao and Zhang, 2011
FP2	Growth in return on investment	Cao and Zhang, 2011
FP3	Return of assets	de Giovanni, 2012
FP4	Profit margin	Cao and Zhang, 2011; de Giovanni, 2012
FP5	Increase in market share	de Giovanni, 2012
FP6	Acquisition of new customers	de Giovanni, 2012
FP7	Decrease in cost of materials purchasing per unit of product	Liu et al., 2020
FP8	Decrease in cost for energy consumption per unit of product	Liu et al., 2020

SOCIAL PERFORMANCE

Table A 1.10 Measurement items of Social Performance

Item	Measurement items	Reference
SP1	Using social performance indicators	Sancha et al., 2016
SP2	Employees' health and safety	de Giovanni, 2012; Gualandris and Kalchschmidt, 2016
SP3	Incentives and engagement for local employment	de Giovanni, 2012
SP4	Improvement of community health and safety	de Giovanni, 2012

SP5	Development of economic activities	de Giovanni, 2012
SP6	Employee satisfaction	Gualandris and Kalchschmidt, 2016
SP7	Improvement in human right compliance	Gualandris and Kalchschmidt, 2016
SP8	Improvement in labour safety and labour conditions in our facilities	Sancha et al., 2016
SP9	Reduction of number of industrial accidents	Sancha et al., 2016

APPENDIX 2 – CONTENT VALIDITY TEST OF GENERATED ITEMS (PILOT TEST VERSION)

A2.1 OVERVIEW OF THE FIRST ROUND CONTENT VALIDITY TEST

The items shown in Table A1.1- Table A1.10 are the first set of items generated by the author for the survey. They were sent to an expert panel, including industrialists (Manufacturing firm director: Mr. Xianjin Ren, Mr. Tao Jin) and academics (Dr. Mike Tse, Pro Jilian MacBryde, and Dr. Luisa Delfa Huaccho Huatuco) for comments. The panel members were required to comment on the items based on three following questions. (i) Are the question items understandable? (ii) Do the question items clearly represent the meaning of each construct? (iii) Since Dr Mike Tse is the only expert panel who are good at both English and Chinese, Dr Mike Tse was required to comment about does the Chinese translation of the items represent the same meaning as the English version? The review process started on June 2019 and finished at the end of the August 2019. Additionally, Dr. Mike Tse noted that a proper content validity test should not only request the panel board to review the above-mentioned three aspects. He further suggested more robust procedures to use in the content validity test. The details of the revised content validity test are mentioned in the methodology chapter (Chapter 4, section 4.4.3). This includes Cohen's kappa test, followed by the inter-judge agreement test. The final set of items which were translated into Chinese, and then translated back into English. The tables below show the summaries of the comments of each measurement item in the pilot test version.

A2.2 PANEL'S COMMENTS ON THE PILOT TEST MEASUREMENT ITEMS

a. Green product innovation (GPDI)

Description: Green product innovation is the green innovation practice which incorporate the environmental factors (e.g. material usage, energy consumption, etc.) into product design considerations for both new and (modification of) existing products, with the prime objective to reduce the negative environmental impacts over the products' life-cycle.

Critical comments from the panel:

Some activities of product and process innovation are similar, such as the use of green materials and the reduction of pollutants on manufacturing lines. When designing surveys, it's important to distinguishing between similar items or determining which construct the item belongs to. For instance, designing a green product line is more closely related to process innovation than produce innovation, and firm may outsource the product line as a cost-cutting measure instead of designing a new product line. So GPDI 8 is suggested to be deleted.

Action taken:

GPDI 3 and GPCI 5 have similar meaning and were revised to be distinguished. Besides, GPDI 8 is more of a GPCI activity, it is still removed since cannot always represent GPCI.

Table A.2.1 Green product innovation pilot test items

Item	**Measurement items**	**Comment from Expert Panel**	**Keep in final set of generated items?**
GPDI1	Design of products for reduce consumption of material/energy during the full life cycle. 在设计产品时，确保产品的整个生命周期能消耗更少的材料/能源消耗	N/A	Keep
GPDI2	Design of products for reduce waste generation during the full life cycle. 在设计产品时，确保产品的整个生命周期能产生更少的废物	N/A	Keep
GPDI3	Create a product that uses less or non-polluting/toxic components. 企业使用少污染少毒或者无污染无毒的材料	Both GPDI and GPCI relate to the usage of environmentally friendly materials, it's critical to distinguish their measurement items.	Revised
GPDI4	Improving and designing environmentally friendly packaging (e.g., less paper and plastic material used) for existing and new products. 企业不断改进和设计现有和新产品的环保包装（例如：使用更少的纸和塑料材料）	N/A	Keep
GPDI5	Design for disassembly, reusability, recyclables and recovery 我们的产品设计具有进行可拆卸性，可重复使用性，可回收性，可恢复性的特征	N/A	Keep
GPDI6	Using eco-labelling, environment management system and ISO 14000	N/A	Keep

	我们使用生态标签、环境管理系统和 ISO 14000		
GPDI7	Degree of new green product competitiveness understand customer needs 新的绿色产品竞争力的程度是建立在对客户需求的了解上	N/A	Keep
GPDI8	Designing at least one produce line that is designed to have positive effects on the environment or which is environmentally labelled and marketed 设计至少一条旨在对环境产生积极影响或带有环境标签和销售的生产线	Expert panel comments that designing environmentally friendly product lines is more of a practice of green process innovation.	Deleted
GPDI9	Designing product features and applications that will promote responsible, efficient, cost-effective and environmentally preferable use 我们通过设计产品功能和应用程序，以促进负责任的，有效的，具有成本效益的和对环境有利的使用	N/A	Keep

b. Green process innovation (GPCI)

Description: Green process innovation is any adaptation to the manufacturing process that reduces the negative impact on the environment during material acquisition, production, and delivery (Chiou et al., 2011).

Critical comments from the panel:

Having green suppliers is crucial since it helps to reduce the negative impact of process innovation from a supply chain perspective. There are several methods for identifying whether a supply chain is environmentally friendly, and while GPCI7 is too specific, it is recommended that only GPCI1 be kept.

Action taken:

This item GPCI7 was deleted since it can be represented by GPCI1. Meanwhile, this study does not particularly consider green technology innovation, so GPCI4 was not appropriate to be included in the measurement items.

Table A.2.2 Green process innovation pilot test items

Item	**Measurement items**	**Comment from Expert Panel**	**Keep in final set of generated items?**
GPCI1	Sources from suppliers who comply with environmental regulations. 企业从遵守环境法规的供应商进货。	N/A	Keep
GPCI2	Low cost green provider: unit cost versus competitors' unit cost. 我们选择低成本且环保的提供商：通过对比本公司的单位成本对比竞争对手的单位成本。	N/A	Keep
GPCI3	Consumption low energy (such as water, electricity, gas and petrol) during production/use/disposal. 企业致力于在生产/使用/处理过程中消耗低能耗（例如水，电，气和汽油）。	Some examples of low energy are suggested to provide to help respondents understand this concept.	Keep
GPCI4	Use of cleaner technology to make savings and prevent pollution. 使用清洁能源来节省能源并且阻止污染。	This item emphasis on technology innovation rather than process innovation.	Deleted
GPCI5	Recycle, reuse and remanufacture of materials internal to the company 公司内部使用可回收，可再利用，可再制造的材料。	N/A	Keep
GPCI6	Controls operations process to reduce waste from all sources 公司控制操作流程以减少从各个来源产生的浪费。	N/A	Keep
GPCI7	Sending in-house auditor to appraise environmental performance of supplier 公司派遣内部审核员评估供应商的环境绩效。	GPCI1 and GPCI7 are similar to be included in a questionnaire. Panel suggested to keep GPCI1 as it was more applicable.	Deleted

GPCI8	Updates manufacturing processes to meet standards of environmental law 企业不断更新制造流程以符合环境法的标准。	N/A	Keep
GPCI9	Utilizes cleaner transportation modes 我们使用更清洁的交通方式。	N/A	Keep

c. Exploitation (EXPLOIT)

Description: Exploitation includes things as refinement, choice, production, efficiency, selection, implementation.

Critical comments from the panel:

No Critical comments

Table A.2.3 Exploitation pilot test items

Item	**Measurement items**	**Comment from Expert Panel**	**Keep in final set of generated items?**
EXPLOIT1	Improvement of product quality 企业不断提高产品质量。	N/A	Keep
EXPLOIT2	Improvement of product flexibility 企业不断提高产品的灵活性。	N/A	Keep
EXPLOIT3	We place strong emphasis on improving efficiency 我们十分重视提高效率。	N/A	Keep
EXPLOIT4	Reduction of production cost 企业会降低生产成本。	N/A	Keep
EXPLOIT5	Enhancement of existing markets 企业不断深入现有市场。	N/A	Keep
EXPLOIT6	Upgraded current knowledge and skills for familiar products and technologies. 企业会一直改进对所熟悉产品和技术的相关知识与技能。	N/A	Keep
EXPLOIT7	Enhanced skills in exploiting well-established technologies that improve productivity of current innovation operations. 企业会增强开发已成熟技术的能力，从而使这些能力来提高当前创新运营的生产率。	Panels suggested to provide detailed information on the skills that firms should possess.	Revised
EXPLOIT8	We frequently adjust procedures, rules, and policies to make things work better	N/A	Keep

	我们经常调整程序、规则和政策，以使事情更好地运作。		

d. Exploration (EXPLORAT)

Description: Exploration includes things captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, innovation.

Critical comments from the panel:

It is important to differentiation exploitative and explorative activities, while the new generations of products can be created by both exploitation exploration, which may cause confusion to respondents. Therefore EXPLORAT 1 is suggested to be deleted. Meanwhile, product development skills (EXPLORAT7) and managerial/organizational skills (EXPLORAT8) are presented as means of exploration in two different items; while respondents may not understand the differences between these two types of skills, some examples would be useful to improve the readability of the questionnaire.

Action taken:

This item EXPLORAT 1 has been deleted as it does not emphasize about the explorative activities included in the new product innovation. Examples are provided in EXPLORAT7 and EXPLORAT 8.

Table A.2.4 Exploration pilot test items

Item	**Measurement items**	**Comment from Expert Panel**	**Keep in final set of generated items?**
EXPLORAT1	Introduction of new generations of products. 推出新一代产品。	Both exploitative and explorative activities could lead to product innovation.	Deleted
EXPLORAT2	Extension of product range. 企业会扩展产品的范围	N/A	Keep
EXPLORAT3	Opening up new markets. 企业不断积极开拓新市场	N/A	Keep
EXPLORAT4	Acquired technologies and skills entirely new to the business unit. 企业会向业务部门注入全新的科技和技能	N/A	Keep
EXPLORAT5	We frequently experiment with significant new ideas or ways of	N/A	Keep

	doing things. 企业会经常尝试一些重要的新想法或做事方式		
EXPLORAT6	Our employees frequently come up with creative ideas that challenge conventional ones. 我们企业的员工会经常提出有创意的想法来挑战已有的产品或方案	N/A	Keep
EXPLORAT7	Learned product development skills and processes entirely new to the industry (e.g. product design, prototyping new products, timing of new product introductions and customizing products for local markets) 我们学习行业全新的产品开发技能和流程，（例如产品设计、 新产品原型设计、新产品推出的时间安排、和为当地市场定制产品等。	Some examples of above-mentioned product development skills and processes suggested to be provided.	Revised
EXPLORAT8	Acquired entirely new managerial and organizational skills that are important for innovation (e.g. forecasting technological and customer trends; identifying emerging markets and technologies; integrating R&D, marketing, manufacturing and other functions; managing the product development process) 我们获得了对创新很重要的全新管理和组织技能（例如预测技术和客户趋势；识别新兴市场和技术；整合研发、营销、制造和其他职能；管理产品开发过程）	Some examples of above-mentioned new managerial and organizational skills are suggested to be provided.	Revised
EXPLORAT9	Compared to the competition, a high percentage of our sales come from new products launched in the past three years. 与竞争对手相比，我们的销售额很大一部分来自过去三年推出的新产品。	N/A	Keep

e. BIG DATA ANALYTICS INFRASTRUCTURE CAPABILITY (BDAI)

Description: Big data analytics infrastructure capability, also called as big data analytics technology capability, refers to the ability of the big data analytics infrastructure (e.g., applications, hardware, data, and networks) to enable the big data analytics staff to quickly develop, deploy, and support necessary system components for a firm.

Critical comments from the panel:

No Critical comments

Table A.2.5 Big Data Analytics Infrastructure capability pilot test items

Item	**Measurement items**	**Comment from Expert Panel**	**Keep in final set of generated items?**
BDAI 1	System is capable to handle semi-structured and unstructured data. 我们的系统能够处理半结构化和非结构化数据	N/A	Keep
BDAI 2	Compared to rivals within our industry, our organization has good infrastructure and facilities. 与我们行业内的竞争对手相比，我们的组织拥有良好的基础设施和设施	N/A	Keep
BDAI 3	Compared to rivals within our industry, our organization has the foremost available analytics systems 与我们行业内的竞争对手相比，我们的组织拥有十分先进的数据分析系统	N/A	Keep
BDAI 4	All other (e.g., remote, branch, and mobile) offices are connected to the central office for sharing analytics insights 所有其他（例如，远程，分支和移动）办公室都连接到中心办公室，以共享分析结果	N/A	Keep
BDAI 5	Our organization utilizes open systems network mechanisms to boost analytics connectivity 我们的组织利用开放的系统网络机制来增强分析的连接性	N/A	Keep
BDAI 6	There are no identifiable communications bottlenecks within our organization for sharing analytics insights 组织内部分享分析结果时，没有通信的困难	Poor translation in Chinese.	Keep
BDAI 7	Software applications can be easily used across multiple analytics platforms 软件应用程序可以轻松地在多个分析平台上使	N/A	Keep

	用		
BDAI 8	Analytics-driven information is shared seamlessly across our organization, regardless of the location 无论机构位于何处，都可以在整个组织中无缝共享分析驱动信息	N/A	Keep
BDAI 9	Applications can be adapted to meet a variety of needs during analytics tasks 应用程序可以被调整，从而满足分析任务的各种需求	N/A	Keep

f. BIG DATA ANALYTICS MANAGEMENT CAPABILITY (BDAM)

Description: Big Data Analytics Management Capability refers to the BDA unit's ability to handle routines in a structured (rather than ad hoc) manner to manage IT resources in accordance with business needs and priorities.

Critical comments from the panel:

Big Data Analytics Management Capability contains a series of management practices to facilitate business analytics, while the items which most respondent would give a high score should be avoided.

Action taken:

This item BDAM 5 was deleted.

Table A.2.6 Big Data Analytics Management Capability pilot test items

Item	**Measurement items**	**Comment from Expert Panel**	**Keep in final set of generated items?**
BDAM1	We continuously examine innovative opportunities for the strategic use of business analytics. 我们不断研究创新机会，以达到战略性地使用业务分析的目的	N/A	Keep
BDAM 2	We frequently adjust business analytics plans to better adapt to changing conditions 我们经常调整业务分析计划，以更好地适应不断变化的条件	N/A	Keep
BDAM 3	When we make business analytics investment decisions, we estimate the effect they will have on the productivity	Poor translation in Chinese.	Keep

	of the employees' work 在制定业务分析投资决策时，我们估计它们将对员工工作效率产生影响		
BDAM 4	When we make business analytics investment decisions, we project how much these options will help end-users make quicker decisions 在做出业务分析投资决策时，我们预计这些选择将在多大程度上帮助最终用户做出更快的决策	N/A	Keep
BDAM 5	In our organization, the responsibility for analytics development is clear. 在我们的组织中，在分析这一领域发展的责任是明确的。	Every respondent will most likely give a high score for this question. The panel board suggests removing this item or asking in another way.	Deleted
BDAM 6	In our organization, business analysts and line people coordinate their efforts harmoniously. 在我们的组织中，业务分析人员和业务人员和谐地协调工作	N/A	Keep
BDAM 7	Real-time assess of data and information has helped organization in better decision making. 通过对数据和信息的实时评估，组织能做出更好的决策	N/A	Keep
BDAM 8	We constantly monitor the performance of the analytics function 我们不断监控分析功能的性能	N/A	Keep
BDAM 9	Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process 相比竞争对手，我们的公司在业务流程中能更好的联系其他合作者（例如，交流和信息共享）	N/A	Keep
BDAM 10	Our company is better than competitors in bringing detailed information into a	N/A	Keep

	business process 相比竞争对手，我们公司更善于将详细信息引入业务流程方面		

g. BIG DATA ANALYTICS PERSONNEL CAPABILITY (BDAP)

Description: Big Data Analytics Management Capability, also called as big data analytics talent capability, refers to staff's professional ability (e.g., skills or knowledge) to undertake assigned tasks (Kim et al., 2012). Akter et al (2016) also refer big data analytics personnel capability as in their research about how big data analytics influence firm performance.

Critical comments from the panel:

No Critical comments

Table A 1.7 Measurement items of Big Data Analytics Personnel Capability

Item	**Measurement items**	**Comment from Expert Panel**	**Keep in final set of generated items?**
BDAP1	Our analytics personnel is capable of parallel computing to address voluminous data. 我们的数据分析人员能够通过并行计算来处理大量数据	N/A	Keep
BDAP 2	Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE tools, etc.). 我们的数据分析人员拥有编程技巧（例如，结构化编程，基于 Web 的应用程序，CASE 工具等）	N/A	Keep
BDAP 3	Our analytics personnel are very capable in the areas of data management and maintenance. 我们的数据分析人员在数据管理和维护领域非常有能力	N/A	Keep
BDAP 4	Our analytics personnel are very capable in decision support systems (e.g., expert systems, artificial intelligence, data warehousing, mining, marts, etc.) 我们的数据分析人员在决策支持系统方面非常有能力（例如专家系统，人工智能，数据仓储，数据挖掘技术，数据集市等）	Some examples of decision support systems are suggested to provide to help	Revised.

		respondents understand this concept.	
BDAP 5	Our analytics personnel show superior understanding of technological trends 我们的数据分析人员十分了解技术发展的趋势	N/A	Keep
BDAP 6	Our analytics personnel show superior ability to learn new technologies 我们的数据分析人员能快速学习新技术	N/A	Keep
BDAP 7	Our analytics personnel are very knowledgeable about the critical factors for the success of our organization 我们的数据分析人员十分了解能使组织获得成功的关键因素	N/A	Keep
BDAP 8	Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions 我们的数据分析人员能够准确的理解业务上的问题，并开发适当的技术解决方案	Poor translation in Chinese.	Keep
BDAP 9	Our analytics personnel are very knowledgeable about the business environment 我们的数据分析人员十分了解业务环境	N/A	Keep
BDAP 10	Our analytics personnel are very capable in terms of managing projects 我们的数据分析人员非常擅长管理项目	N/A	Keep

h. ENVIRONMENTAL PERFORMANCE (EP)

Description: Environmental performance implies positive results for the natural environment, such as the reduction of solid/liquid wastes, reduction of emissions, resource reductions, decrease of consumption of hazardous/harmful/toxic materials, decrease of frequency of environmental accidents, and increase in compliance with environmental standards.

Critical comments from the panel:

No Critical comments

Table A 1.8 Measurement items of Environmental Performance

Item	**Measurement items**	**Comment from Expert**	**Keep in final set generated items?**

		Panel	
EP1	Significant improvement in its over environmental situation 企业在整体环境状况方面得到重大改善	N/A	Keep
EP2	Significant improvement in its compliance environmental standards 企业对环境标准的合规性有了显着提高	N/A	Keep
EP3	Significant reduction in emission of pollutants 企业显著减少空气污染物排放	N/A	Keep
EP4	Significant reduction in energy consumption 企业大幅降低能耗	N/A	Keep
EP5	Significant reduction in wastewater 企业大幅减少废水排放	N/A	Keep
EP6	Significant reduction the consumption hazardous/harmful/toxic materials 企业大幅减少危险/有害/有毒物质的消耗	N/A	Keep
EP7	Improve a company's environmental situatio 提高企业环境	EP1 and EP7 are too similar to be included in a questionnaire. Panel suggests keeping EP1 if Likert scale is used.	Deleted
EP8	Significant reduction in environmen resource impact controversies 企业大幅减少有关环境资源影响的争议	N/A	Keep

i. FINANCIAL PERFORMANCE (FP)

Description: Firm performance refers to how well a firm fulfils its financial goals compared with the firm's primary competitors.

Critical comments from the panel:

No Critical comments.

Table A 1.9 Measurement items of Financial Performance

Item	**Measurement items**	**Comment from Expert Panel**	**Keep in final set of generated items?**

FP1	Growth of sales 企业的销售增长	N/A	Keep
FP2	Growth in return on investment 企业的投资回报率增长	N/A	Keep
FP3	Return of assets 企业的资产收益增长	N/A	Keep
FP4	Profit margin 企业的利润率提高	N/A	Keep
FP5	Increase in market share 企业的市场份额增加	N/A	Keep
FP6	Acquisition of new customers 企业不断获取新客户	N/A	Keep
FP7	Decrease in cost of materials purchasing per unit of product 降低单位产品的材料采购成本	N/A	Keep
FP8	Decrease in cost for energy consumption per unit of product 降低单位产品的能耗成本	N/A	Keep

j. SOCIAL PERFORMANCE (SP)

Description: Social performance refers to the translation of an institution's social goals into actions in line with the accepted social values, such as improving the quality and appropriateness of financial services, improving the economic and social conditions of clients, and ensuring social responsibility to clients, employees, and the community they serve.

Critical comments from the panel:

No Critical comments.

Action taken:

This item SP 5 was deleted.

Table A 1.10 Measurement items of Social Performance

Item	Measurement items	Comment from Expert Panel	Keep in final set of generated items?
SP1	Using social performance indicators 企业使用社会绩效指标	N/A	Keep
SP2	Employees' health and safety 企业十分关注员工的健康与安全	N/A	Keep
SP3	Incentives and engagement for local employment 企业对当地就业的激励和参与	N/A	Keep

SP4	Improvement of community health and safety 企业积极改善社区健康与安全	N/A	Keep
SP5	Development of economic activities 发展经济活动	This item emphasis on the development on finance rather than social.	Deleted
SP6	Employee satisfaction 企业注重员工的满意度	N/A	Keep
SP7	Improvement in human right compliance 企业不断改善人权遵守情况	N/A	Keep
SP8	Improvement in labour safety and labour conditions in our facilities 企业不断改善工人的劳动安全和劳动条件	N/A	Keep
SP9	Reduction of number of industrial accidents 减少工业事故的数量	N/A	Keep

APPENDIX 3 – CONTENT VALIDITY TEST OF GENERATED ITEMS (SECOND ROUND)

Validity Assessment
“Ambidexterity and Green Innovation:
The Moderating Effect of Big Data Analytics Capability”

1. Description

Green innovation (GI) is defined as a type of innovation that brings to a decrease of reduce the environmental risk, pollution, and other negative impacts on resource use, without considering whether that is intended (Huang and Li, 2017). Through reducing the environmental impact on environment, firms can integrate environment benefit and meet eco-requirements, therefore, GI is deemed as the key strategic tool to maintain firms’ long-term development in industries in response the growing environmental pressure (Abdullah et al., 2016).

This study focuses on a specific strategy as an antecedent on GI in order to help firm effectively adopt it: ambidexterity, which is as an important strategy for firms to pursue short-term increment innovation and long-term radical innovation (Andriopoulos and Lewis, 2009; Cao et al., 2009; O’Reilly III and Tushman, 2013; Raisch and Birkinshaw, 2008; Wei et al., 2014a), and it has been proved to significantly facilitate new product innovation by researchers. This study aims to investigate how ambidexterity supports firms to achieve better GPI. Meanwhile, with the increasing number of firms integrate big data in their operations, Big Data Analytics (BDA) has been considered a tool to improve business efficiency and effectiveness due to its high operational and strategic potential. With the ongoing revelation from traditional industries to intelligent industries, there will be more firms adopt this new technology for improving decision-making processes in business, thus, it is important to understand how BDAC influence firm’s strategies. In this research, the moderate role of BDAC will also be examined on the relationship between ambidexterity and GI. Considering the. Last but not least, considering the debates of the relationship between GI and firm performance can be found in literature, this study will further investigate the overall impact of GI on firm triple bottom line, i.e. financial, environmental, social performance simultaneously to scrutinize the benefit of GI from different aspects. The followings are the definition of each construct in the study:

a. Green product innovation (GPDI)

The activity that takes the environmental factors into product design considerations for both new and (modification of) existing products, with the prime objective to reduce the negative environmental impacts over the products' life cycle.

b. Green process innovation (GPCI)

Any adaptation to the manufacturing process that reduces the negative impact on the environment during material acquisition, production, and delivery.

c. Exploitation (EXPLOIT)

Exploitation includes things as refinement, choice, production, efficiency, selection, implementation.

d. Exploration (EXPLORAT)

Exploration includes things captured by terms such as search, variation, risk taking, experimentation, play, flexibility, discovery, innovation.

e. Big Data Analytics Infrastructure Capability (BDAI)

BDAI is the ability of the big data analytics infrastructure (e.g., applications, hardware, data, and networks) to enable the BDA staff to quickly develop, deploy, and support necessary system components for a firm.

f. Big Data Analytics Management Capability (BDAM)

BDAM is the BDA manager's ability to handle routines in a structured (rather than ad hoc) manner to manage IT resources in accordance with business needs and priorities.

g. Big Data Analytics Personnel Capability (BDAP)

BDAP is staff's professional ability (e.g., skills or knowledge) to undertake assigned tasks (Kim et al., 2012). Akter et al (2016) also refer BDA personnel capability as in their research about how BDA influence firm performance.

h. Environmental Performance (EP)

EP is how well a firm contributes for the natural environment.

f. Financial Performance (FP)

FP is how well a firm fulfils its financial goals compared with the firm's primary competitors.

j. Social Performance (SP)

SP is how well a firm translate social goals into actions in line with the accepted social values.

Below is the item measurement generated from reviewing literatures and gathering the practitioners' suggestions. The measurement items listed below are aimed to measure the degree of agreement of adopting supply chain quality risk management practices.

**Note: PLEASE let the researcher (Wenjuan Zeng) knows if you have finished task 1. The* *correct answer of task 1 will be given before task 2 begins*

2. Please rate the statements to the most relevant dimension* and then mark the adequacy to the specific dimension. <u>One statement only belongs to one dimension.</u>

	TASK 1	TASK 2						
Statement	**Belong to Which dimension?**	**Adequacy? (1=barely adequate;7=almost perfect) Put "x" in the selected adequacy level**						
	1 / 2 / 3 / 4	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Low cost green provider: unit cost versus competitors' unit cost								
Improvement of product flexibility								
Extension of product range								
Learned product development skills and processes entirely new to the industry (e.g. product design, prototyping new products, timing of new product introductions and customizing products for local markets)								
There are no identifiable communications bottlenecks within our organization for sharing analytics insights								
In our organization, business analysts and line people coordinate their efforts harmoniously								
Our analytics personnel is capable of parallel computing to address voluminous data								
Our analytics personnel are very knowledgeable about the business environment								
Significant reduction in waste water								
Return of assets								
Decrease in cost of materials purchasing per unit of product								
Improvement of community health and safety								
Increase in market share								
Significant reduction in environmental resource impact controversies								
Significant improvement in its compliance to environmental standards								
Our analytics personnel show superior understanding of technological trends								
Our company is better than competitors in bringing detailed information into a business process								
When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work								
We continuously examine innovative opportunities for the strategic use of business analytics								
Our organization utilizes open systems network mechanisms to boost analytics connectivity								
Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions								
Significant reduction the consumption for hazardous/harmful/toxic materials								
Using eco-labelling, environment management system								

	TASK 1	TASK 2						
Statement	**Belong to Which dimension?**	**Adequacy? (1=barely adequate;7=almost perfect) Put “x” in the selected adequacy level**						
and ISO 14000								
Designing product features and applications that will promote responsible, efficient, cost-effective and environmentally preferable use								
Controls operations process to reduce waste from all sources								
Improvement of product quality								
Enhancement of existing markets								
Enhanced skills in exploiting well-established technologies that improve productivity of current innovation operations								
Acquired entirely new managerial and organizational skills that are important for innovation (e.g. forecasting technological and customer trends; identifying emerging markets and technologies; integrating R&D, marketing, manufacturing and other functions; managing the product development process)								
All other (e.g., remote, branch, and mobile) offices are connected to the central office for sharing analytics insights								
Analytics-driven information is shared seamlessly across our organization, regardless of the location								
When we make business analytics investment decisions, we project how much these options will help end-users make quicker decisions								
Significant improvement in its overall environmental situation								
Growth in return on investment								
Incentives and engagement for local employment								
Improving and designing environmentally friendly packaging (e.g.: less paper and plastic material used) for existing and new products								
Updates manufacturing processes to meet standards of environmental law								
Design of products for reduce waste generation during the full life-cycle								
Degree of new green product competitiveness understand customer needs								
Utilizes cleaner transportation modes								
Upgraded current knowledge and skills for familiar products and technologies								
Acquired technologies and skills entirely new to the business unit								
Compared to the competition, a high percentage of our sales come from new products launched in the past three years.								
Compared to rivals within our industry, our organization has good infrastructure and facilities.								
Applications can be adapted to meet a variety of needs during analytics tasks								
Our company is better than competitors in connecting								

	TASK 1	TASK 2						
Statement	**Belong to Which dimension?**	**Adequacy? (1=barely adequate;7=almost perfect) Put "x" in the selected adequacy level**						
(e.g., communication and information sharing) parties within a business process								
Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE tools, etc.)								
Our analytics personnel are very knowledgeable about the critical factors for the success of our organization								
Growth of sales								
Improvement in labour safety and labour conditions in our facilities								
Improvement in human right compliance								
Using social performance indicators								
Acquisition of new customers								
Significant reduction in energy consumption								
Our analytics personnel are very capable in decision support systems (e.g., expert systems, artificial intelligence, data warehousing, mining, marts, etc.)								
Opening up new markets								
Design of products for reduce consumption of material/energy during the full life-cycle								
Sources from suppliers who comply with environmental regulations								
Recycle, reuse and remanufacture of materials internal to the company								
Reduction of production cost								
We frequently adjust procedures, rules, and policies to make things work better								
System is capable to handle semi-structured and unstructured data.								
We constantly monitor the performance of the analytics function								
Our analytics personnel are very capable in the areas of data management and maintenance								
Significant reduction in emission of air pollutants								
Reduction of number of industrial accident								
Profit margin								
Employee satisfaction								
Our analytics personnel show superior ability to learn new technologies								
We frequently adjust business analytics plans to better adapt to changing conditions								
Our employees frequently come up with creative ideas that challenge conventional ones								
Employees' health and safety								
Decrease in cost for energy consumption per unit of products								
Our analytics personnel are very capable in terms of managing projects								
Real-time assess of data and information has helped organization in better decision making.								

	TASK 1	**TASK 2**						
Statement	**Belong to Which dimension?**	**Adequacy? (1=barely adequate;7=almost perfect) Put “x” in the selected adequacy level**						
Software applications can be easily used across multiple analytics platforms								
Using less or non-polluting/toxic materials. (Using environmentally friendly material)								
Consumption low energy (such as water, electricity, gas and petrol) during production/use/disposal								
Compared to rivals within our industry, our organization has the foremost available analytics systems								
We frequently experiment with significant new ideas or ways of doing things								
Design for disassembly, reusability, recyclables and recovery								
We place strong emphasis on improving efficiency								

APPENDIX 4 – QUESTIONNAIRE (ENGLISH VERSION)

Survey: An Investigation into Green Innovation

Survey Objective

The purpose of this study is to examine the role of ambidexterity in firm's green innovation as well as the moderator role that information technology may play between them. This study is being conducted by a PhD researcher based at The York Management School, University of York, UK. By targeting executives and senior managers, the questionnaire aims at exploring firms' attitude to adopt information technology and big data analytics in either an exploitative or explorative mode, how they conduct different types of green innovation, and the types of activities undertaken in order to adopt information technology and big data analytics.

Please DO NOT write your name on this questionnaire. Your responses will be anonymous and will never be linked to your personally. Thank you for your cooperation.

Part 1: BioData

1 Name of the company:

2 Gender:

3 Do you adopt green innovation (the production, assimilation or exploitation of a product, process, management or technology that is novel to the organization and which results in a reduction of environmental risk, pollution and other negative impacts to relevant alternatives) in your firm?

□Yes □No

4 Do you adopt big data analytics technology in your firm?

□Yes □No

5 Types of business:

□Manufacturing □Agriculture, food production
□Building industry □Service, consultancy
□Processes for natural resources □Chemicals
□Biological engineering/Pharmacy □Other

6 Ownership structure

□State owned or state holding company □Private company
□Joint venture □ Wholly foreign owned company
□Other

7 Number of employees: □≤50 □51 – 100 □101 – 200 □201 – 500 □≥500

8 Sales (millions RMB$):

□≤10$ □11 – 50$ □51-100$ □101-200$ □≥200$

9 Role of responder:

□Vice president or above □President's assistant □Department manager
□Senior manager □Operator □Other

Part 2: Green Innovation

Part 2.1 Green product innovation

10 When adopting green product innovation, we do the following (Please encircle your response)

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)

GPDI1: Design of products for reduce consumption of material/energy during the full life cycle

1 2 3 4 5 6 7

GPDI2: Design of products for reduce waste generation during the full life cycle

1 2 3 4 5 6 7

GPDI3: Using less or non-polluting/toxic materials. (Using environmentally friendly material)
1 2 3 4 5 6 7
GPDI4: Improving and designing environmentally friendly packaging (e.g.: less paper and plastic material used) for existing and new products
1 2 3 4 5 6 7
GPDI5: Design for disassembly, reusability, recyclables and recovery
1 2 3 4 5 6 7
GPDI6: Using eco-labelling, environment management system and ISO 14000
1 2 3 4 5 6 7
GPDI7: Degree of new green product competitiveness understand customer needs
1 2 3 4 5 6 7
GPDI8: Designing product features and applications that will promote responsible, efficient, cost-effective and environmentally preferable use
1 2 3 4 5 6 7

Part 2.2 Green process innovation

11 When adopting green process innovation, we do the following (Please encircle your response)
(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)
GPCI1: Sources from suppliers who comply with environmental regulations
1 2 3 4 5 6 7
GPCI2: Low-cost green provider: unit cost versus competitors' unit cost
1 2 3 4 5 6 7
GPCI3: Consumption low energy (such as water, electricity, gas and petrol) during production/use/disposal
1 2 3 4 5 6 7
GPCI4: Recycle, reuse and remanufacture of materials internal to the company
1 2 3 4 5 6 7
GPCI5: Controls operations process to reduce waste from all sources
1 2 3 4 5 6 7
GPCI6: Updates manufacturing processes to meet standards of environmental law
1 2 3 4 5 6 7
GPCI7: Utilizes cleaner transportation modes
1 2 3 4 5 6 7

Part 3: Ambidexterity

Part 3.1 Exploitation

12 With regard to exploitation practices, we do the following (Please encircle your response)
(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)
EXPLOIT1: Improvement of product quality
1 2 3 4 5 6 7
EXPLOIT2: Improvement of product flexibility
1 2 3 4 5 6 7
EXPLOIT3: We place strong emphasis on improving efficiency
1 2 3 4 5 6 7
EXPLOIT4: Reduction of production cost
1 2 3 4 5 6 7
EXPLOIT5: Enhancement of existing markets
1 2 3 4 5 6 7
EXPLOIT6: Upgraded current knowledge and skills for familiar products and technologies
1 2 3 4 5 6 7
EXPLOIT7: Enhanced skills in exploiting well-established technologies that improve productivity of current innovation operations
1 2 3 4 5 6 7
EXPLOIT8: We frequently adjust procedures, rules, and policies to make things work better
1 2 3 4 5 6 7

Part 3.2 Exploration

13 With regard to exploration practices, we do the following (Please encircle your response)

Please indicate, on a 1-7 Likert scale, the extent to which eight different statements were true regarding product development in their firm over the past three years (or since its founding if the firm was younger than three years old).

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)

EXPLORAT1: Extension of product range

1 2 3 4 5 6 7

EXPLORAT2: Opening up new markets

1 2 3 4 5 6 7

EXPLORAT3: Acquired technologies and skills entirely new to the business unit

1 2 3 4 5 6 7

EXPLORAT4: We frequently experiment with significant new ideas or ways of doing things

1 2 3 4 5 6 7

EXPLORAT5: Our employees frequently come up with creative ideas that challenge conventional ones

1 2 3 4 5 6 7

EXPLORAT6: Learned product development skills and processes entirely new to the industry (e.g. product design, prototyping new products, timing of new product introductions and customizing products for local markets)

1 2 3 4 5 6 7

EXPLORAT7: Acquired entirely new managerial and organizational skills that are important for innovation (e.g. forecasting technological and customer trends; identifying emerging markets and technologies; integrating R&D, marketing, manufacturing and other functions; managing the product development process)

1 2 3 4 5 6 7

EXPLORAT8: Compared to the competition, a high percentage of our sales come from new products launched in the past three years.

1 2 3 4 5 6 7

Part 4: Big Data Analytics Capability

Part 4.1 Big data analytics infrastructure capability

14 With regard to big data analytics infrastructure capability (firms' ability to develop, deploy, and support necessary system components), our firm is effective in the following (Please encircle your response)

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)

BDAI1: System is capable to handle semi-structured and unstructured data.

1 2 3 4 5 6 7

BDAI2: Compared to rivals within our industry, our organization has good infrastructure and facilities.

1 2 3 4 5 6 7

BDAI3: Compared to rivals within our industry, our organization has the foremost available analytics systems

1 2 3 4 5 6 7

BDAI4: All other (e.g., remote, branch, and mobile) offices are connected to the central office for sharing analytics insights

1 2 3 4 5 6 7

BDAI5: Our organization utilizes open systems network mechanisms to boost analytics connectivity

1 2 3 4 5 6 7

BDAI6: There are no identifiable communications bottlenecks within our organization for sharing analytics insights

1 2 3 4 5 6 7

BDAI7: Software applications can be easily used across multiple analytics platforms

1 2 3 4 5 6 7

BDAI8: Analytics-driven information is shared seamlessly across our organization, regardless of the location

1 2 3 4 5 6 7

BDAI9: Applications can be adapted to meet a variety of needs during analytics tasks

1 2 3 4 5 6 7

Part 4.2 Big data analytics management capability

15 With regard to big data analytics management capability (firms' ability to to handle routines in a structured manner to manage IT resources in accordance with business needs and priorities), our firm is effective in the following (Please encircle your response)

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)

BDAM1: We continuously examine innovative opportunities for the strategic use of business analytics
1 2 3 4 5 6 7

BDAM2: We frequently adjust business analytics plans to better adapt to changing conditions
1 2 3 4 5 6 7

BDAM3: When we make business analytics investment decisions, we estimate the effect they will have on the productivity of the employees' work
1 2 3 4 5 6 7

BDAM4: When we make business analytics investment decisions, we project how much these options will help end-users make quicker decisions
1 2 3 4 5 6 7

BDAM5: In our organization, business analysts and line people coordinate their efforts harmoniously
1 2 3 4 5 6 7

BDAM6: Real-time assess of data and information has helped organization in better decision making.
1 2 3 4 5 6 7

BDAM7: We constantly monitor the performance of the analytics function
1 2 3 4 5 6 7

BDAM8: Our company is better than competitors in connecting (e.g., communication and information sharing) parties within a business process
1 2 3 4 5 6 7

BDAM9: Our company is better than competitors in bringing detailed information into a business process
1 2 3 4 5 6 7

Part 4.3 Big data analytics personnel capability

16 With regard to big data analytics personnel capability (staff's professional ability to undertake assigned tasks), our firm is effective in the following (Please encircle your response)

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)

BDAP1: Our analytics personnel is capable of parallel computing to address voluminous data
1 2 3 4 5 6 7

BDAP2: Our analytics personnel are very capable in terms of programming skills (e.g., structured programming, web-based application, CASE tools, etc.)
1 2 3 4 5 6 7

BDAP3: Our analytics personnel are very capable in the areas of data management and maintenance
1 2 3 4 5 6 7

BDAP4: Our analytics personnel are very capable in decision support systems (e.g., expert systems, artificial intelligence, data warehousing, mining, marts, etc.)
1 2 3 4 5 6 7

BDAP5: Our analytics personnel show superior understanding of technological trends
1 2 3 4 5 6 7

BDAP6: Our analytics personnel show superior ability to learn new technologies
1 2 3 4 5 6 7

BDAP7: Our analytics personnel are very knowledgeable about the critical factors for the success of our organization
1 2 3 4 5 6 7

BDAP8: Our analytics personnel are very capable in interpreting business problems and developing appropriate technical solutions
1 2 3 4 5 6 7

BDAP9: Our analytics personnel are very knowledgeable about the business environment
1 2 3 4 5 6 7

BDAP10: Our analytics personnel are very capable in terms of managing projects
1 2 3 4 5 6 7

Part 5: Firm performance

Part 5.1 Environmental performance

17 By adopting green innovation, we have achieved the following to fulfil the environmental goal (Please encircle your response)

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7:

Strongly agree)

EP1: Significant improvement in its overall environmental situation

1 2 3 4 5 6 7

EP2: Significant improvement in its compliance to environmental standards

1 2 3 4 5 6 7

EP3: Significant reduction in emission of air pollutants

1 2 3 4 5 6 7

EP4: Significant reduction in energy consumption

1 2 3 4 5 6 7

EP5: Significant reduction in waste water

1 2 3 4 5 6 7

EP6: Significant reduction the consumption for hazardous/harmful/toxic materials

1 2 3 4 5 6 7

EP7: Significant reduction in environmental resource impact controversies

1 2 3 4 5 6 7

Part 5.2 Financial performance

18 When adopting green innovation, we have achieved the following for the aims of fulfilling the financial goal (Please encircle your response)

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)

FP1: Growth of sales

1 2 3 4 5 6 7

FP2: Growth in return on investment

1 2 3 4 5 6 7

FP3: Return of assets

1 2 3 4 5 6 7

FP4: Profit margin

1 2 3 4 5 6 7

FP5: Increase in market share

1 2 3 4 5 6 7

FP6: Acquisition of new customers

1 2 3 4 5 6 7

FP7: Decrease in cost of materials purchasing per unit of product

1 2 3 4 5 6 7

FP8: Decrease in cost for energy consumption per unit of products

1 2 3 4 5 6 7

Part 5.3 Social performance

19 When adopting green innovation, we have achieved the following for the aims of fulfilling the social goal (Please encircle your response)

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)

SP1: Using social performance indicators

1 2 3 4 5 6 7

SP2: Employees' health and safety

1 2 3 4 5 6 7

SP3: Incentives and engagement for local employment

1 2 3 4 5 6 7

SP4: Improvement of community health and safety

1 2 3 4 5 6 7

SP5: Employee satisfaction

1 2 3 4 5 6 7

SP6: Improvement in human right compliance

1 2 3 4 5 6 7

SP7: Improvement in labour safety and labour conditions in our facilities

1 2 3 4 5 6 7

SP8: Reduction of number of industrial accidents

1 2 3 4 5 6 7

20 When adopting green innovation, we have achieved the following for the aims of fulfilling the <u>quality goal</u> (Please encircle your response)

(1: Strongly disagree 2: Disagree 3: More or less disagree 4: Undecided 5: More or less agree 6: Agree 7: Strongly agree)

QP1: Our company implements frequent quality improvements

1 2 3 4 5 6 7

QP2: The product provided conforms to prearranged specifications

1 2 3 4 5 6 7

QP3: The product has higher technical durability than competitors

1 2 3 4 5 6 7

QP4: The product functions above average when compared to competitors

1 2 3 4 5 6 7

QP5: The product has higher value for money than competitors

1 2 3 4 5 6 7

QP6: Our company implements frequent cost reduction measures

1 2 3 4 5 6 7

QP7: The cost of scrap and rework as a percentage of sales has decreased