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Firm Performance in the Era of Big Data Analytics: The Effects of Analytical Human Capital on Firm Capabilities and Performance

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FIRM PERFORMANCE IN THE ERA OF BIG DATA ANALYTICS:

THE EFFECTS OF ANALYTICS HUMAN CAPITAL

ON FIRM CAPABILITIES AND PERFORMANCE

by

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ABSTRACT

The Big Data phenomenon has revolutionized the way firms do business by providing immense opportunities for valuable business insights from large amounts of data. Big data analytics (BDA) has emerged as one of the top technology investment areas as firms consider it a significant impetus for superior firm performance. However, many firms adopting BDA find it challenging to gain an advantage from their BDA investments. Scholars note the need to further understand the factors and mechanisms of BDA success. Some anecdotal evidence has indicated that a critical barrier to BDA success may be the lack of a necessary workforce with analytics skills. A review of recent BDA literature revealed a lack of research on the role of analytics human capital in relation to firm performance.

In this dissertation study, I draw upon the theoretical perspectives of knowledge-based view and dynamic capabilities to examine the impacts of analytics human capital (HC) on firm performance and identify related firm capabilities. Noting the crucial role of managerial skills in business strategy, I further classify analytics HC into managerial and employee analytics HC and hypothesize that both these types of human capital are a source of superior firm performance.

This study empirically examines the effects of managerial and employee analytics HC on firm performance while also investigating the mediating firm capabilities. As prior studies have found that managerial skills impact strategic change capabilities, and

employee skills affect productive efficiency capabilities, the mediating role of these capabilities is investigated. In addition, the moderating influence of environmental dynamism and information technology (IT) infrastructure is also considered.

The sample of Fortune 500 companies was used in the study as this sample has been widely used and found appropriate for strategy studies linked to firm performance. The study results confirm that both managerial and employee analytics HC have a significant positive impact on firm performance. The results also support the partial mediating effect of strategic change capability in the relationship between managerial analytics HC and firm performance. Further, the partial mediating effect of productive efficiency capability in the relationship between employee analytics HC and firm performance is also supported. Furthermore, Environmental dynamism was found to marginally moderate the impact of managerial analytics skills on firm performance. Finally, the moderating role of IT Infrastructure quality was also marginally supported. The study results confirmed the key role of analytics HC in improving the firm performance and identified the firm capabilities that mediate the effects of analytics HC on firm performance.

In summation, the focus of BDA initiatives has been predominantly on big technology investments while often neglecting the development of analytics HC in the firms. This research study highlights the crucial role of analytics HC on firm performance. It provides a strong empirical basis for firms to develop their managers' and employees' analytics skills to derive business value from their BDA investments. The empirical evaluation of the firm capabilities: strategic-change capability and productive capability, also contribute to research on dynamic and ordinary capabilities. This study is one of the early empirical studies to examine the impacts of analytics human capital on firm performance in the context of Big data analytics and therefore has important implications for both academia and practice in this area.

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CHAPTER 1

INTRODUCTION

Overview

The “Big data” phenomenon has grown rapidly over the recent years providing firms with large amounts of relevant business data and new opportunities for valuable business insights (Barton & Court, 2012; Braganza et al., 2017; George, Haas, & Pentland, 2014). Unprecedented growth in analytics has the potential to transform strategic decision-making and improve business productivity (Abbasi, Sarkar & Chiang, 2016; Wamba et al., 2017). Big data analytics (BDA), which has been broadly defined as the use of analytical techniques to derive useful information and insights from large data sets, is emerging as a critical factor for superior firm performance (Chen, Chiang, & Storey, 2012; Grover et al., 2018). Managers across the businesses have noted the advantages offered by BDA, making it one of the top technology investment areas, with the BDA market expected to surpass $203 billion in 2020 (Tabesh et al., 2019). However, many firms adopting BDA find it difficult to derive strategic value from their BDA investments, focusing on the analytics knowledge, skills, and abilities of managers and employees (Kiron & Shockley, 2011; Ransbotham et al., 2016). Realizing the profound impact of BDA on management practice, scholars have also called for further research investigating the role of analytics human capital (Corte Real et al., 2017; George et al., 2014; Grover, 2018).

BDA involves the people, processes, and technologies that turn data into insights, and involves individuals deriving insights using analytic tools and making decisions to solve important business problems, thereby triggering actions that generate business value (Wixom, Yen & Relich, 2013). Leading firms that have effectively used BDA, such as Google, Facebook, and Amazon, have gained superior profitability and revenue growth from their analytics initiatives (Jagdish et al., 2014; Kiron & Shockley, 2011). For example, Amazon stores data for millions of consumer transactions daily and uses predictive analytics to make product recommendations relying on customers' search preferences and order history, providing crucial strategic value (Hu et al., 2014). Prior research has found that BDA applications can provide superior firm performance in areas such as price optimization and profit maximization (Barton & Court, 2012; Davenport & Harris, 2010), as well as productivity (Corte-Real et al., 2017; McAfee & Brynjolfsson, 2012). Among the Fortune 1000 companies, the investment in BDA applications has been steadily increasing every year, with some surveys indicating that over 91% of these companies are investing in BDA applications (Kiron et al., 2013). However, many companies implementing BDA initiatives cannot gain business value from these investments, often due to a lack of necessary BDA human capital (Abbasi et al., 2016; Chen et al., 2012; Grover, 2018).

Motivation of the Study

Data analytics is becoming a crucial component of firms' decision-making processes at all levels, highlighting the importance of employees' analytics skills (Ghasemaghaei et al., 2018). Data and people are inexorably linked as never before, and the need for firms to develop analytics human capital, necessary to gain meaningful business insights, has never been greater (Chen et al., 2012). According to the knowledge-based view, a firm's human resources knowledge base profoundly influences shaping firm performance (Grant, 1996). A firm's human capital in terms of its employees' collective knowledge, skills, and abilities, contributes to achieving its business objectives and is an obvious key determinant of firm performance. (Huselid, Jackson, & Schuler, 1997). Effective use of big data also requires BDA knowledge and skills across functional areas such as customer relationship management, sales/market development, and new product development (Kiron & Shockley, 2011; Xu, Frankwick, & Ramirez, 2016). Prior research suggests that employees with superior analytics skills can effectively use data at all stages of business processes, enhancing firm productivity and efficiency (Corte Real et al., 2017; Grover, 2018).

Several strategy scholars have linked knowledge-enabled capabilities to organizational outcomes (Kogut & Zander, 1992; Teece et al., 1997; Zollo & Winter, 2002). Kogut and Zander (1992) examined the transformation of personal into organizational knowledge. Scholars posit that the firm's ability to effectively apply existing knowledge forms the basis for gaining an advantage, and data analytics techniques enhance and expedite knowledge management (Alavi & Leidner, 2001). Prior works have emphasized the importance of human capital in the knowledge-based perspective (Coff & Kryscynski, 2011). Kogut and Zander (1992) observe that individuals hold knowledge, yet it is also embedded in firm organizing principles by which people cooperate in an organizational context. Firms' human capital in terms of the knowledge and skills of its employees has also been linked to strategic performance (Marler & Fisher, 2013).

Human capital (HC) theory predicts that investments in human capital (HC) enhancement generate superior firm-level performance. (Becker & Huselid, 2006). Scholars have often defined HC as an individual's stock of knowledge, skills, and abilities that can be increased through mechanisms like education, training, and experience (Coff & Kryscynski, 2011); while strategy scholars characterize human capital as a unit-level resource (Ployhart & Moliterno, 2011). The strategy research focuses on more macro focus level aggregate HC resources available to the firm (Kor & Leblebici, 2005). As the modern world is becoming a knowledge society, scholars have emphasized the increasing role of human capital for firm performance (Kogut & Zander, 1996). It has become a widely held premise that effective management of not the physical capital but the human capital is the ultimate determinant of organizational performance (Adler, 1991; Youndt et al., 1996). Recent BDA surveys have also indicated that a key barrier to BDA success may be the lack of managerial analytics skills needed to exploit the array of the market, consumer, and process data available (Kiron et al., 2013; Lavalle et al., 2011), which can be studied in terms of macro managerial analytics HC.

In order to take advantage of analytics, firms need senior executives who understand data-based decision-making and can manage analytics initiatives successfully (Ghasemaghaei et al., 2018; Grover et al., 2018). As manifested by managers' knowledge and experience, the managerial HC of a firm represents a critical resource shaping the firm's dynamic capabilities (Teece, 2007). Previously, the dynamic capabilities perspective has provided a useful framework for understanding organizational capabilities and management practices (Eisenhardt & Martin, 2000; Teece, 2007). Dynamic capabilities help explicate the role that managers play in identifying and capturing new strategic opportunities (Helfat, 2007). At a time when firms in many industries offer similar products and use comparable technologies, effective use of analytics by managers can facilitate differentiated strategy development in various business processes (Davenport et al., 2001). In conjunction with BDA research, strategy scholars have also pointed out the need to examine strategic change capabilities because top executives, using the results of BDA, influence their firms' performance through these capabilities (Helfat & Martin, 2015).

Purpose and Research Questions

While researchers have started investigating multiple factors influencing BDA firm outcomes, there is a lack of research work investigating the impacts of analytics HC in the BDA context. Further, the specific role of managerial analytics HC and employee analytics HC has been under-researched. This study aims to fill this gap in the literature by examining the impacts of these factors on firm capabilities and overall firm performance. The purpose of this study is to empirically examine the impacts of managerial and employee analytics HC on firm capabilities and firm performance. The firm performance outcomes are investigated, as has been emphasized in prior strategy studies (Carpenter, 2000; Kor & Mesko, 2013) and highlighted in the BDA literature (Akter et al., 2016; Davenport & Harris, 2007; McAfee & Brynjolfsson, 2012). Some prior scholars have proposed relationships between firms' analytics HC and firm performance, enabled by improvements in strategic and operational capabilities (Grover, 2018; LaValle et al., 2011). Further, this study intends to investigate the mediating and moderating factors involved in the relationship between managerial and employee analytics HC and firm performance. As prior studies have found that managerial skills impact strategic change capabilities (Zhang & Rajagopalan, 2010); and employee skills impact operational efficiency capabilities (Chen et al., 2011), the mediating role of these capabilities is examined as they relate to data analytics' impact on firm performance.

Dynamic capabilities are regarded as a transformer for converting resources into improved performance, and that dynamic capabilities mediate between firms' human resources and performance (Wang & Hajli, 2017; Zollo & Winter, 2002). The resource alteration processes in some firms also demonstrate how dynamic capability operates and reveal the important roles of resources; and the relationship between resources and dynamic capabilities in achieving precise resource allocations (Winter, 2003). Researchers have investigated firms to examine their capabilities in terms of how they leverage existing resources, create new resources, access external resources, and release resources to adapt to a changing environment (Zott, 2003). There is increasing evidence that firm performance is affected by these dynamic capabilities (Teece et al., 1997).

BDA literature indicates that a successful BDA strategy can provide superior firm performance in sales efficiency and market-share growth (Davenport & Harris, 2007), productivity, and profitability (Barton & Court, 2012; McAfee & Brynjolfsson, 2012). With the increasing role of data, management must convert data into meaningful information and intelligence related to a business (Xu et al., 2016). Analytic skills of managers such as interpretive and inferential skills are important for firms as the full import of facts, statistics, and developments are rarely obvious (Teece, 2007). To take advantage of analytics, firms need senior executives passionate about analytics and fact-based decision-making and can manage the changes in business processes motivated by analytics initiatives (Davenport & Harris, 2007). Knowledge-based view and dynamic capability perspectives also suggest that intangible knowledge resources, such as those embedded in human capital, are most likely to generate superior firm performance (Grant, 1996; Teece et al., 1997).

Given this background, the main research question investigated in this empirical study is: Do higher levels of managerial and employee analytics HC lead to superior firm performance? The related questions are: Does managerial analytics HC influence the firm's strategic change capability, and to what degree does the strategic change capability mediate the relation between managerial analytics HC and firm performance? Also, does employee analytics HC influence the firm's productive efficiency capability, and to what degree does the productive efficiency capability mediate the relation between employee analytics HC and firm performance? The study also examines the moderating effect of employee analytics HC on the managerial analytics HC's firm's productive efficiency capability, and to what degree does the productive efficiency capability mediate the relation between employee analytics HC and firm performance? The study also examines the moderating effect of employee analytics HC on the managerial analytics HC's impact on firm performance. Finally, the moderating role of environmental dynamism and information technology (IT) infrastructure are examined.

Strategy research suggests that environmental dynamism can moderate the impact of managerial actions on firm performance due to differences in information requirements between high and low-velocity environments (Eisenhardt, 1989; Garg, Walters & Priem, 2003). Also, BDA studies have noted the potential moderating role of Information technology (IT) infrastructure quality, as it relates to the employees' ability to share information across different functions, and exploit business opportunities (Corte-

Real et al., 2019). In this study, the moderating role of environmental dynamism is examined regarding the relationship between managerial analytics HC and firm performance. The moderating role of IT Infrastructure quality is also investigated regarding the relationship between employee analytics HC and firm performance. The hypothesized research model of this study is depicted in Figure 1-1. The detailed hypotheses arguments are described and discussed in the following chapter.

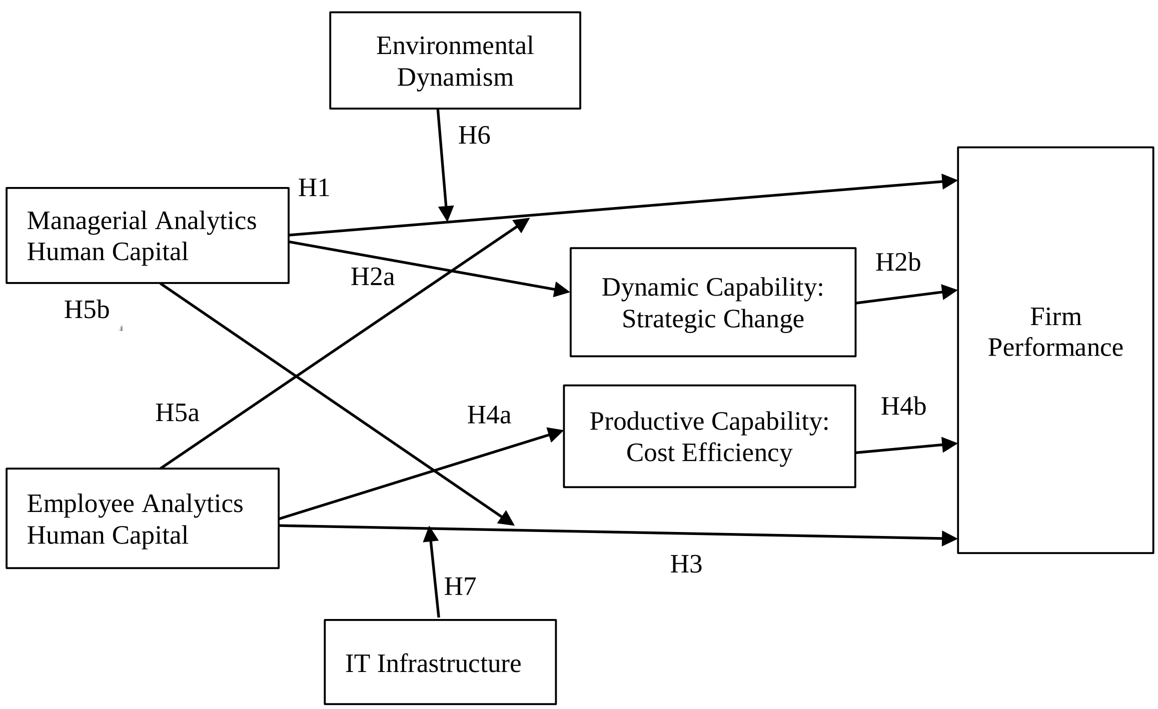

Figure 1-1: Hypothesized Research Model: The Impact of Managerial and Employee Analytics Human Capital on Firm Performance

Significance of the Study

Prior strategy scholars have investigated the influence of managerial abilities on a firm's strategic performance in different resource contexts (Holcomb, Holmes, & Connelly, 2009). Currently, BDA presents an important context for such a study. The knowledge and insights provided by BDA are being recognized as providing an immense opportunity for improving strategic value (Abbasi et al., 2016; Agarwal & Dhar, 2014; LaValle et al., 2011). This study empirically examines the influence of managerial and employee analytics human capital on firm performance while also testing the mediating impact of strategic change and efficiency capabilities.

Further, this study aims to find empirical evidence on the importance of making data-driven decisions based on the insights derived from the large amounts of available market data. I have seen that the management of firms such as Netflix and Amazon have innovated their business models by using insights from the massive amounts of market data they generate and enhance their customer experiences, providing the firms with superior returns. This study also examines the impact of analytics skillsets of employees on firm performance. It supports the moderating impact employees' analytics skillsets have on the relationship between managerial analytics skills and firm performance.

The knowledge-based view has theorized that knowledge resources will increasingly play a defining role in creating a firm's competitive advantage and ultimately determining its performance. Employee knowledge skills and experience are also thought to help firms develop new business processes and embed knowledge in the organization. In the age of big data, employees' analytics skills are expected to play a key role in generating superior performance, and the empirical results of this study validate this argument. Scholars have pointed out that employees with analytics skills can provide the firm with access to new data sources and techniques and improve existing processes in terms of efficiency and effectiveness (Woerner & Wixom, 2015). This study helps investigate how organizations effectively leverage big data to achieve greater productivity and efficiency by testing the mediating role of efficiency capabilities between employee analytics skills and firm performance.

Previous research has discussed the importance of senior managers in shaping strategic capabilities (Tushman & Rosenkopf, 1996). Strategy scholars have also pointed out that management is responsible for strategic change capabilities that may influence firm performance (Helfat & Martin, 2015). BDA literature also suggests that analytics skills may help managers enhance the strategic change capabilities of the firm by gaining insights from large amounts of consumer and market data. In this study, I investigated the mediating role of these capabilities in the relationship between managerial analytics skills and firm performance.

This research helps in examining both managerial and employee HC in the context of the big data revolution and the increasingly significant role played by analytics in firms' success. This empirical study used the sample of Fortune 500, the largest 500 public U.S. firms by total revenue, which has been used in several prior strategy studies linked to firm performance (Wiersema & Bantel, 1992). This sample includes firms characterized by considerable variation in competitive dynamics, profitability, and stages of the industry life cycle (Crossland et al., 2014) and therefore was found appropriate for examining the strategic outcomes of managerial analytics capabilities. Previous studies examining top management impacts on strategic change have also used samples of Fortune 500 companies (Maritan & Brush, 2003). Annual financial data for these firms were obtained from Standard and Poor's Capital IQ database and the Thomson Reuters database for the most recent year. Full data were available at the time of the study, 2019.

Recently, studies have measured managerial, and employees' skill sets using professional social media data (Hitt, Jin & Wu, 2016; Tambe, 2014); I also followed that approach. Some studies have detailed the specific skills relevant to big data and analytics positions (Cegielski & Jones-Farmer, 2016), and similarly, I used a BDA skillset in this study. This study empirically validates the insights of the knowledge-based view and firm dynamic capabilities in the BDA context. The impact of managers' BDA skills is tested in terms of positively influencing firms' performance. The key role of employee analytics skills is tested with direct impacts on firm performance and moderating impact on the relationship between managerial analytics skills and performance. In the context of BDA HC, this is one of the first empirical studies examining the key role played by analytics HC in improving firm performance.

Organization of the study

The present chapter provides an overview of the research problem by introducing the concepts of managerial and employee analytics HC in BDA. The purpose of the study, along with its theoretical lens, is also introduced, explicating the significance of this study. The conceptual hypothesized model consisting of potential mediators and moderators and the direct relationship of managerial and employee analytics HC on firm performance is briefly discussed. Chapter 2 provides a review of the theoretical background of the knowledge-based view, human capital theory, and dynamic capabilities perspective while also presenting the study's hypotheses supported by conceptual and anecdotal evidence from the literature. Finally, the proposed research methodology details are provided in Chapter 3, including the data samples used, the research model variables, the description of the data collection process, and the operationalization of constructs used in the study.

CHAPTER 2

LITERATURE REVIEW AND HYPOTHESES

This chapter reviewed the theoretical background of the knowledge-based view, human capital theory, and dynamic capabilities perspective. The importance of the resource and dynamic capability perspectives in the strategic management field in relation to firm performance is discussed. The knowledge-based view (KBV) review also includes discussing the broader concept of the resource-based view (RBV) with a focus on examining intangible knowledge resources. Next, human capital theory is reviewed along with its emergence in management literature across strategy and human resources fields. Further, the chapter discusses the growing literature on the importance of dynamic capabilities for superior firm performance in the current business environment. The dynamic capabilities view provides a key conceptual framework to examine the impacts of the intangible knowledge resources, which are often considered to influence firm performance through enhancements of the firm’s strategic and operational capabilities. In the review of dynamic capabilities, the literature on ordinary/operational capabilities is also reviewed, noting their differences with dynamic capabilities. Finally, the literature on BDA and firm performance is reviewed along with the hypothesis development, with the discussion of specific BDA studies related to each hypothesis.

Knowledge-Based View of the Firm

The knowledge-based view (KBV) of the firm has emerged as an important conceptual perspective for examining knowledge resources and capabilities in the field of strategic management (Eisenhardt & Santos, 2002; Grant, 1996). This perspective considers knowledge to be the most strategically significant resource of the firm (Grant, 1996) and argues that heterogeneous knowledge bases and capabilities among firms can provide a competitive advantage and superior firm performance for some (Winter & Szulanski, 1999). As organizational and managerial practice has recently become more knowledge-focused, there is an increasing realization of the employees' importance of knowledge, skills, and abilities (Teece, 2007). The KBV is also considered an extension of the resource-based view (RBV) of the firm (Barney 1991), where the concept of resources is extended to include intangible knowledge-based resources (Alavi & Leidner, 2001).

Theories of the firm are conceptualizations of business enterprises that explain and predict their structure and behaviors. Scholars use the term 'theory of the firm' in many contexts, as there is no single, multipurpose theory (Grant, 1996). Drawing on the work of prior researchers like Katz and Kahn (1966), Luthans and Stewart (1977) defined an organization as a social system consisting of subsystems of resource variables interrelated by various management policies, practices, and techniques that interact with variables in the environmental supra-system to achieve a set of goals or objectives. The primary system includes environmental, resource, and management variables. Economic theories of the firm are concerned primarily with predicting the behavior of firms in external markets (Grant, 1996). Attempts at integrating economics and organizational approaches to the firm's theory have included the firm's behavioral theory (Cyert & March 1963) and the evolutionary theory of the firm (Nelson & Winter, 1982).

Strategic management has drawn its theories from both economics and organization theory, though its primary goals are to explain firm performance and determinants of firm strategy (Grant, 1996). As highlighted by Porter (1981), the industrial economics approach is that a firm's performance is primarily a function of the industry environment in which it competes. The rise of the resource-based view (Barney, 1991; Wernerfelt, 1984) focused on the firm's internal resources (Hoskisson et al., 1999). The resource-based view of the firm is less a theory of firm structure and behavior as an attempt to explain and predict why some firms can sustain competitive advantage and earn superior returns. (Grant, 1996). Strategy research notes that KBV has emerged out of the resource-based thinking where the concept of resources is extended to include intangible assets and, specifically, knowledge-based resources (Grant,1996); while researchers also see KBV as a useful extension of organizational learning to strategy, an extension that is capable of informing research and providing new insights into organizational functioning (Eisenhardt & Santos, 2002; Kogut & Zander, 1996).

Noting the emergence of KBV, Eisenhardt and Santos (2002), in a seminal study, pointed that the knowledge movement is sweeping through the field of strategy. KBV perspective considers knowledge as the most strategically significant resource of the firm (Grant, 1996). Its proponents argue that heterogeneous knowledge bases and capabilities among firms are the main determinants of sustained competitive advantage and superior corporate performance (Winter & Szulanski, 1999). Earlier, the information-processing perspective postulated organizations almost as machines that use rules and routines to address the individual information processing requirements caused by interdependent work and environmental uncertainty. Knowledge was considered as unambiguous and easily transferable construct, while knowing is associated with processing information (Eisenhardt & Santos, 2002).

The traditional view considered Knowledge as justified true belief, and the focus of theories is on the explicit nature of knowledge (Nonaka & Takeuchi, 1995). In contrast with this traditional conception, a newer view of knowledge perspective distinguishes explicit and tacit knowledge (Polanyi, 1962), and where truth is considered more as a goal of the knowledge creation process than an absolute characteristic of knowledge. According to Eisenhardt and Santos (2002), the newer epistemology of knowledge associates it with a process phenomenon of knowing that is clearly influenced by the social and cultural settings in which it occurs.

Several early researchers in the knowledge-based paradigm emphasized the importance of accounting for individuals to clearly understand the formation of knowledge-based organizational capabilities (Conner & Prahalad, 1996; Grant, 1996; Nonaka, 1994). Nonaka (1994) explored the creation of organizational knowledge through the interplay between tacit/explicit and individual/organizational knowledge. Significant research efforts also went into linking knowledge-based capabilities directly to organizational knowledge outcomes (Kogut & Zander, 1992; Teece et al., 1997; Zollo & Winter, 2002). Kogut and Zander (1992) examined the transformation of personal into organizational knowledge. Demsetz (1991) analyzed the firm as an institution for knowledge integration. Jensen and Meckling (1976) examined how imperfections of knowledge transfer influence the relative efficiencies of firms and markets, and the allocation of decision rights within the firm.

Kogut and Zander (1992:384) conceptualized the firms as “social communities” in which dispersed knowledge is transformed “into economically useful products and services by the application of a set of higher-order organizing principles”; and they have superior mechanisms that make them better at generating, integrating, and applying knowledge to business activities. Earlier, Nelson and Winter (1982) were among the first to integrate organizational knowledge and routines with the notion of dynamic competitive environments. In their approach, the firm is understood to be a repository of knowledge, represented by routines that guide organizational action.

Under the KBV perspective, firm heterogeneity results from interfirm variations in leveraging widely dispersed knowledge available to the firm (Tsoukas, 1996); firms that are superior at managing knowledge gain competitive advantage by exploiting their knowledge to earn economic profit rents. KBV considers firms as special, deliberate organizations that outperform markets in their ability to manage knowledge and compete to leverage knowledge more effectively to gain a competitive advantage (Theriou et al., 2009). Grant (1996) noted that to the extent that KBV focuses upon knowledge as the most important of the firm’s resources, it is an outgrowth of the resource-based view. However, at the same time, knowledge is central to several distinct research areas, notably organizational learning, the management of technology, and managerial cognition.

KBV and Resource-Based View

The resource-based view (Barney 1991; Wernerfelt, 1984) is a major theoretical perspective in strategic management research explaining persistent, firm performance variations (Barney, 2001). The key tenet of this view is that a firm can have a sustained competitive advantage if they have valuable, rare, inimitable, and non-substitutable (Barney, 1991). RBV is based on resource heterogeneity, which postulates that different firms hold different resource bundles, resulting in differences in competitive advantage and firm performance (Barney, 1991; Peteraf, 1993). Although firms may attempt to imitate resources held by successful competitors, resource bundles remain heterogeneous due to imperfect imitability, created by isolating mechanisms such as long-term experience, historical uniqueness, and connectedness of resources (Powell & Dent-Micllef, 1997). The central notion of RBV is that to create and sustain long-term competitive advantage, a firm should acquire or develop resources and capabilities that are unique and heterogeneous (Santhanam & Hartono, 2003).

RBV assumes that firms can be conceptualized as bundles of heterogeneously distributed resources across firms and that resource differences persist over time (Peteraf, 1993). The key tenet of this view is that a firm can have sustained competitive advantage if it has resources that are Valuable, Rare, In-imitable, and Non-Substitutable (VRIN attributes), as the competing firms cannot easily duplicate these (Barney, 1991; Peteraf, 1993). RBV perspective focuses on the internal organization of firms, and so is a complement to the prior emphasis of strategy on industry structure and strategic positioning within that structure as a determinant of competitive advantage (Eisenhardt & Martin, 2000). Barney (1991) noted the two key assumptions of RBV: (1) resources are distributed heterogeneously across firms, and (2) these productive resources cannot be transferred from firm to firm without cost (Barney 2001).

Given resource heterogeneity and cost-based transfer assumptions, Barney (1991) argues that rare and valuable resources can produce a competitive advantage. When such resources are also simultaneously not imitable and not substitutable, those resources may produce a sustainable competitive advantage (Priem & Butler, 2001). Some theorists have emphasized that the more fundamental contribution of resources to a sustainable advantage for firms is examining why resources contribute to the advantage of one firm over another in a product/market (Barney, 2001).

The RBV of the firm is applied to explain differences in performance within an industry (Hoopes et al., 2003). The RBV of the firm states that differences in performance happen when successful organizations possess valuable resources that others do not have (Wernerfelt, 1984). The existence of capabilities and resources heterogeneity within a population of firms is a key principle of the RBV (Helfat & Peteraf, 2003). The organizations are heterogeneous entities characterized by their unique resource bases (Barney, 1991; Nelson & Winter, 1982). The RBV of the firm explains the heterogeneous competition based on the premise that close competitors differ significantly in their resources and capabilities (Helfat & Peteraf, 2003). This perspective recognizes that the type, magnitude, and nature of resources and capabilities are important determinants in their capacity to generate profit and business value (Amit & Schoemaker, 1993).

According to Barney (1991), firm resources can be physical, human, or organizational. Resources can also be tangible or intangible (Hoskisson et al., 1999). Grant (1991) also provided a classification of resources into tangible, intangible, and personnel-based resources. RBV postulates that to create and sustain competitive advantage, a firm should acquire or develop resources and capabilities that are unique and not easily substitutable by competitors (Santhanam & Hartono, 2003). Although firms may attempt to imitate resources held by successful competitors, resource bundles remain heterogeneous due to imperfect imitability, created by isolating mechanisms such as long-term experience, historical uniqueness, and connectedness of resources (Powell, 1992).

The RBV of the firm is a strategic line of thought that analyses the organization's strengths and weaknesses (Curado & Bontis, 2006). The organization's attributes that allow it to conceive of and implement value-creating strategies are resources. The resources, assets, and capabilities the firm possesses are used to build its competitive advantage. The resources and capabilities, tangible and intangible, generate economic returns to the firm (Amit & Schoemaker, 1993). The RBV of the firm considers that resources are not limited to the traditional economic productive factors; they also include socially complex resources, such as interpersonal relationships within firm managers and the firm's culture (Barney, 1991). Physical resources may originate returns above-average levels but are intangible resources, developed through a unique historical sequence and having a socially complex dimension that can create and sustain the firm's competitive advantage (Curado & Bontis, 2006).

As an extension of RBV, the knowledge-based view (KBV) suggests that knowledge is a critical firm resource (Grant, 1996); further heterogeneous knowledge bases and capabilities are the main determinants of sustained competitive advantage (Winter & Szulanski, 2001). When knowledge is conceptualized as a resource, Eisenhardt and Santos (2002) argue that the KBV can be considered a special case of the resource-based view of the firm. Resource and knowledge-based research generally maintain that firm-specific knowledge has great potential to serve as a source of sustainable competitive advantage (Grant, 1996; Kogut & Zander, 1992). Firm-specific knowledge often results from searching for and accumulating new solutions that build upon a firm's established knowledge base (Cohen & Levinthal, 1990; Teece, 1986).

Several researchers argue that KBV is primarily an outgrowth of resource-based thinking where the concept of resources is extended to include intangible assets and, specifically, knowledge-based resources (Grant, 1996; Decarolis & Deeds, 1999). Other researchers note that KBV may be a useful extension of organizational learning to strategy, an extension capable of informing research and providing new insights into organizational functioning (Kogut & Zander, 1992; Kogut & Zander, 1996). According to Eisenhardt and Santos (2002), once knowledge is conceptualized as a resource, it becomes a special case of the resource-based view of the firm. However, KBV also offers enormously useful theoretical insights, well-grounded in empirical findings that address the multi-level social processes through which knowledge is sourced, transferred, and integrated within and across organizations. The possession of knowledge resources gives the firm basic foundations to renew or reconfigure its resource base and to build dynamic capabilities (Corte-Real et al., 2017).

Human Capital Theory

Since the economist Becker (1964) proposed "human capital theory," the study of human capital has emerged across various disciplines. Within the management discipline, both the strategy and human resources management (HRM) fields have devoted considerable attention to the concept of human capital (Wright & McMahan, 2011). From microeconomics, human capital theory suggests that people possess skills, knowledge, and abilities that provide economic value to firms (Youndt et al., 1996). One of its central arguments is that the acquisition of both general and unit-specific human capital contributes to individual and unit effectiveness (Becker, 1964). Many scholars expressing the view that the modern world is becoming a knowledge society have emphasized the importance of human capital for organizational performance (Kogut & Zander, 1996; Pfeffer, 1994). It has become a widely held premise that effective management of not the physical capital but the human capital is the ultimate determinant of organizational performance (Adler, 1991; Youndt et al., 1996).

Management researchers working in the human resources (HR), organizational behavior (OB), and industrial/organizational (I/O) psychology domains, who are generally interested in individual-level phenomena, have largely studied how employee knowledge, skills, abilities, and other characteristics (KSAOs) are linked to individual-level outcomes (Schmidt & Hunter, 1998). Coff and Kryscynski (2011) defined human capital at the micro-level as an individual's stock of knowledge, skills, and abilities that can be increased through mechanisms like education, training, and experience; while other conceptualizations utilized by strategy scholars characterize human capital as a unit-level resource (Ployhart & Moliterno, 2011). Macro-level organizational theorists and strategy scholars, who are generally interested in firm-level phenomena, have studied how the aggregate organizational-level experience, education, and skills of employees are resources (Penrose, 1959; Wernerfelt, 1984) that can be leveraged to achieve competitive advantage ((Barney, 1991; Peteraf, 1993).

According to human capital theory, organizations that invest in developing their human capital are likely to recover these costs through increased productivity. Their employees gain valuable knowledge related to their job and the organization (Ployhart, Weekley, & Ramsey, 2009). Understanding the key determinants of firm performance at the macro or firm-level has long been an important goal (Rumelt, 1998; Santhanam & Hartono, 2003); theories at both the micro and macro levels predict that human investments in human capital enhancement generate better firm-level performance. (Becker & Huselid, 2006). Since firm investments to increase employee skills, knowledge, and abilities carry both out-of-pocket and opportunity costs, they are only justified if they produce future returns via increased productivity (Duncan & Hoffman, 1981). Research in strategic management indicates that investing in human capital can yield positive organization-level performance outcomes (Huselid, 1995; Subramony et al., 2008; Subramaniam & Youndt, 2005).

Noting the contribution of employee HC, Youndt et al. (1996) asserted that increased productivity derived from human capital investments by a firm depends on the increased employee skills and abilities, and the more the firm will invest in human capital, the higher will be the individual productivity and firm performance. Strategic human resource management literature has also focused on the importance of employee-oriented human resource management practices, also interchangeably denoted as ‘human capital-enhancing practices' that provide employees at middle and lower levels the skills, information, and authority to make decisions at the workplace (Subramaniam & Youndt, 2005). Knowledge is increasingly becoming an important factor in securing competitive advantage (Grant, 1996). Since much organizational knowledge resides within its people, HC represents a key intangible asset that competitors cannot easily imitate or substitute because the knowledge embedded within it is valuable and imperfectly imitable (Crook et al., 2011; Grant, 1996).

In terms of managerial knowledge resources, the skills and abilities of managers are considered key contributors to the bundle of a firm's intangible resources that have important implications for firm performance (Castanias & Helfat, 2001). The notion that managerial skills are valuable is fictional in strategy research (Andrews,1971). Given the complexity of managerial work (Mintzberg, 1973), the many skills that must be developed, and the need to develop industry- and firm-specific knowledge to guide decision-making (Thomas, Clark & Gioia, 1993), superior managerial capabilities also appear to be rare (Combs & Skill, 2003). Earlier, Castanias and Helfat (1991) examined a managerial rents model with the basic proposition that managers differ in the type and quality of their skills. Therefore, they have heterogeneous managerial human capital that enables some firms to generate rents. Researchers have noted that managers' human capital, including experiences in specific contexts (e.g., industry, technology regime, and geographical location), may allow managers to acquire and develop specialized knowledge and skills (Harris & Helfat, 1997; Kor, 2003).

A firm's human capital can improve the effectiveness and efficiency of its business routines and exploit market opportunities (Barney, 1991; Lepak, David & Snell, 2002). Several strategy researchers have noted that human capital can provide sustained competitive advantage with the weakening of other differentiators due to globalization and other environmental changes (Thompson & Heron, 2005). Human capital begins with human resources in the form of knowledge and skills embodied in people. The stock of human capital in a firm comes from its employee selection, development, and use (Koch & McGrath, 1996; Snell & Dean, 1992). Pfeffer (1994) made the case that firms wishing to succeed in today's global business environment must make appropriate investments to acquire and build employees who possess better skills and capabilities than their competitors (Youndt et al., 1996). Given the likely impacts of human capital, one credible answer to the critical question in strategic management regarding why firms vary in performance is that they differ in human capital (Hitt et al., 2001).

Dynamic Capabilities and Ordinary Capabilities

The dynamic capability perspective helps understand the organizational abilities that create, renew or alter their resource configurations in dynamic environments (Teece, Pisano, & Shuen, 1997). Dynamic capabilities are generally defined as the competencies that determine the firm's ability to integrate, build, and reconfigure internal and external resources to address rapidly changing business environments (Teece et al., 1997; Teece, 2007). Dynamic capabilities are the antecedent organizational and strategic routines by which managers alter their resource base-acquire, shed resources, integrate them, and recombine them to generate new value-creating strategies (Grant, 1996). Scholars noted that RBV has not adequately explained why certain firms gain an advantage in a rapidly changing market environment; the dynamic capabilities view extends RBV to account for the source of competitive advantage in dynamic environments (Eisenhardt & Martin, 2000). Dynamic capabilities determine the speed at, and degree to which, the firm's resources can be aligned and realigned to match the requirements of the business environment (Teece, 2012). The manipulation of knowledge resources is especially critical in dynamic markets (Grant, 1996; Kogut, 1996).

Earlier, strategy scholars noted RBV could not adequately explain why some successful firms demonstrated timely responsiveness and management capability to effectively coordinate and redeploy internal and external competencies in dynamic environments (Teece & Pisano 1994; Eisenhardt & Martin, 2000). The dynamic capabilities framework analyzes the sources and methods of business value creation by firms in environments of rapid technological change, focusing on the firms' distinctive processes, shaped by the firm's resources and the evolution paths (Teece et al., 1997). The resource-based view (RBV) argues that resources that are simultaneously valuable, rare, imperfectly imitable, and non-substitutable (VRIN) are a source of competitive advantage (Barney, 1991); with the assumptions that resources are heterogeneous across organizations and that this heterogeneity can sustain over time (Barney, 1995). While RBV explains how some firms can earn competitive advantage and superior performance, it is essentially a static view (Barney 2001). It does not address how future valuable resources could be created or how the current stock of VRIN resources can be refreshed in changing environments (Priem & Butler 2001). The dynamic capability perspective, which is argued to be an extension of the RBV (Barney 2001), helps us understand how a firm's resource stock evolves over time and thus how advantage is sustained (Ambrosini & Bowman, 2009).

The RBV thinking considers the firm to be a bundle of heterogeneous resources, is shared by the dynamic capability view and other related theories such as the knowledge-based view (Ambrosini & Bowman, 2009). Hoskisson et al. (1999) noted that RBV (Barney,1991) focuses on the factors internal to the firm, and its foundations can be traced back to Penrose's (1959)'s theory of the growth of the firm. According to Wang and Ahmed (2007), the dynamic capabilities encapsulate wisdom from several earlier works such as distinctive competence (Hitt & Ireland, 1986), organizational routine (Nelson &Winter, 1982), core competence (Prahalad & Hamel, 1990), core capability (Leonard-Barton,1992), and combinative capability (Kogut & Zander, 1992). Several researchers have shifted their emphasis to intangible resources, such as those arising from knowledge and experience, as central to differentiating performance among firms (Barney, 1991; Teece et al., 1997).

Bellner and MacLean (2015) noted that the dynamic capabilities perspective provides an understanding that the firm's competitive advantage under a dynamic environment is derived from resource allocation processes and asset base positions and paths the firm takes (Teece et al., 1997); that dynamic capabilities consist of identifiable processes and routines; and, although they are idiosyncratic in detail, they have common features (Eisenhardt & Martin, 2000), involve absorptive capacities (Zahra & George,2002), and include knowledge and experience (Zollo & Winter, 2002). Dynamic capabilities are the organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve, and die. (Eisenhardt & Martin, 2000). Researchers have investigated firms to examine their capabilities in terms of how they leverage existing resources, create new resources, access external resources, and release resources to adapt to a changing environment (Zott, 2003).

Dynamic capabilities can be regarded as a transformer competence for converting resources into improved performance (Zollo & Winter, 2002). The resource alteration processes in firms also demonstrate how dynamic capability operates and reveals the important roles of resources; and the relationship between resources and dynamic capabilities in achieving precise resource allocations (Lin & Wu, 2014). Dynamic capabilities reflect an organization's ability to achieve new and innovative forms of competitive advantage given path dependencies and market positions (Leonard-Barton, 1992). Dynamic capabilities consist of strategic and organizational processes that create value for firms within dynamic markets by manipulating resources into new value-creating strategies (Eisenhardt & Martin, 2000). There is increasing evidence that firm performance is affected by these dynamic capabilities (Teece et al., 1997).

Teece (2007) extended the dynamic capabilities view by drawing from the social and behavioral sciences to specify the nature and micro-foundations of the capabilities necessary to sustain superior firm performance and identify the distinct managerial skills micro-foundations of dynamic capabilities. The concept of dynamic capabilities helps augment the resource-based literature on managerial resources (Castanias & Helfat, 1991, 2001). The manipulation of knowledge resources is especially critical in rapidly changing markets (Grant, 1996). More recently, Helfat and Peteraf (2015) noted that the micro-foundations of dynamic capabilities had assumed greater importance in searching for managerial factors that facilitate strategic change capability. Wu (2007) noted that dynamic capabilities mediate between firms' human resources and performance

Although Teece's (2007) primary concern was with enterprise-level sensing, seizing, and reconfiguring capacities, he acknowledges that the cognition of top executives contributes to the micro-foundations of dynamic capabilities. Previously, Helfat and Peteraf (2003) brought together cognition aspects with strategic management research on capabilities. Building on both Teece (2007) and Adner and Helfat (2003), Helfat and Peteraf (2015) showed how dynamic managerial capabilities could be disaggregated for analytical purposes into sensing, seizing, and reconfiguring components that have important cognitive underpinnings. While dynamic capabilities research has produced insights on strategic renewal and dynamic fit, there is a need for further research when it comes to how managerial capabilities produce changes in the firm's configuration of resources and competencies (Priem & Butler, 2001; Sirmon & Hitt, 2009).

The dynamic capabilities framework was created with an ambitious agenda to provide a general framework to help scholars and practitioners understand the foundations of firm-level competitive advantage and associated enterprise value creation in business environments where there is strong innovation-driven competition, often global in scope. (Teece, 2014). Strategy scholars have explicitly acknowledged the importance of dynamic processes, including acquiring, developing, and maintaining differential bundles of resources and capabilities over time (Dierick & Cool, 1989; Kogut & Zander, 1992; Szulanski, 1996; Zander & Kogut, 1995). Dynamic capabilities are embedded in organizational processes that guide the evolution of a firm's resource configuration (Zollo & Winter, 2002: Zott, 2003). Dynamic capabilities create and shape a firm's resource positions (Eisenhardt & Martin, 2000) and strategic capabilities (Kogut

& Zander, 1992), and in turn, these mediating variables determine the firm's product market position and therefore its performance (Zott, 2003).

The field of strategic management includes a large amount of literature devoted to the concepts related to organizational capabilities (Amit & Schoemaker, 1993; Dosi, Nelson & Winter, 2000; Helfat & Peteraf, 1993). A specific organizational capability typically implies that the organization has the capacity to perform a particular activity in a reliable and at least minimally satisfactory manner (Helfat et al., 2007; Helfat & Winter, 2011). While ordinary capabilities allow the firm to make a living in the present (Cepeda & Vera, 2007), dynamic capabilities are higher-order routines that represent a capacity to change the organizational resource base (Helfat & Winter, 2011). Teece (2014) noted that there are two important classes of capability: ordinary and dynamic, where ordinary capabilities involve the performance of administrative, operational, and governance-related functions that are (technically) necessary to accomplish tasks; and dynamic capabilities involve higher-level activities that can enable an enterprise to direct its ordinary activities toward high-payoff endeavors, which may require managing, or orchestrating the firm's resources to address and shape rapidly changing business environments. There is a broad consensus in the literature that 'dynamic capabilities' contrast with ordinary or operational capabilities by being concerned with change, and while the difference may not be clear and compelling in all cases; firms can use a heuristic guide that conforms to common sense and existing practice to note the differences (Pezeshkan et al., 2016; Winter, 2003).

A capability, ordinary or dynamic, can be harnessed to produce desirable outcomes, distinct from an organization's intentions, motivations, or strategy (Teece, 2014). Capabilities are often developed over time through complex interactions between the firm's resources (Amit & Schoemaker, 1993). Capabilities arise in part from learning, organizational resources, and organizational histories. They are untethered from particular products, such as a capability to make machines powered by internal combustion engine can manifest itself in the manufacturing of automobiles, boat motors, or lawnmowers (Teece, 2014). Dynamic capabilities may involve long-term commitments to specialized resources and pervasive patterning of the activity involved, resulting in higher costs of the commitments. Such additional costs may often outweigh the competitive value of the novelty achieved for some processes, highlighting the need for balance between the costs of the capability and the use that is made of it (Winter, 2003).

Ordinary capabilities, if well-honed, may enable a firm to perform its current activities efficiently (Teece, 2012; Zollo & Winter, 2002). Ordinary capabilities are perhaps rooted more firmly in routines than are dynamic capabilities (Teece, 2012). Organizational routines transcend the individuals involved, although the routines can, for some purposes, be usefully studied as developed and embedded in the minds of multiple employees (Miller et al., 2012). Capabilities are often built on the collective learning derived from how employees have worked together and on special equipment or facilities to which the firm has access (Teece, 2012). Ordinary capabilities permit some degree of sufficiency in the performance of well-delineated tasks (Teece, 2014). Operational capabilities are geared towards the operational functioning of the firm, including both staff and line activities (Cepeda & Vera, 2007). Ordinary capabilities help achieve technical efficiency and do things right in the business functions of operations, administration, and governance (Teece, 2014). While a firm's ordinary capabilities can enable it to perform current routine activities efficiently, dynamic capabilities, when combined with a good strategy (Rumelt, 2011), enable the enterprise to position itself to address the technological and competitive opportunities of the future (Teece, 2012).

Dynamic capabilities are 'strategic' and distinct from ordinary capabilities, and firms can maintain and extend competitive advantage by layering dynamic capabilities on top of ordinary capabilities (Teece, 2012). The dynamic capabilities emphasize a firm's constant pursuit of the renewal, reconfiguration, and re-creation of resources and capabilities to address the environmental change (Wang & Ahmed, 2007). Dynamic capabilities can govern other organizational activities. They allow an enterprise to generate superior profits by developing and producing differentiated products and services that address new and existing markets where demand is robust (Teece, 2014). Eisenhardt and Martin (2000) identify cross-functional RandD teams, new product development routines, quality control routines, technology transfer and/or knowledge transfer routines, and certain performance measurement systems as important elements of dynamic capabilities (Teece, 2012). Strong dynamic capabilities enable the firm to produce the best product type and something unique and exceptional in value (Teece, 2014).

Managerial skills around sensing, seizing, and transforming are required to sustain dynamic capabilities highlighting an important managerial function to achieve semi-continuous asset orchestration and renewal, including redesigning routines (Teece, 2012). Top managers help develop dynamic capabilities in businesses, such as an integrative capability in ambidexterity to perform targeted integration of emerging and mature businesses (Helfat & Winter, 2011). The deployment of dynamic capabilities is typically geared towards creating new configurations of functional competencies that better match the environment (Cepeda & Vera, 2007). Strong dynamic capabilities need to be complemented by difficult-to-imitate resources and good strategy. The combined strength of a firm's dynamic capabilities determines the speed and degree to which the firm's idiosyncratic resources can be aligned and realigned consistently with the firm's strategy (Teece, 2014). The combinative capabilities that allow the synthesis of existing resources into new applications are key knowledge-enabled dynamic capabilities (Kogut & Zander, 1992). Strategy scholars have noted that the "resources" and "dynamic capabilities" approaches have significantly helped management improve the understanding of the fundamental sources of competitive advantage and firm performance. Given this theoretical background, the KBV and Dynamic Capabilities perspective provides the conceptual framework to examine the role of Managerial Analytics HC and Employee Analytics HC in the context of BDA firm performance.

BDA and Firm Performance

Big data is characterized by the rapid growth of data volume, velocity and variety, and significant developments in data storage technologies (Mikalef et al., 2019). BDA has been used to describe the analytical techniques in data applications that are so large and complex that they require advanced data storage, management, and analysis technologies (Chen et al., 2012; Davenport, 2010). The modern business environment is highly digitalized, where massive amounts of data and valuable insights are available to firms, which can be used for business growth (Chen et al., 2012; Pappas et al., 2018). Firms use BDA to analyze data and enhance their business models in terms of enhanced customer service or increase operational efficiency (Corte-Real et al., 2017; Pappas et al., 2018). For example, Netflix moved to online video streaming services; and further used BDA data to analyze and recommend consumer content (Gunther et al., 2017; Vial, 2019).

BDA can offer invaluable insights and business value with the right technological and organizational resources (Agarwal & Dhar, 2014; Corte-Real et al., 2017; LaValle et al., 2011). Of the firms focusing their investments on BDA, the majority have the primary aim to derive important insights that can provide them with a competitive advantage and superior performance (Constantiou & Kallinikos 2015; Mikalef et al., 2018). The emerging literature on BDA has examined the relationship between BDA and firm performance. I review and summarize the key BDA factors from prior BDA and firm performance studies in Table 2.1, based on a search of journal articles on this topic from the EBSCO database. As shown in Table 2.1, Corte-Real et al. (2019) noted that the key factors for gaining BDA business value include BDA capabilities, BDA use, and the strategic role of BDA.

Table 2.1

BDA Firm Performance Studies, Research Agenda, and BDA Factors

BDA Study	**Research Agenda**	**BDA Factors**
Corte-Real et al. (2019).	Examine drivers of Big data analytics (BDA) value in firms, identifying antecedents of BDA business value at the firm level.	BDA Dynamic capabilities BDA Use Strategic Alignment of IT and Business. Strategic Role of BDA Environmental Volatility
Gunasekaran., et al. (2018).	Examine the role of big data and business analytics (BDBA) in agile manufacturing practices.	BDBA Capability Agile Enabling Practices Market Turbulence
Corte-Real, N., et al. (2017).	Explore Big Data Analytics (BDA) value chain based on a knowledge-based view.	Knowledge Assets Agility Process-level performance
Al Jabri, H. A., et al. (2017).	Exploring the usage of big data analytical tools in telecommunication industry.	BDA Tools Infrastructure BDA Tools Features BDA Tools Usage
Khan, Z., & Vorley, T. (2017).	Examine the role of big data text analytics as an enabler of knowledge management.	BDA utility Text Analytics Data visualization
Sanders, N. R. (2016).	How to use big data to drive your supply chain.	BDA Capabilities Supply Chain Coordination
Chen, D.Q., et al. (2015)	Value creation from organizational BDA usage and key antecedents of organizational-level BDA usage.	Technological factors Organizational factors Environmental factors BDA usage
Hagen, C. & Khan, K. (2014)	Examine Leadership Excellence in Analytic Practices (LEAP).	Top Management Support Explorer Leadership Follower Leadership Laggard Leadership
Hart, R. & Hiltbrand, T. (2014).	Bridging the Big Data Analytics Skill Gap with Crowdsourcing.	Business Skills Analytics Skills Technical Skills
McCafferty, D. (2014).	Explore Big Data's Promise of Competitive Advantage.	Analytical databases Relational databases Data warehouses Big Data Tools

Other studies, such as Gunasekaran et al. (2018), have examined factors such as BDA Capability, and Agile practices, while Al Jabri et al. (2017) explored BDA Tools Infrastructure and BDA Usage. Before 2017, most BDA studies primarily focused on infrastructure, and analytics tools, while several related resources, such as knowledge, have been largely disregarded (Mikalef et al., 2018). Although BDA knowledge assets were earlier often ignored, recently Corte-Real et al. (2017) explored BDA knowledge in relation to competitive advantage and hypothesized that BDA endogenous and exogenous knowledge would positively influence dynamic capabilities such as organizational agility. The literature shows a lack of empirical research especially related to the managers' and employees' knowledge, skills, and abilities. I examine these under-researched factors of analytics human capital and associated firm capabilities in this study.

Hypotheses Development

Based on the literature review and theoretical background, I hypothesize that managerial and employee analytics human capital are valuable knowledge resources that are vital sources of competitive advantage and superior firm performance. I posit that impact on firm performance will be greater in firms with higher levels of managerial and employee analytics human capital. I further argue that the impacts of managerial analytics HC on firm performance will be mediated through the firm's strategic-change dynamic capability. In contrast, the productive operational capability will mediate the impacts of employee analytics HC on firm performance. I also posit that employee analytics HC would positively moderate the relation between managerial analytics HC and firm performance. Considering the other key moderating factors, I posit that the environmental dynamism would moderate the managerial analytics HC impacts on performance, while IT infrastructure quality would moderate the impact of employee analytics HC on firm performance. The research model and hypotheses are depicted in Figure 1-1.

Managerial Analytics HC, Strategic Dynamic Capabilities, and BDA Firm Performance

Management scholars have now firmly established the role of knowledge as one of the key firm resources of modern times (Drucker, 1993; Penrose, 1959) and have underscored the importance of knowledge in strategic and competitive contexts (Grant,1996). Strategic leaders create an advantage rooted in the development of unique knowledge and valuable insights that can create distinctive firm capabilities (Nag & Gioia, 2012). Prior strategy scholars have investigated the influence of managerial abilities on a firm’s strategic performance in different resource contexts (Holcomb, Holmes, & Connelly, 2009). Currently, BDA presents an important context to examine the managerial analytics of HC resources.

The knowledge and insights provided by BDA are being recognized as providing an immense opportunity for improving strategic value (Abbasi et al., 2016; Agarwal & Dhar, 2014; LaValle et al., 2011). BDA literature indicates that a successful BDA strategy can provide superior firm performance in multiple areas such as profitability and market-share growth (Barton & Court, 2012; Davenport & Harris, 2007; McAfee & Brynjolfsson, 2012). With the increasing role of data, it is imperative for management to convert data into meaningful information and intelligence related to a business (Fitz-Enz, 2000). Analytic skills of managers such as interpretive and inferential skills are important for firms as the full import of facts, statistics, and developments are rarely obvious (Teece, 2007). To take advantage of analytics, firms need senior executives who are passionate about analytics and fact-based decision-making and can manage the changes in business processes motivated by analytics initiatives (Harris et al., 2011).

Prior research indicates that managers in professional roles may possess greater cognitive complexity, which in turn provides greater ability to use innovative technology effectively and derive business value for the firm (Li et al., 2006; López-Muñoz 2017). Some scholars have studied the impact of managers' actions on resource value creation and found that managerial ability affects firms' productivity (Holcomb, Holmes & Connelly, 2009). In the context of BDA, it has been noted that performance improvements arise when managers use these resources to effectively predict and optimize outcomes for specific business problems (Barton & Court, 2012). For example, using analytics to guide future pricing strategies, senior executives can make data-driven decisions based on insights from patterns and simulations provided by available data (Lavalle, 2011).

Managers can use BDA-informed strategies to set optimal prices, detect product-quality problems, or identify loyal and profitable customers (Davenport & Harris, 2007). Senior managers' general knowledge and abilities have been positively related to discovering and satisfying emerging customer needs with novel technological solutions (Talke et al., 2011). Analytics applications and the use of analytical methods by managers can provide valuable decision-making knowledge by accurately forecasting market trends (Hedgebeth, 2007; LaValle et al., 2011). As more data becomes available, managers cannot make effective use of the available market data, resulting in lost sales and market share (Kiron & Shockley, 2011). For example, top executives at Errazuriz, a leading European wine company, made the wrong decision to impose a 25% price increase on the wines sold to a partner firm, ignoring extensive market data indicating that Errazuriz wines were already at the upper boundary of customers' expected price range; resulting in a major loss in sales and market share (Guesalaga, 2014).

Managers using analytics solutions effectively can create models of spending patterns that can improve firm profitability outcomes (Piccolo & Watson, 2008). For example, top management at Marriott International has used analytics successfully to achieve price optimization and profit maximization. Marriott developed its Total-Hotel Optimization Program for setting the optimal price for guest rooms, a key analytics process in hotel operations and made the analytics tool available to its revenue managers (Davenport, 2006). While some effects of managerial analytics skills should be evident from a firm's financial accounting performance measures, other long-term effects can be assessed by improving its market performance. Therefore, I hypothesize that:

> ***H1:*** *Firm's Managerial analytics human capital will be positively related to firm performance*

More specifically, I hypothesize that:

> ***H1a:*** *Firm's Managerial analytics human capital will be positively related to firm performance in terms of its market performance.*

> ***H1b:*** *Firm's Managerial analytics human capital will be positively related to firm performance in terms of its financial accounting performance.*

Scholars have pointed out that firms' managerial human capital has important implications for strategic capabilities and performance (Kor & Leblebici, 2005). Trkman et al. (2010) argued that data analytics skills lie at the heart of managerial decision-making in all business analytics applications as relevant decisions must be based on bundles of very large volumes of internal and external data. Several prior studies have also documented that differences in managerial knowledge levels are associated with strategic changes in firm resource allocations (Kaplan, Murray, & Henderson, 2003).

Analyzing market data reports is crucial for top managers who want to develop crucial data-driven decision-making abilities (Kiron & Shckley, 2011; Lavalle et al., 2012).

According to the dynamic managerial capabilities view, managerial abilities, such as their data analytics skills, impact firms' strategic change capability (Helfat & Martin, 2015), In the management literature, strategic change has been defined as the overall change in a firm's pattern of resource allocation in multiple key strategic dimensions (Carpenter, 2000; Finkelstein & Hambrick, 1990; Zhang, 2006). This conceptualization of strategic change is based upon the notion that strategy is defined by the pattern in a firm's resource allocations (Mintzberg, 1978). Scholars have noted that managerial analytics skills are likely to significantly impact firms' resource allocations and strategic change capability (Kiron et al., 2014; Lavalle et al., 2011). Based on these insights, I hypothesize that:

> ***H2a:*** *Firm's managerial analytics human capital will be positively related to the strategic change capability of the firm*

Differences in firms' managerial and strategic capabilities can, in turn, lead to heterogeneity in firm performance (Adner & Helfat, 2003). The management's strategic decision-making and the firm's strategic flexibility in resource deployment are important factors for the firm's success (Nadkarni & Narayanan, 2007). Managers' ability to provide firms with an effective product allocation strategy can be enhanced by the effective use of customer analytics applications, which can provide insights into customer loyalty patterns and, in turn, help increase sales (Piccolo & Watson, 2008). Analytics applications and analytical methods can enhance valuable decision-making abilities for managers, helping the firm inaccurately forecasting market trends (Hedgebeth, 2007).

Big data analytics is a major technological advancement that presents a need to assess the impact of the capabilities that impact firm profitability (Abbasi et al., 2016).

Case studies and anecdotal examples illustrate the link between firms' analytics linked strategic capabilities and firms' revenue and market growth (Kiron & Shockley, 2011). For instance, continuing with the earlier Marriott example, it also provided an analytics application to its managers to optimize offerings to frequent guests and assess the likelihood of those customers' defecting to competitors, leading to increased customer retention (Davenport, 2006). Strategic resource allocation capabilities can positively impact firms' pioneering initiatives and market shares (Marimuthu et al., 2009; Shrader & Siegel, 2007). Scholars have noted that strategic change capability enhanced my managerial skills is likely to significantly impact firm performance (Kor & Leblebici, 2005; Trkman et al., 2010). I extend that notion to BDA-driven strategic change. I anticipate that the relationship between managerial analytics human capital and firm performance will be mediated by the firm's dynamic strategic change capabilities, as managerial analytics skills drive change, driving firm performance. This expectation leads to our next hypothesis:

> ***H2b:*** *BDA-enabled strategic change capability will at least partially mediate the positive relationship between managerial analytics human capital and firm performance.*

Employee Analytics Human Capital, Operational Productive Capability, and BDA Firm Performance

Human capital begins with human resources in the form of knowledge and skills embodied in people, and the key stock of human capital in a firm comes from its employee skill base (Koch & McGrath, 1996; Snell & Dean, 1992). Within organizational research, an organization's human capital in terms of employee skills has been recognized as potentially important performance implications (Takeuchi et al., 2007). Scholars have noted that BDA brings new opportunities for the firms in knowledge and expertise collaboration (Bi & Cochran, 2014). According to the knowledge-based view, unique abilities to create and exploit wisdom enhance outcomes (Grant, 1996); thus, the knowledge-based view provides a foundation to expect that BDA-related employee knowledge development impacts firms' outcomes (Hult et al., 2004). The knowledge and skills of the workforce separate the winning companies from the also-rans, and the power of human capital is largely held in the knowledge and skills an employee possesses (Fitz-Enz, 2000).

To take advantage of the opportunities provided by data analytics, firms need to find and nurture analytical talent, the employees who conduct quantitative analysis and apply statistical models to make better decisions and achieve better results. Connecting these specialists with the business will ensure that they understand how their human capital can drive value for the business (Harris et al., 2011). Employees having business analytics capabilities can help in gaining insights parsed from data sources and help initiate value-creating firm outcomes (Shanks et al., 2010). In a recent study, Wamba et al. (2017) noted the role of effective BDA usage by firms to enhance performance, such as Target Corporation, which uses BDA through its loyalty card program to track customers' purchasing behaviors and predict their future buying trends; while GE, which is planning to use BDA to improve the efficiency of the 1500 gas turbines it monitors by means of software and network optimization, as well as to improve the dispatching of service and the coordination of gas and power systems (Ward, 2014).

While scholars have found support for a positive relationship between human capital and firm performance generally (Shrader & Siegel, 2007), I anticipate a specific relationship between employee analytics human capital and firm performance. For example, Procter and Gamble developed a sophisticated analytics program to improve the profitability of promotional spending with its retailers. Its launch included training and a new promotions analysis tool for sales representatives, which produced a shift in mindset. The power of promotions analytics is now used to further the common goal of increasing profitability (Barton & Court, 2012). Given these observations of improvements in firm performance, I hypothesize that:

> ***H3:*** *Firm's Employee analytics human capital will be positively related to firm performance*

More specifically, I hypothesize that:

> ***H3a:*** *Firm's Employee analytics human capital will be positively related to firm performance in terms of its market performance.*
>
> ***H3b:*** *Firm's Employee analytics human capital will be positively related to firm performance in terms of its financial accounting performance.*

The employee human capital of a firm, as manifested by employee knowledge and experience, represents a key element of a firm's efficiency capabilities (Schulz et al., 2013). Operational firm capabilities can be measured against the requirements of specific tasks, such as productivity and inventory turns. They can thus be benchmarked to best operational practices are those that increase its efficiency (Teece, 2014). Knowledge codification by staff into procedures and technologies also makes experience and routines easier to apply (Zander & Kogut, 1995). For example, most firms today have systems to monitor inventories. However, firms with effective BDA capabilities can also predict problems with demand and supply chains, achieve low inventory rates, and higher rates of flawless orders (Davenport, 2006). United Airlines implemented a BDA solution that improved the accuracy of time schedules for its pilots and cabin crews, which helped it drastically eliminate gaps between estimated and actual arrival times, gaining productivity benefits worth several million dollars a year (McAfee & Brynjolfsson, 2012). Studies have also shown that BDA's insights help lower healthcare costs by reducing the amount of waste and fraud (Srinivasan & Arunasalam, 2013).

Recently Wamba et al. (2017) noted the impacts of BDA enabled operational capabilities across a variety of industries noting that major retailing firms are leveraging BDA to make just-in-time recommendations (Tweney, 2013); while BDA helped the healthcare sector to reduce operational costs (Liu, 2014); and in the manufacturing sector, BDA enables better asset and business process monitoring (Davenport et al., 2012). Strategy scholars have noted the role of human capital as key to effective use of technology leading to productivity gains (Kor & Leblebici, 2005; Skaggs & Youndt, 2004). Employees develop domain-specific knowledge structures or mental schemas (Lord & Maher, 1990), which confers an ability to achieve superior performance due to the continued mapping of ordered mental steps pertinent to a particular activity (Read, 1987).

Intangible firm resources such as knowledge allow firms to add value to incoming factors of production, and much of an organization's knowledge resides in its human capital. (Hitt et al., 2001). Thus, firms create value through their selection, development, and use of human capital (Lepak & Snell, 1999). Since firm investments to increase employee skills, knowledge, and abilities carry both out-of-pocket and opportunity costs, they are only justified if they produce future returns via increased productivity (Youndt et al., 1996). Human capital contributes to the strategic value of the firm through its potential to improve firm efficiency and effectiveness (Barney, 1991; Lepak, David & Snell, 2002). Prior empirical studies have also found that human capital can positively impact firms' productivity (Gong, 2003). Hence, I posit that BDA employee human capital helps to improve firms' productive capabilities. Based on these arguments, I hypothesize that:

> ***H4a:*** *Employee analytics human capital will be positively related to firm productive capability.*

Firm capabilities are often built on the collective learning of routines derived from employees that work together (Teece, 2012), and such capabilities help in the performance of well-delineated tasks (Teece, 2014). Firms with improved production capabilities help increase firm efficiency and drive value for the business (Harris et al., 2011; Kiron & Shockley,2011). A firm's ordinary capabilities can help achieve technical efficiency and do things right in the business' operational functions; and provide business value (Teece, 2014). The use of analytics applications by employees with extensive analytics capabilities leading to greater production capabilities should ultimately result in better firm performance (Davenport & Harris, 2007). As a consequence, I anticipate that while employee analytics human capital ultimately improves firm performance, its influence on performance is in good measure mediated by the superior firm productive capabilities it engenders, as employees come to use data to optimize business processes, thus enhancing performance (Shanks et al., 2010; Watson & Wixom 2007). Based on this notion, I hypothesize:

> ***H4b:*** *The relationship between a firm's employee analytics human capital and firm performance will be mediated by the firm's productive capability*.

Moderating Role of Employee Analytics and Managerial Analytics Human Capital

Strategy scholars have noted that firm performance outcomes such as market growth and profitability are impacted by managerial abilities and employee knowledge stocks (Holcomb, Holmes & Connelly, 2009; Kor & Mesko, 2013). Researchers have noted that human capital influences firm performance in terms of skills, education, and training (Becker, 1983). For BDA success, data collection and technology systems are not enough. Instead, firms need individuals who can focus attention on and use their data analytics talents and their leaders to interpret meaning in their data and communicate effectively (Nold & Michel, 2016). For example, a major retailer intended its BDA model to optimize returns on advertising spending. However, despite considerable BDA investment by top management, the data were not used by frontline marketers, who made key decisions on ad spending but had little familiarity with utilizing the data being generated (Barton & Court, 2012).

Scholars have found support for both the direct and interaction effect of human capital in the strategy-performance relationship (Hitt et al., 2001). Strong dynamic capabilities are enabled by the firm's valuable resources (Teece, 2014), such as employee HC and managerial HC, to align the resources consistent with the firm's strategy. Since much of organizational knowledge resides within its people, employee HC represents valuable knowledge embedded within the firm that can help solve unique problems of the firm (Prajogo & Oke, 2016; Kor & Mahoney, 2005); and therefore, help managers in their endeavors to develop strategic change capability and superior firm performance. Some researchers have found that the effect of managerial ability on firm outcomes varies with the quality of firms' overall human resources. (Holcomb, Holmes & Connelly, 2009). Given the likely impact of employee analytics human capital on the managerial analytics' human capital, I hypothesize as follows:

> ***H5a:*** *The level of firms' employee analytics human capital will positively moderate the relationship between firms' managerial analytics human capital and firms' performance.*

> ***H5b:*** *The level of firms' managerial analytics human capital will positively moderate the relationship between firms' employee analytics human capital and firm performance.*

Moderating Role of Environmental Dynamism

Strategy scholars have been investigating the role of environmental factors in the effectiveness of managerial, strategic outcomes (Eisenhardt, 1989; Pisano,1994; Zahra, 1996). Many scholars classify environment characteristics into dynamism, complexity, and munificence dimensions (Dess & Beard, 1984; Li & Liu, 2014; Mintzberg, 1983). Several studies show that the business environment's dynamism has significantly influenced the firm's strategy (Davis, Eisenhardt, & Bingham, 2009; Priem, Rasheed, & Kotulic, 1995; Zahra & Covin, 1993). Environmental dynamism refers to the rate and the unpredictability of change in a firm's external environment (Dess & Beard, 1984). It may influence relationships between various firm-level constructs and firm performance, including business-level strategy (e.g., Miller, 1988) and strategy-making processes (Garg, Walters & Priem, 2003; Rajagopalan, Rasheed, & Datta, 1993). Firms can be located on an environmental continuum ranging from stable to dynamic (Priem et al., 1995).

The environmental context in which firms exist might augment or diminish the performance effects associated with their resources (Lepak, Takeuchi, & Snell, 2003). Researchers note that environmental dynamism impacts firms' decision-making (Dess & Beard 1984), and unexpected market change can compel firms to revise their business strategy. Many researchers argue that environmental dynamism plays an important role in developing dynamic capabilities and firm performance (Teece, 2007; Wu, 2010). Highly dynamic environments are likely to compel firms to develop new products, new processes, or new services (Zahra & Covin, 1993; Zahra, 1996). When the environment is highly volatile, the environment reduces current capabilities' potential value, forcing enterprises to carry out frequent changes, requiring strong dynamic capabilities (Li & Liu, 2014).

Under such dynamic environments, firms can harness their HC, including strategic problem-solving skills, to develop capabilities to gain an advantage in the market and boost firm performance (Prajogo, & Oke, 2016). In dynamic environments, the executives need real-time information, especially in a firm's competitive environment (Eisenhardt, 1989). Managers are increasingly relying on big data analytics to inform their decision-making in real-time and direct their future firm initiatives (Constantiou & Kallinikos, 2015). The knowledge necessary for matching key environmental conditions with the right organizational capabilities is crucial for executives in dynamic environments to make sound decisions (Garg et al., 2003).

While there is an assumption that BDA-enabled capabilities may be more valuable under conditions of high uncertainty, there is a limited empirical understanding of the impact that the external environment has in highly dynamic and complex markets. The impact of environmental uncertainty on a firm's BDA-enabled capabilities and competitive performance needs to be further examined (Mikalef et al., 2019). The dynamic environment challenges may require better BDA skills that enable firms to be more proactive and swifter in identifying new business opportunities. Given the likely impact of environmental dynamism on managerial analytics human capital in relation to dynamic capabilities and firm performance, it is hypothesized that:

> ***H6:*** *The degree of environmental dynamism will positively moderate the relationship between firms' managerial analytics human capital and firms' performance.*

Moderating Role of IT Infrastructure Quality

IT Infrastructure quality typically refers to the ability provided by a firm's IT platform to share information across different functions, innovate, and exploit business opportunities (Bhatt & Grover, 2014; Corte-Real et al., 2019). IT infrastructure represents a firm's technology platform and information foundation, and it is normally conceived to include hardware, software, networks, and data processing architecture (Zhu, 2004; Weill et al., 1998). Previously, IT infrastructure was considered an important organizational factor that influences business value from new technological initiatives (Bharadwaj, 2000; Lewis & Byrd, 2003). IT infrastructure involves the expertise required to provide reliable physical services and extensive electronic connectivity for the firm, and the firms that have developed a higher level of IT infrastructure capabilities can implement their business initiatives more efficiently (Broadbent, Weill & St. Clair, 1999; Weill, Subramani, & Broadbent, 2002). IT infrastructure in the form of communications networks and shared databases can constrain or enable knowledge sharing and business initiatives across the firm (Ryan et al., 2010; Zhu, 2004).

Organizations that have succeeded in using IT to support knowledge sharing applications have found that technology platforms and other organizational practices and policies influence knowledge sharing efforts (Brazelton & Gorry, 2003). While technology alone is not a panacea for ensuring that knowledge will be shared, the knowledge-based perspectives recognize that IT can be a powerful tool for enabling and coordinating the distribution of knowledge within and across organizational boundaries (Ryan et al., 2010). The technological infrastructures of sharing knowledge can alleviate problems regarding the distribution of knowledge that the hierarchical structure may have reinforced (DeSanctis & Poole, 1994). Early Information systems researchers also viewed IT infrastructures as a critical resource of the firm (Keen 1991, Weill & Broadbent 1998). According to Armstrong and Sambamurthy (1999), quality of IT infrastructure refers to the extent to which a firm has diffused key information technologies into its base foundation for supporting business applications. Previously, Keen (1991) argued that a sophisticated infrastructure enhances the inter-organizational connectivity across departmental units throughout the enterprise with key external business partners.

The IT infrastructure of firms tends to be firm-specific and evolves over long periods, during which gradual enhancements are made to reflect changing business needs. While individual components of the firm’s overall IT infrastructure can be purchased in markets, an integrated infrastructure that is tuned to the specific needs of the firm cannot be acquired easily as new technologies are often wrapped around the old and carefully stitched together in a complex ensemble of interlocking systems (Segars & Grover, 1998; Zhu, 2004). The IT infrastructure quality mirrors an organization's historic progress with the use of IT and tends to influence the success of future technology-based solutions (Lewis & Byrd, 2003). IT researchers often regard IT infrastructure as an architecture of technical components shared across the organization, and define it using four categories: platforms, networks and telecommunications, data, and core applications (Fink & Neumann, 2009).

Scholars have also noted that the IT human capital in terms of the IT personnel's knowledge and skills is closely related to the IT investments and IT infrastructure quality (Lee et al., 2002; Zhu, 2004). Researchers have noted the need to empirically examine the interrelationships of IT Infrastructure with other business value outcomes; and pointed that this view is theoretically strengthened and extended by using strategic management's conceptualization of firm resources and capabilities (Fink & Neumann, 2009). The need for effective IT infrastructure has also been previously found in terms of the benefits from other enterprise system applications (Gefen & Ragowsky, 2005; Mueller et al., 2010).

BDA research has also noted the key role of IT infrastructure as an enabling platform for the success of BDA initiatives, which are facilitated by integrated IT platforms to deliver effective data-driven business models (Agarwal et al., 2010; Wang, Kung, & Byrd, 2018). BDA capabilities to gain business value of information need appropriate and cost-effective IT infrastructure starting with data collection, repository and process, and dissemination of data (Jagadish et al., 2014; Wang et al., 2018). Prior research on a firm's IT capabilities has also noted that IT personnel-enabled capabilities are influenced by IT infrastructure quality, which in turn is related to firm performance (Kim, Shin, & Kwon, 2012; Wamba et al., 2017). Strong IT-enabled BDA can improve data-driven decision-making, reinforce customer relationship management, and enhance operational efficiency and overall firm performance (Kiron, 2013; Wamba et al., 2017). Given this background on the positive influence of IT Infrastructure quality, it is hypothesized that:

> ***H7:*** *The level of IT Infrastructure quality will positively moderate the relationship between firms' employee analytics human capital and firms' performance.*

CHAPTER 3

METHODOLOGY

This chapter provides information regarding the methodology to be used in this dissertation study, including the sample generation, operationalization of the variables, and the statistical procedures employed in hypothesis testing. First, the information is provided regarding the sample and the procedures used to collect data for the empirical study. Next, the operationalization of dependent, independent, mediating, moderating, and control variables is described. Finally, the chapter concludes with the details of the statistical techniques used to analyze the research hypotheses.

Sample and Data Collection

As this study aims to measure the impacts on firm-level performance, the unit of study is an organization. Consistent with similar studies in strategic management, an appropriate representative sample population for the business organizations were found in the Fortune 500 companies, which is the list of the largest 500 public U.S. firms by total revenue that operate in multiple industries (Crossland et al., 2014; Feldman & Montgomery, 2015; Li & Greenwood, 2004; Wiersema & Bantel, 1992). This sample includes firms characterized by considerable variation in competitive dynamics, profitability, and stages of the industry life cycle (Crossland et al., 2014; Li & Greenwood,

2004) and therefore was found appropriate for examining the strategic effects of managerial and employee analytics HC. Previous studies examining top management impacts on strategic firm outcomes have also used samples of Fortune 500 companies (Feldman & Montgomery, 2015; Maritan & Brush, 2003; Westphal & Fredrickson, 2001). Annual financial data for these firms would be obtained from the Thomson Reuters database provided by WRDS (Wharton Research Data Services) for the most recent year for which full financial data is available at the time of the study, which is 2019.

Dependent Variables

Firm Performance

Several empirical studies have noted that firms' market performance measures are often more important indicators of financial performance than other performance measures based on accounting data, especially in studies involving firms' human capital and impacts of technology solutions (Abdolmohammadi, 2005; Jayaraman et al., 2000). Important reasons for using a market-based performance measure are that, firstly, unlike other accounting performance measures, stock market-based performance measures are not influenced by firm-specific financial reporting rules. Secondly, a firm's managers are expected to maximize the firm's market value (Jayaraman et al., 2000). Therefore, in the study, we also use a firm's Market capitalization as the key indicator of firm performance, consistent with multiple prior managerially relevant studies (Abdolmohammadi, 2005; Kumar & Shah, 2009). The Thomson Reuters database provided by Wharton Research Data Services (WRDS) was used to collect data, with

2019 as the focal year, which was the most recent fiscal year at the time of data collection.

As some strategy scholars have noted the need to consider both market-based and accounting-based firm performance, we also check our main effects with a financial accounting-based firm performance measure. A review of empirical studies in strategic management reveals that the accounting measure, Net Sales Growth is a critical measure of firm performance in evaluating the success of new firm initiatives (McNamara, Haleblian, & Dykes, 2008; Zollo & Singh, 2004). Also, Net Sales Growth as a performance measure has been used in studies involving the effects of technology solutions and dynamic capabilities (Nicolaou, A. I., & Bajor, L. H., 2004; Hill et al., 2018)). Also, being a growth measure is a better measure when comparing firms among different industries and business domains. Therefore, Net Sales Growth was deemed appropriate for this study’s accounting-based firm performance. The Thomson Reuters database provided by Wharton Research Data Services (WRDS) was used to collect data for 2019, which is the most recent fiscal year for which annual data is available.

Mediating Variables

Strategic Change Dynamic Capability

Consistent with major prior studies on strategic change (Carpenter, 2000; Finkelstein & Hambrick, 1990; Zhang & Rajagopalan, 2010), I used six key strategic dimensions to create a composite measure of strategic change dynamic capability:
(1) advertising intensity (advertising/ sales), (2) research and development intensity (RandD/sales), (3) plant and equipment newness (net P&E/gross P&E),
(4) nonproduction over-head (selling, general, and administrative [SGA] expenses/sales),

(5) inventory levels (inventories/ sales), and (6) financial leverage (debt/equity). The data for these variables will be obtained from the Thomson Reuters database for the most recent year, 2019. For this measure, I calculated the differences in the various ratios between the most recent and prior years and then adjusted for the industry effect by subtracting the industry median changes in these ratios. The relevant industry was defined as the focal firm's primary four-digit (SIC code), and the focal firm was excluded in calculating industry median values (Huson, Malatesta, & Parrino, 2004).

Productive Capability – Cost Efficiency

Several prior scholars have noted that improvements in cost efficiencies, especially reducing production costs, are a key indicator of a firm's productive capability (Hill & Miller, 2018; Nicolaou & Bajor, 2004). A key measure to indicate this cost efficiency is the widely used Cost of Goods Sold / Sales ratio, commonly called the COGS/Sales measure (Feng et al., 2005; Nicolaou & Bajor, 2004). As this a well-established measure has been especially useful in studies involving the impacts of new technology, we adopt this measure in our study. As a reduction in cost indicates improved productive capability, the productive capability variable in this study is the additive inverse of the COGS/Sales measure.

Independent Variables

Managerial Analytics Human Capital

LinkedIn is a widely used professional networking portal on which users report professional information in their profiles, including employment histories, education, and skills (Gerard, 2012). LinkedIn includes much of the white-collar US workforce, and LinkedIn appears to contain profiles of over 80% of the total US information technology-related workforce as reported by the Bureau of Labor Statistics (Tambe, 2014). The LinkedIn database has been used to assess firm employees' analytic skills and abilities in several recent big data studies (Stanton & Stanton, 2016; Tambe, 2014). Recently studies have measured managerial, and employees' skill sets using professional networking portal data (Hitt et al., 2016; Tambe, 2014). Some studies have detailed the specific skills that are relevant for big data and analytics positions (Cegielski & Jones-Farmer, 2016). Similarly, we used a BDA skill set in this study that included the following skills: Big Data Analytics, Business Analytics, Business Intelligence, Analytics, Data Mining, Analytical Skills, Business Analysis, Machine Learning, Big Data, and Data Analysis (Appendix A).

The LinkedIn database provides options to search for managers with specific skills for each company, providing managers with such skills. I can also find the total number of managers for a given company and, therefore, get managers with analytics skills. I use the percentage of managers having BDA skillsets as our measure of managerial analytics HC. I calculate this for all Fortune 500 companies, most of which are available on the LinkedIn database. A similar approach for measuring human capital has been used in several recent studies using employee data from the online professional network with specialized skills (Azelius & Johansson, 2019; Tambe & Hitt, 2012; Tambe, 2014). The LinkedIn data is collected for 2018 to have a year lag for dependent variables, which come from financial WRDS data from 2019.

Employee Analytics Human Capital

Using the procedure and LinkedIn database as mentioned for operationalizing Managerial Analytics HC, I derived the measure for Employee analytics HC. The

LinkedIn database provides options to search for the employees with specific skills for each company, providing the number of employees with such skills. As mentioned in the previous section, I use the BDA skill-set to find employees with BDA skills and find the total number of employees for a given company. I, therefore, get the percentage of employees with analytics skills. I calculated this for the Fortune 500 companies, most of which were available on the LinkedIn database. I used the percentage of employees with BDA skillsets (Appendix A) as our employee analytics human capital measure. This approach for measuring human capital has been used in prior studies especially related to IT employee skills research (Azelius & Johansson, 2019; Tambe, 2014). The LinkedIn data is collected for the year 2018 to have a year lag for dependent variables, which come from financial WRDS data from 2019.

Moderating Variables

Environmental Dynamism

Environmental dynamism is a widely used moderating variable in strategic management studies (Boyd, Gove, & Hitt, 2005), especially in dynamic capabilities and firm performance (Girod & Whittington, 2017). Several prior studies apply Dess and Beard's (1984) widely used industry-based "environmental dynamism" measure (Boyd, Gove, & Hitt, 2005), which measures the rate of change of annual industry sales. Following methods previously reported in the strategy literature, I group sales at the industry-level using SIC Code to derive environmental dynamism as the variance of sales of the five years preceding the focal year. The Thomson Reuters database for 2019 provided by Wharton Research Data Services (WRDS) was used for this measure.

IT Infrastructure Quality

The companies' data for Computer Software and Equipment expenses has been widely used to measure a firm's IT infrastructure in IT productivity and IT adoption research (Brynjolfsson & Hitt, 2003, Forman et al., 2005; Hong & Rezende, 2012; Tambe et al., 2014). Following prior scholars, I use the Computer Software and Equipment data from the Thomson Reuters database for 2019 provided by Wharton Research Data Services (WRDS) to measure IT Infrastructure quality in this study.

Control Variables

Firm Size

Firm size has been argued to be directly related to issues of strategic outcomes (Carpenter, 2000; Mintzberg, 1978; Zhang & Rajagopalan, 2010), and following prior research, the firm size was controlled and operationalized as the logarithm of the number of firm employees. The data for this variable is obtained from the WRDS database.

Prior Firm Performance

Prior firm performance has been considered an important control variable in prior strategy research (Carpenter, 2002; Zhang & Rajagopalan, 2010) and was found relevant for this study. It was measured using return on assets (ROA) in the prior year (Carpenter, 2000). I consider that inclusion of “Prior firm performance” helps to avoid the issue of omitted variables in the research model, as “Prior firm performance” has also been used as an instrumental variable in several strategy studies (Zhang & Rajagopalan, 2010) and it is important for the research model. The data was collected from the WRDS Thompson Reuters database for the year 2018, being the prior year for the focal year of the firm performance in the study, which is 2019.

Industry Effect

For the industry effect, I used relevant industry groups as a control variable based on the sample firms' primary four-digit SIC codes, which were categorized into seven groups with the use of dummy variables (Carpenter, 2002; Zhang & Rajagopalan, 2010). Similar prior strategy research has controlled the sampled firms' industry effect using SIC groups (Carpenter, 2002; Girod & Whittington, 2017).

Capital Intensity

Scholars investigating business and process capabilities stress the need to control for capital intensity as higher capital-intensive firms are likely to differ in quality processes from lower capital-intensive firms in areas such as technology adoption (Elmasr, 2007; Hendricks & Singhal, 2001). I follow prior scholars and measure capital intensity as the value of property, plant, and equipment divided by the total no. of employees (Elmasr, 2007; Huselid et al., 1997).

Firm Age

Prior strategy research has noted that the firms' age may affect the firm's productivity as older firms may differ from younger firms in technical abilities (Cucculelli et al., 2014). Therefore, I control for firm age when modeling for productive capability in this study. Firm Age was measured as the number of years since the firm's self-reported establishment. Firm age was log-transformed to normalize its distribution and then standardized before inclusion in the research model (Anderson & Eshima, 2013).

Hypotheses Testing

Analytical Method

In this study, I aim to examine the relationships between the operationalized independent, mediating, and dependent variables, and the popular statistical technique to assess such relationship is regression analysis, where the most common type of regression is the linear form employing the ordinary least square (Chenhall & Moers, 2007). For testing the hypotheses of this study, I would employ ordinary least squares (OLS) hierarchical regression models, which have been widely used in similar empirical strategy studies (Garg et al., 2003; Le & Kroll, 2017). The basic OLS regression equation is often represented as: $y(i) = \alpha + \beta.x(i) + \varepsilon(i)$, where "y" represents the dependent variable, "α" represents a constant, "β" the coefficient, "x" represents the independent variable, and "ε" represents the error term (Semadeni et al., 2014).

This study employs cross-sectional data (with lagged dependent variable) using a single observation for each sample firm, and hypotheses testing for such research model can be done by the variants of ordinary least squares (Hitt et al., 2001; Le & Kroll, 2017). The hierarchical regression approach helped assess each set of variables (Aiken & West, 1991) and was suitable for this study. The research questions involving moderation and mediation effects are best examined using variants of least squares regression (Hayes, 2013). I employ the widely recommended PROCESS macro for SAS (Hayes, 2018) for mediation and moderation regression analysis, as it allows for advanced estimation of mediated and moderated regression models.

Testing Hypothesis 1 and 2a, 2b Mediated Relationship

Hypothesis 1 anticipates a positive linear relationship between managerial analytics HC and firm performance. Therefore I test this relation by regressing the managerial analytics HC variable and the control variables on the firm performance measures. Hypotheses 2a and 2b anticipate that strategic change capability would mediate between managerial analytics HC and firm performance. In effect, they propose that the managerial analytics HC will positively impact firm performance and that impact is brought about in large measure through strategic change capability.

In order to test the hypothesized mediated relationships, I will estimate two regression models using the PROCESS procedure, a macro developed by Hayes (2013). The resulting coefficients will provide indications of the influence that managerial analytics HC has on the mediator, strategic change capability (as represented in the first equation below), and the combined influence managerial analytics HC and strategic change capability have on the dependent variable, firm performance (as represented in the second equation below):

$$\text{Strategic-change} = i_1 + b_1(\text{managerial AHC}) + e_{sc} \qquad \text{(Eq. 1)}$$

$$\text{Firm performance} = i_2 + b_2(\text{strategic-change}) + b_3(\text{managerial AHC}) + e_{fp} \qquad \text{(Eq. 2)}$$

These two equations provide the total effect of managerial analytics HC on firm performance (i.e., the combination of direct effect [b3] and indirect effect [b1 * b2]). The significance of the direct effect of managerial analytics HC on firm performance may be determined with standard probability values. In order to assess the indirect effect, the

PROCESS procedure provides 95% bootstrap confidence intervals to test for significance.

Testing Hypothesis 3 and 4 a, 4b Mediated Relationship

As Hypothesis 3 anticipates a positive linear relationship between employee analytics HC and firm performance, I test this relation by regressing the employee analytics HC variable and the control variables on the firm performance measure. Hypotheses 4a and 4b anticipate that productive capability would mediate between employee AHC and firm performance. This mediated relationship would be analyzed using the PROCESS model for mediated analysis (Hayes, 2013).

The resulting coefficients will provide indications of the influence that employee analytics HC has on the mediator, production capability, and the combined influence employee analytics HC and productive capability have on the dependent variable, firm performance (as represented in the equations below):

$$\text{Productive capability} = i_3 + d_1(\text{employee AHC}) + e_{sc} \qquad \text{(Eq. 5)}$$

$$\text{Firm performance} = i_2 + d_2(\text{productive capability}) + d_3(\text{employee AHC}) + e_{fp} \qquad \text{(Eq. 6)}$$

These two equations provide the total effect of employee analytics HC on firm performance (i.e., the combination of direct effect [d3] and indirect effect [d1 * d2]). The significance of the direct effect of managerial analytics HC on firm performance may be determined with standard probability values. In order to assess the indirect effect, the PROCESS procedure provides 95% bootstrap confidence intervals to test for significance.

Testing Hypotheses 5a and 5b Moderated Relationship

Hypothesis 5a anticipates that employee analytics HC as a moderator will strengthen the managerial analytics HC and firm performance relationship. Specifically, the firms having higher employee analytics HC will result in managerial analytics HC bringing even better firm performance. I employ moderated regression analysis to test Hypothesis 5a. The expectation is that a high level of the moderator should be associated with materially greater firm performance than is the case at low levels of the moderator variable. Hypotheses 5b expects that managerial analytics HC as a moderator will strengthen the relationship between employee analytics HC and firm performance. I would use the PROCESS macro for moderation analysis (Hayes, 2013) for testing this hypothesis, which will provide the models represented as:

$$\text{Firm performance} = i_1 + a_1(\text{managerial AHC}) + a_2(\text{employee AHC}) + + a_3(\text{managerial AHC} * \text{employee AHC}) + e_{sc} \quad \text{(Eq. 3)}$$

In a moderated relationship such as I explore in H5a, the moderating effect of employee analytics HC is conditioned upon the level of employee analytics HC. Similarly, in H5b, the moderating effect of managerial analytics HC is conditioned upon the level of managerial analytics HC. The strength of the managerial analytics HC and employee analytics HC, as represented in Equation 3, is tested by adding the interaction term to the hierarchical regression model. Further, analysis is done using the PROCESS moderation model (Hayes, 2013) for the SAS system.

Testing Hypothesis 6 Moderated Relationship (Environmental Dynamism)

Hypothesis 6 expects that environmental dynamism (ED) as a moderator will positively affect the managerial analytics HC and firm performance relationship, suggesting that a higher ED level will result in higher firm performance. I employ moderated regression analysis to test Hypothesis 6, where we expect that ED as a moderator will strengthen the relationship between managerial analytics HC and firm performance. Adopting Hayes's (2013) representation of a test of moderation, I will estimate the following model in order to examine the moderating effect of ED:

$$\text{Firm Performance} = i_1 + j_1(\text{managerial AHC}) + j_2\text{ED} + j_3(\text{managerial AHC} * \text{ED}) + e_{sc} \qquad \text{(Eq. 7)}$$

Testing Hypothesis 7 Moderated Relationship (IT Infrastructure)

Hypothesis 7 anticipates that IT Infrastructure quality as a moderator will strengthen the employee analytics HC and firm performance relationship. The firms having higher IT infrastructure quality should help employee analytics HC bring better firm performance. In Hypothesis 7, the expectation is that high level of the IT Infrastructure quality should be associated with materially greater firm performance than is the case at low levels of the moderator variable. I employ moderated regression analysis to test Hypothesis 7. Adopting Hayes's (2013) representation of a test of moderation, I will estimate the following model in order to examine the moderating effect of IT Infrastructure quality:

$$\text{Firm Performance} = i_3 + k_1(\text{employee AHC}) + k_2(\text{IT Inf. Quality}) + k_3(\text{employee AHC} * \text{IT Inf. Quality}) + e_{sc} \qquad \text{(Eq. 8)}$$

In order for H7 to be supported, the coefficient for the interactive terms (i.e., k3) should prove to be positive and significant. Also, the simple regression slopes for employee analytics HC at relatively high levels of the moderator, IT Infrastructure quality should be associated with materially better firm performance than is the case at low levels of IT Infrastructure quality.

CHAPTER 4

DATA ANALYSIS AND RESULTS

This chapter provides the data analysis and results of the statistical procedures that were employed in hypothesis testing. First, the information is provided regarding the descriptive statistics of the variables used in the study. Next, the model specifications for the dependent, independent, mediating, moderating, and control variables are noted. Finally, the chapter concludes with the details of the results of hypotheses testing. As mentioned in Chapter 3, the financial data for this study was taken from the Thomson Reuters database for 2017, 2018, and 2019 provided by Wharton Research Data Services (WRDS). The hierarchical regression approach, which helps to assess each set of variables (Aiken & West, 1991), was applied for the hypothesis testing in this study. The moderation and mediation effects were examined using the PROCESS macro for SAS, which is widely used in statistical analysis (Hayes, 2018).

Descriptive Statistics

In Table 4.1, the basic descriptive statistics and correlations of the measures are presented. The *managerial analytics human capital* and *employee analytics human capital* are mean-centered to address multi collinearity. Before mean centering, the average *managerial analytics human capital* was 13.7% (SD = .10), *while employee analytics human capital* had a mean of 11.7% (SD = .079).

Table 4.1

Descriptive Statistics and Correlations

Variables	Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1. Firm Size (Employees Ln)	4.492	0.50	1											
2. Prior Firm Perf. (ROA)	6.738	5.45	0.110*	1										
3. Firm Age (Years)	38.47	28.61	0.133*	-0.019	1									
4. Capital Intensity (Ln)	5.132	0.642	-0.403**	-0.047	0.013	1								
5. Manager Analytics HC	0	0.101	-0.17**	-0.109*	-0.066	-0.08	1							
6. Employee Analytics HC	0	0.079	-0.23**	-0.094	-0.092	-0.05	0.929**	1						
7. IT Infrastructure (z)	0	1	0.219**	0.015	-0.043	0.24**	-0.049	-0.05	1					
8. Env. Dynamism (z)	0	1	0.048	-0.020	-0.081	-0.16**	0.405**	0.365**	-0.01	1				
9. Strategic Change Capability	-0.01	2.051	-0.067	-0.024	0.014	-0.008	0.269**	0.279**	0.01	0.10*	1			
10. Productive Capability (- COGS)	58.89	23.62	-0.033	0.108*	0.058	0.303**	0.338**	0.345**	0.05	0.14**	0.35**	1		
11. Firm Performance (Market Capital)	10.31	0.671	0.419**	0.217**	0.103*	0.181**	0.116**	0.106**	0.23**	0.02	0.09	0.52**	1	
12. Firm Performance (Net Sales Growth)	3.356	14.92	0.093	-0.018	-0.061	-0.13**	0.18***	0.20***	-0.03	0.07	0.11*	0.12*	0.13**	1

N = 376
* Correlation is significant at the 0.1 level (2-tailed).
** Correlation is significant at the 0.05 level (2-tailed).
*** Correlation is significant at the 0.01 level (2-tailed).
Variables Manager Analytics HC and Employee Analytics HC are mean-centered.
Variables IT Infrastructure (z) and Env. Dynamism (z) is standardized.

In terms of correlations, *managerial analytics human capita*l relates positively to firm performance measure of Market Capitalization ($r = 0.116$, $p < 0.05$), and *employee analytics human capital* relate positively to firm performance measure of Market capitalization ($r = .106$, $p < 0.05$), providing some initial evidence supporting these relationships.

Further, in Table 4.1, we note the correlations between all the independent variables: managerial analytics HC and employee analytics HC; control variables: Firm Size (Employees Ln), Prior Firm Performance (ROA), Firm Age (Years), and Capital Intensity (Ln). The Industry effect control variables are not included in this Table as it is implemented as a set of seven dummy variables in the data-set. We include the mediating variables: Strategic change capability and Productive cost-efficiency capability. The moderating variables: Environmental Dynamism and IT Infrastructure, are also included. Finally, we include the dependent variables for firm performance: market-based variable, Market Capitalization, and financial accounting-based variable, Net Sales Growth.

Model Specifications

The independent variables of this study are *managerial analytics human capital* and *employee analytics human capital*. Both these variables have been mean-centered to address possible multi collinearity issues. Examining the variance inflation factors (VIF), we found multi-collinearity was within acceptable limits, as VIF values are well below the threshold of 10. Most of the variables in the study are numeric continuous ratio variables, and the composite variables have been developed by standardizing relevant variables included in the composite measure. The models involved some variables with large positive amounts, such as Market capitalization, which was log-transformed, because such dollar amounts can be positively skewed and log transformations reduces such skewness to acceptable levels (Karuna, 2007; Robbennolt & Studebaker, 1999).

The key dependent variable in this study is firm performance. I have the market performance measure of Market Capitalization, while accounting firm performance measure of Net Sales Growth has been an additional measure to test the main effects. For strategic change capability, I use six key strategic dimensions to create a composite measure of strategic change: (1) advertising intensity (advertising/ sales), (2) research and development intensity (R&D/sales), (3) plant and equipment newness (net P&E/gross P&E), (4) nonproduction over-head (selling, general, and administrative [SGA] expenses/sales), (5) inventory levels (inventories/ sales), and (6) financial leverage (debt/equity). Therefore, each of these six variables was standardized before developing the composite strategic change measure. Moderation variables were also mean-centered or standardized, as is the recommended practice for moderation testing to generate appropriate interaction terms and interpret the results.

The equations for the hypothesis's models have been discussed in the previous chapter. They range from direct relation models, such as the main effect model for managerial analytics HC and firm performance (also includes control variables) as:

Model Equation: Firm performance = $i_i + b_1$(managerial AHC) + e_{fp}

Whereas mediation and moderator analysis models involve multiple predictor variables and interaction terms in case of moderation analysis, such as moderating effect of employee analytics HC on the relation between managerial analytics HC and firm performance:

$$\text{Model Equation: Firm performance} = i_2 + c_1(\text{managerial AHC}) + c_2(\text{employee AHC}) + c_3(\text{managerial AHC} * \text{employee AHC}) + e_{fp}$$

Hypotheses Testing

The hypotheses of this study examined the relationships between the operationalized independent, mediating, moderating, and dependent variables. The statistical technique of ordinary least squares (OLS) hierarchical regression models, which have been widely used in similar empirical studies has been employed. The hypotheses that check the linear relationships between analytics HC and firm performance, are tested by regressing the analytics HC variables and the control variables on the firm performance measures. The results of the hypotheses testing are presented in this section. I present the results of different models, each with the included predictor variables and dependent variables, and compare the different models in the tables in this chapter. The mediation and moderation relationship are additionally analyzed using the Hayes (2018) PROCESS macro for mediation and moderation analysis.

Hypothesis 1a tests the main relation of managerial analytics HC with market-based firm performance, Market capitalization. Hypothesis 1 anticipates a positive linear relationship between managerial analytics HC and firm performance; therefore, this is tested by regressing the managerial analytics HC variable and the control variables on the firm performance measures. As shown in Table 4.2, Model 1 contains only the control variables, including the firm size (number of employees), prior firm performance (ROA), capital intensity, firm age, and dummy variables for Industry groups (based on SIC codes). Model 1 is significant ($F=32.213$, $p <0.01$) and explains 47.7 % of the variance in firm performance.

Table 4.2

Regression Analysis for Relationship Between Managerial Analytics HC and Firm Performance-Market Capitalization (MCP) and Net Growth Rate (NGR)

Variables	**Model 1 DV=MCP**	**Model 2 DV=MCP**	**Model 5 DV=NGR**	**Model6 DV=NGR**
Firm Size (Employees Ln)	0.610***	0.679***	0.078	0.117*
Prior Firm Perf. (ROA)	0.242***	0.248***	0.017	0.021
Firm Age (Years)	0.069*	0.065*	-0.054	-0.056
Capital Intensity (Ln)	0.468***	0.504***	-0.076	-0.056
Industry Grp. (SIC)	Yes	Yes	Yes	Yes
Manager Analytics HC		0.272***		0.157***
R^2	0.477	0.529		
Adjusted R^2	0.462	0.514	0.074	0.091
ΔR^2	0.477	0.051	0.048	0.062
ΔF	32.213***	38.370***	0.074	0.017
F Score	32.213***	35.873***	2.815***	6.627***

* Relation is significant at the 0.1 level (2-tailed).
** Relation is significant at the 0.05 level (2-tailed).
*** Relation is significant at the 0.01 level (2-tailed).

In Model 2, the managerial analytics HC variable was added in addition to control variables. Model 2 is significant ($F=35.873$, $p<0.01$) and explains 52.9 % of the variance in firm performance. Managerial analytics HC has a statistically significant positive coefficient ($\beta = .272$, $p < .01$), indicating strong support for Hypothesis 1a, which proposed a positive relationship between managerial analytics HC and market capitalization.

Next, we test the Hypothesis 1b test, which tests the relation of managerial analytics HC with accounting-based firm performance, Net Sales Growth. The relation was tested in Table 4.2 Model 3 and Model 4, where Model 3 contains only the control variables. We find that Model 3 is significant ($F=2.815$, $p<0.01$) and explains 7.4 % of the variance in firm performance. The managerial analytics HC was added to Model 4 in addition to control variables. Model 4 is also significant ($F=3.203$, $p <0.01$) and explains 9.1 % of the variance in firm performance (Net Growth Rate). The results show that managerial analytics HC has a statistically significant positive coefficient ($\beta = 0.157$, $p < 0.01$), indicating strong support for Hypothesis 1b, which proposed a positive relationship between managerial analytics HC and Net Sales Growth. The analysis in Table 4.2 shows that managerial analytics HC has a strong relationship with market-based firm performance (Market Capitalization) and financial accounting-based firm performance (Net Sales Growth). We now proceed with further analysis using the Market Capitalization variable for the mediation analysis.

Hypothesis 2a was tested using Models 3 and 4 of Table 4.3, where Model 3 contained the control variables, with the dependent variable being the strategic change capability. The composite measure of strategic change capability included standardized measures for plant and equipment newness (net P&E/gross P&E), nonproduction over-head (selling, general, and administrative [SGA] expenses/sales), and financial leverage (debt/equity). Model 3 was significant and explained a 22.7% variance in strategic change capability. In Model 4, the managerial analytics HC variable was added to control variables, and the model was significant and explained a 24.4% variance in strategic change capability. Managerial analytics HC has a statistically significant positive coefficient ($\beta = .154$, $p < .05$) for Strategic change, hence Hypothesis 1b, which proposed a positive relationship between managerial analytics HC and Strategic change capability, is supported.

Table 4.3

Regression Analysis for Relationship Between Managerial Analytics HC, Strategic Change Capability (SCC) and Firm Performance-Market Capitalization (MCP)

Variables	**Model 1 DV=MCP**	**Model 2 DV=MCP**	**Model 3 DV=SCC**	**Model 4 DV=SCC**	**Model 5 DV=MCP**	**Model6 DV=MCP**	**Model7 DV=MCP**
Firm Size (Employees Ln)	0.610***	0.679***	-0.044	-0.005	0.611***	0.678***	0.679***
Prior Firm Perf. (ROA)	0.242***	0.248***	0.113**	0.117**	0.231***	0.258***	0.243***
Firm Age (Years)	0.069*	0.065*	0.042	0.041	0.066*	0.07*	0.065*
Capital Intensity (Ln)	0.468***	0.504***	-0.02	-0.001	0.478***	0.513***	0.513***
Industry Grp. (SIC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Manager Analytics HC		0.272***		0.154**		0.293***	0.273***
Strategic Change Cap					0.167***		0.13**
R^2	0.477	0.529	0.227	0.244	0.485	0.522	0.535
Adjusted R^2	0.462	0.514	0.204	0.219	0.468	0.506	0.518
ΔR^2	0.477	0.051	0.227	0.016	0.022	0.059	0.013
ΔF	32.213***	38.370***	9.891***	7.268***	13.958***	41.196***	9.079***
F Score	32.213***	35.873***	9.891***	9.821***	28.552***	33.163***	31.892***

* Relation is significant at the 0.1 level (2-tailed).
** Relation is significant at the 0.05 level (2-tailed).
*** Relation is significant at the 0.01 level (2-tailed).

Next, Hypothesis 2b tested whether the strategic change capability mediated between managerial analytics HC and firm performance. It was tested using Models 5, 6, and 7 (Table 4.2), with the dependent variable being the firm performance (Market Capitalization). As previously noted, Model 2 had found a significant relationship between managerial analytics HC and firm performance. In Model 5, I add strategic change capability to the model, and the relationship between strategic change and firm performance is significant ($\beta = .167$, $p < .05$). In Model 7, even after addition of strategic change capability, the relationship between managerial analytics HC and firm performance remained significant (β = .273, $p < .05$), though slightly reduced coefficient from (β = .293, $p < .05$) in Model 6. The relationship between strategic change capability and firm performance in Model 7 was also significant (β = .13, $p < .05$), indicating that the mediation is partially supported, which was confirmed using PROCESS procedure PROCESS v3.5.3 for SAS Hayes (2018) as shown in Table 4.4. The indirect effect of strategic change between managerial analytics HC and firm performance was significant as the Bootstrap Confidence Interval {.0167, .3230} did not include zero.

Table 4.4

Mediation of Strategic Change Capability in the Relationship Between Manager Analytics HC and Firm Performance – Market Capitalization

	Effect	se	t	p	LLCI	ULCI
Total effect of X on Y	1.7817	0.2776	6.4184	0.0000	1.2357	2.3278
Direct effect of X on Y	1.6602	0.2772	5.9880	0.0000	1.1148	2.2055
Indirect effect of X on Y: zStrChan (Boot CI)	0.1215	0.0782			0.0167	0.3230

Y: MktCap19 (Market Capitalization)
X: mngrAnaH (Manager Analytics HC)
M: zStrChan (Strategic Change Capability)
PROCESS Procedure Mediation (Model 4) Output (Hayes, 2018).

Further, we test the direct effect of employee analytics HC on firm performance (market capitalization) in Hypothesis 3a using Model 1 and 2 in Table 4.5. Model 1, which included only the control variables, is significant (F=32.213, $p < 0.01$) and explains 47.7 % of the variance in firm performance. Model 2 additionally includes the employee analytics HC variable, and the model is significant (F=37.020, $p < 0.01$), explaining 53.6 % of the variance in firm performance. Employee analytics HC has a statistically significant positive coefficient (β = .295, $p < .05$), indicating that The study data support

Hypothesis 3a, and employee analytics HC has a strong relationship with firm performance (market capitalization).

Table 4.5

Regression Analysis for Relationship Between Employee Analytics HC and Firm Performance-Market Capitalization (MCP) and Net Sales Growth (NSG)

Variables	**Model 1 DV=MCP**	**Model 2 DV=MCP**	**Model 3 DV=NSG**	**Model4 DV=NSG**
Firm Size (Employees Ln)	0.610***	0.699***	0.078	0.138**
Prior Firm Perf. (ROA)	0.242***	0.24***	0.017	0.016
Firm Age (Years)	0.069*	0.071*	-0.054	-0.052
Capital Intensity (Ln)	0.468***	0.494***	-0.076	-0.059
Industry Grp. (SIC)	Yes	Yes	Yes	Yes
Employee Analytics HC		0.295**		0.202***
R^2	0.477	0.536	0.074	0.101
Adjusted R^2	0.462	0.522	0.048	0.073
ΔR^2	0.477	0.059	0.074	0.028
ΔF	32.213***	44.968***	2.815***	10.900***
F Score	32.213***	37.020***	2.815***	3.622***

* Relation is significant at the 0.1 level (2-tailed).
** Relation is significant at the 0.05 level (2-tailed).
*** Relation is significant at the 0.01 level (2-tailed).

Next, in Hypothesis 3b, I test the direct effect of employee analytics HC on financial accounting-based firm performance, measured as Net Sales Growth using Model 3 and 4 of Table 4.5. Model 3, which included only the control variables, is significant ($F=2.815$, $p <0.01$) and explains 7.4 % of the variance in Net Sales Growth. The employee analytics HC variable is added in Model 4, and the model is significant ($F=3.622$, $p <0.01$), explaining 10.1 % of the variance in firm performance (Net Sales Growth). Employee analytics HC has a statistically significant positive coefficient ($\beta = .202$, $p < .01$), indicating that The study data support hypothesis 3b, and employee analytics HC has a strong positive relationship with firm performance (Net Sales Growth). We find that employee analytics HC has a strong relationship with market-based firm performance (Market Capitalization) and financial accounting-based firm performance (Net Sales Growth).

As previously mentioned, this study uses the measure of Cost of goods sold over sales to measure a firm's productive capability in terms of cost efficiency; additive inversed as productive cost capability. The impact of employee analytics HC on Productive cost capability is tested in Hypothesis 4a using models 3 and 4 (Table 4.6). Model 3, which included only the control variables, is significant ($F=12.018$, $p <0.01$) and explains 27.4 % of the variance in the productive capacity. Model 4 additionally includes the employee analytics HC variable, and the model is significant ($F=16.051$, $p <0.01$), explaining 35.8 % of the variance in production capability. Employee analytics HC has a statistically significant positive coefficient ($\beta = .354$, $p < .01$), indicating that Hypothesis 4a is strongly supported and employee analytics HC has a significant positive relationship with Productive cost capability supported by the study data. Next, we examine the mediating role of productive capability in Models 5, 6, and 7 of Table 4.4 and the significance of indirect effects in Table 4.7.

Table 4.6

Regression Analysis for Relationship Between Employee Analytics HC, Productive Cost Capability (PCC) and Firm Performance-Market Capitalization (MCP)

Variables	**Model 1 DV=MCP**	**Model 2 DV=MCP**	**Model 3 DV=PCC**	**Model 4 DV=PCC**	**Model 5 DV=MCP**	**Model6 DV=MCP**	**Model7 DV=MCP**
Firm Size (Employees Ln)	0.610***	0.699***	0.08	0.193***	0.564***	0.701***	0.634***
Prior Firm Perf. (ROA)	0.242***	0.24***	0.169***	0.17***	0.177***	0.247***	0.189***
Firm Age (Years)	0.069*	0.071*	0.066	0.068	0.039	0.067	0.044
Capital Intensity (Ln)	0.468***	0.494***	0.238***	0.272***	0.38***	0.51***	0.416***
Industry Grp. (SIC)	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Employee Analytics HC		0.295**		0.354***		0.324***	0.202***
Productive Cap.					0.41***		0.344***
R^2	0.477	0.536	0.274	0.358	0.585	0.533	0.609
Adjusted R^2	0.462	0.522	0.251	0.335	0.570	0.517	0.594
ΔR^2	0.477	0.059	0.274	0.083	0.122	0.070	0.076
ΔF	32.213***	44.968***	12.018***	41.194***	92.683***	47.306***	61.169***
F Score	32.213***	37.020***	12.018***	16.051***	40.468**	32.785***	40.873***

* Relation is significant at the 0.1 level (2-tailed).
** Relation is significant at the 0.05 level (2-tailed).
*** Relation is significant at the 0.01 level (2-tailed).

Table 4.7

Mediation of Productive Cost Capability in the Relationship Between Employee Analytics HC and Firm Performance – Market Capitalization

	Effect	se	t	p	LLCI	ULCI
Total effect of X on Y	2.6394	0.3837	6.8779	0.0000	1.8844	3.3944
Direct effect of X on Y	1.6470	0.3739	4.4047	0.0000	0.9113	2.3826
Indirect effect of X on Y: PrdCostC (Boot CI)	0.9924	0.1910			0.6378	1.3866

Y: MktCap19 (Market Capitalization)
X: empAnaHC (Employee Analytics HC)
M: PrdCostC (Productive Cost Capability)
PROCESS Procedure Mediation Model 4 Output (Hayes, 2018).

Hypothesis 4b tested whether the efficiency capability mediated between employee analytics HC and firm performance. It was tested using Models 5, 6, and 7 (Table 4.6). At the same time, Model 2 found a significant relationship between employee analytics HC and firm performance, and Model 4 found a significant relationship between employee analytics HC and productive capability. The Model 5 finds a strong significant relationship between productive capability and firm performance ($\beta = .410$, $p < .01$). In Model 7, both employee analytics HC and productive capacity were included to predict the firm performance. Here, the impact of employee analytics HC on firm performance was significant ($\beta = .202$, $p < .01$), and the impact of productive capability on firm performance was also significant ($\beta = .344$, $p < .01$), indicating that there was partial mediation by productive capability.

The PROCESS procedure used by Hayes (2018) was also used to confirm the mediation effect by testing the significance of the indirect effect of the employee analytics HC (independent variable) on the firm performance (dependent variable) through the productive capability (mediator) as in Table 4.7. The bootstrap test of the indirect effect was found to be significant with the 95% confidence limits {.6378, 1.3866} not including zero. Therefore, partial mediation by a productive capability is supported.

Hypothesis 5a tests for the moderating impact of employee analytics HC in the positive relationship between managerial analytics HC and firm performance. It was tested using Models 1,2, 3, and 4 (Table 4.8), where Model 2 shows a significant positive relationship between managerial analytics HC and firm performance. Model 4 additionally includes employee analytics HC and the interaction term of managerial analytics HC and employee analytics HC. The interaction term was not found to be significant, indicating that moderation was not supported. We further used the PROCESS procedure developed by Hayes (2018) to check the moderation Hypothesis 5a. The coefficient of the interaction term was not found significant (*b*= .0866, p= 9060), and the CI {-3.6622, 3.8353} included zero, indicating a lack of support for moderating effect.

Table 4.8

Moderating Effect of Employee Analytics HC on the Relationship Between Managerial Analytics HC and Firm Performance-Market Capitalization (MCP)

Variables	**Model 1 DV=MCP**	**Model 2 DV=MCP**	**Model 3 DV=MCP**	**Model 4 DV=MCP**
Firm Size (Employees Ln)	0.610***	0.679***	0.698***	0.697
Prior Firm Perf. (ROA)	0.242***	0.248***	0.241***	0.241
Firm Age (Years)	0.069*	0.065*	0.07*	0.071
Capital Intensity (Ln)	0.468***	0.504***	0.496***	0.496
Industry Grp. (SIC)	Yes	Yes	Yes	Yes
Manager Analytics HC		0.272**	0.042	0.042
Employee Analytics HC			0.257**	0.255**
Interaction MAHC*EAHC				0.002
R^2	0.477	0.529	0.537	0.537
Adjusted R^2	0.462	0.514	0.521	0.519
ΔR^2	0.477	0.051	0.008	0.000
ΔF	32.213***	38.370***	6.097**	0.002
F Score	32.213***	35.873***	33.868***	31.174***

* Relation is significant at the 0.1 level (2-tailed).
** Relation is significant at the 0.05 level (2-tailed).
*** Relation is significant at the 0.01 level (2-tailed).

Hypothesis 5b tests the moderating impact of managerial analytics HC on the positive relationship between employee analytics HC and firm performance. It was tested using Models 1,2, 3, and 4 (Table 4.9), where Model 2 shows a significant positive relationship between employee analytics HC and firm performance. In Model 4, I added managerial analytics HC and the interaction term of managerial analytics HC and employee analytics HC. The interaction term was not found to be significant, indicating that moderation was not supported. The employee analytics HC remained significant even after the addition of managerial analytics HC. I further used the PROCESS procedure developed by Hayes (2018) to check the moderation Hypothesis 5b. The coefficient of the interaction term was not found significant (b= .0866, p= 9060) and the CI {-3.6622, 3.8353} included zero indicating lack of support for moderating effect of managerial analytics HC. In contrast, managerial analytics HC was not significant, indicating a stronger relationship between employee analytics HC and firm performance, even after adding managerial analytics HC in the model.

Table 4.9

Moderating Effect of Managerial Analytics HC on the Relationship Between Employee Analytics HC and Firm Performance-Market Capitalization (MCP)

Variables	**Model 1 DV=MCP**	**Model 2 DV=MCP**	**Model 3 DV=MCP**	**Model 4 DV=MCP**
Firm Size (Employees Ln)	0.610***	0.699***	0.698***	0.697***
Prior Firm Perf. (ROA)	0.242***	0.24***	0.241***	0.241***
Firm Age (Years)	0.069*	0.071*	0.070*	0.071*
Capital Intensity (Ln)	0.468***	0.494***	0.496***	0.496***
Industry Grp. (SIC)	Yes	Yes	Yes	Yes
Manager Analytics HC			0.042	0.042
Employee Analytics HC		0.295***	0.257**	0.255**
Interaction MAHC*EAHC				0.002
R^2	0.477	0.536	0.537	0.537
Adjusted R^2	0.462	0.522	0.521	0.519
ΔR^2	0.477	0.059	0.000	0.000
Δ F	32.213***	44.968***	0.162	0.002
F Score	32.213***	37.020***	33.868***	31.174***

* Relation is significant at the 0.1 level (2-tailed).
** Relation is significant at the 0.05 level (2-tailed).
*** Relation is significant at the 0.01 level (2-tailed).

Next, the Hypothesis 6 tests for the moderating impact of environmental dynamism on the relationship between managerial analytics HC and firm performance. It was tested using Models 1, 2, and 3 (Table 4.10), where Model 1 includes the control variables, and Model 2 shows a significant positive relationship between managerial analytics HC and firm performance. Model 3 additionally includes environmental dynamism and the interaction term of managerial analytics HC and environmental dynamism. The interaction term was significant only at a 0.1 level of confidence, indicating marginal support for the moderation effect of environmental dynamism.

Table 4.10

Moderating Effect of Environment Dynamism (EDM) on the Relationship Between Managerial Analytics HC and Firm Performance-Market Capitalization (MCP)

Variables	**Model 1 DV=MCP**	**Model 2 DV=MCP**	**Model 3 DV=MCP**
Firm Size (Employees Ln)	0.610***	0.679***	0.663***
Prior Firm Perf. (ROA)	0.242***	0.248***	0.247***
Firm Age (Years)	0.069*	0.065*	0.069*
Capital Intensity (Ln)	0.468***	0.504***	0.497***
Industry Grp. (SIC)	Yes	Yes	Yes
Manager Analytics HC (MAHC)		0.272***	0.227***
Interaction MAHC*EDM			0.103*
R^2	0.477	0.529	0.534
Adjusted R^2	0.462	0.514	0.518
ΔR^2	0.477	0.051	0.006
ΔF	32.213***	38.370***	4.316**
F Score	32.213***	35.873***	33.553***

* Relation is significant at the 0.1 level (2-tailed).
** Relation is significant at the 0.05 level (2-tailed).
*** Relation is significant at the 0.01 level (2-tailed).

We further used the PROCESS procedure developed by Hayes (2018) to check the moderation Hypothesis 6. The PROCESS Model, including Control variables, Managerial AHC, Environmental Dynamism, the interaction term of (Managerial AHC*Environmental Dynamism), and Firm Performance (Market Capitalization) was significant (F= 43.133, p<.001) with R-sq. of 0.4589. The coefficient of Managerial Analytics HC was significant (*b* = 2.0334, p <0.001), while the coefficient of Environmental Dynamism was not significant (*b* = -.0001, p =.7776). The coefficient of the Interaction term was not significant (*b*= .0003, p= 9047), and the corresponding CI {-.0048, .0054} included zero, indicating a lack of support for moderating effect of environmental dynamism in this model. Additionally, we may note that the environmental dynamism is significantly correlated with industry effect (r = .509, p<.01), and industry effect is controlled in this study using Industry SIC code (dummy variables).

Next, we test the moderating effect of IT infrastructure quality on the relationship between employee analytics HC and firm performance. The relationship is shown in Table 4.11, and we develop Models 1, 2, and 3 for this purpose, where Model 1 includes the control variables. Hypothesis 7 tests for the moderating impact of IT Infrastructure on the relationship between employee analytics HC and firm performance. It was tested using Models 1, 2, and 3 (Table 4.9), where Model 2 shows a significant positive relationship between employee analytics HC and firm performance. In Model 3, I added employee analytics HC and the interaction term of employee analytics HC and IT Infrastructure. The interaction term was significant only at 0.1 level, indicating that moderation was only marginally supported and not supported at the 0.05 level of confidence.

Table 4.11

Moderating Effect of IT Infrastructure on the Relationship Between Employee Analytics HC and Firm Performance-Market Capitalization (MCP)

Variables	**Model 1 DV=MCP**	**Model 2 DV=MCP**	**Model 3 DV=MCP**
Firm Size (Employees Ln)	0.610***	0.699***	0.653***
Prior Firm Perf. (ROA)	0.242***	0.24***	0.237***
Firm Age (Years)	0.069*	0.071*	0.08*
Capital Intensity (Ln)	0.468***	0.494***	0.44***
Industry Grp. (SIC)	Yes	Yes	Yes
Employee Analytics HC (EAHC)		0.295***	0.305**
IT Infrastructure (ITI)			0.14**
Interaction EAHC*ITI			0.101*
R^2	0.477	0.536	0.543
Adjusted R^2	0.462	0.522	0.526
ΔR^2	0.477	0.059	0.004
ΔF	32.213***	44.968***	3.137*
F Score	32.213***	37.020***	32.003***

* Relation is significant at the 0.05 level (2-tailed).
** Relation is significant at the 0.01 level (2-tailed).
*** Relation is significant at the 0.001 level (2-tailed).

I further used the PROCESS procedure developed by Hayes (2018) to check the moderation Hypothesis 7. The coefficient of the interaction term was not found significant (*b*= .0866, p= 9060), and the CI {-3.6622, 3.8353} included zero, indicating that moderating effect was not supported at 95% confidence level. However, since the interaction term was earlier found significant at 0.1 level of significance in Table 4.9, we can consider marginal support for the moderating effect of IT Infrastructure quality on the relationship between employee analytics HC and firm performance.

CHAPTER 5

DISCUSSIONS, CONTRIBUTIONS, AND LIMITATIONS

Discussion of Findings

The current business environment is characterized by massive amounts of consumer and market data available to firms. Firms can effectively use large amounts of data by using appropriate analytics solutions to analyze data and gain insights. The focus of BDA initiatives has often been on big technology investments while neglecting the development analytics skill-set of their employees and managers. Prior BDA literature shows that researchers have been investigating multiple factors influencing BDA firm outcomes. However, there was a lack of research work investigating the impacts of analytics HC in the BDA context. This study fills this gap in the literature by examining the impacts of managerial analytics HC and employee analytics HC on firm performance. The study also investigates the mediating and moderating factors involved in the relationship between managerial and employee analytics HC and firm performance.

This study has empirically examined the influence of managerial and employee analytics human capital on firm performance. The study results show that human capital has a significant positive influence on firm performance in managerial and employee analytics. The empirical results show that higher managerial analytics skills do indeed help firms to enhance their performance. This evidence is consistent with prior surveys of managers have found them commenting on the importance of making data-driven decisions based on the insights derived from the large amounts of available market data. We have seen that the management of firms such as Netflix and Amazon have been able to innovate their business models by using insights from the massive amounts of consumer data they generate and enhance their customer experiences, providing the firms with higher sales growth and market performance.

This result is consistent with BDA literature, where anecdotal evidence indicates that a successful data-driven managerial decision making can provide superior firm performance, especially in areas such as market performance. Management must convert data into meaningful information and intelligence related to a business. One of the main research questions investigated in this empirical study was whether higher levels of managerial analytics HC lead to superior firm performance and find a significant positive relationship.

The results also find a significant positive relationship between employee analytics human capital (HC) and firm performance. Strategic management studies have also emphasized the importance of human capital (HC) in the knowledge-based perspective. Scholars have often defined HC as an individual’s stock of knowledge, skills, and abilities that can be increased through mechanisms like education, training, and experience. It has become a widely held premise that human capital is the ultimate determinant of organizational performance. In order to take advantage of analytics, firms need senior executives who understand data-based decision-making and can manage analytics initiatives successfully. This study empirically confirms the critical role of employee analytics human capital for firm performance.

The study results are also consistent with the recommendations by many technology and business analysts, who suggest that BDA tools and training need to occur at both managerial and operational levels to gain full benefit from the new BDA applications. The knowledge-based view has theorized that knowledge resources will increasingly play a defining role in creating a firm's competitive advantage and ultimately determining its performance. Employee knowledge skills and experience are also thought to help firms develop new business processes and embed knowledge in the organization. In the age of big data, employees' analytics skills are expected to play a key role in generating superior performance, and the empirical results of this study validate this argument.

Next, we consider that dynamic capabilities are regarded to help improve resources configuration and, in turn, provide improved firm performance. Researchers have investigated firms to examine their capabilities regarding how they leverage existing resources, create new resources, access external resources, and release resources to adapt to the business environment. The resource alteration processes in some firms also demonstrate how dynamic capability operates. Strategic change dynamic capability represents a capacity to change the organizational resource base and commitments to specialized resources to promote superior firm performance.

When firms in many industries offer similar products and use comparable technologies, effective use of analytics by managers can facilitate differentiated strategy development, as strategic change is seen to mediate the relationship between managerial analytics HC and firm performance. This study shows that managerial analytics HC has a significant relationship with a firm's strategic change capability. We know that dynamic capabilities such as strategic change capability are strategic and emphasize a firm's constant pursuit of the renewal, reconfiguration, and re-creation of resources and capabilities to develop products and services that address new and existing markets and generate superior firm performance. We find that strategic change capability has a significant positive relationship with firm performance, and it partially mediates the relationship between managerial analytics HC and firm performance. Therefore, a firm investing in BDA initiatives should emphasize that their managers have the analytics skill to effectively use the consumer and market data to allocate the firm resources and enhance firm performance strategically.

Management scholars have noted two important classes of capability: ordinary and dynamic, where ordinary capabilities involve the operational functions necessary to accomplish business tasks, and dynamic capabilities involve managing the firm's resources to address the business environment. Ordinary productive capabilities are rooted more firmly in routines and enable a firm to perform its current activities efficiently. Organizational routines transcend the individuals involved and are often developed and embedded in the skill-set of multiple employees and teams. Productive operational capabilities are geared towards the operational functioning of the firm, including both staff and line activities, and help achieve technical efficiency and do things right in the business operations.

Further, employee skills are considered to impact the firm's productive efficiency capability, and productive efficiency capability is also a key factor influencing firm performance. The study confirmed that employee analytics HC has a significant positive relation with productive capability in cost efficiency. The positive impact of productive capabilities on firm performance was also confirmed. Further, it is was found that productive capability partially mediates the relation between employee analytics HC and firm performance.

This study also confirms that cost efficiency capabilities are related to firm performance and partially mediate the relationship between employee analytics skills and firm performance. It was also found that the firm's strategic change capabilities do mediate the relationship between managerial analytics human capital and firm performance. While we offer evidence suggesting that managerial analytics skills help firms develop and take advantage of strategic change capabilities and ultimately enhance firm performance, we think future studies should empirically validate this relationship using longitudinal analysis.

Further, we anticipated that employee analytics HC as a moderator would strengthen the managerial analytics HC and firm performance relationship; and that managerial analytics HC as a moderator will strengthen the relationship between employee analytics HC and firm performance. It was expected that there would be a strong interaction effect of managerial and employee analytics human capital in their firm-performance relationship. However, in this study, the interaction effect was not found to be significant.

Furthermore, this research study tested the moderating role of environmental dynamism on the managerial analytics HC and firm's performance relationship. From prior strategy studies, we know that environmental dynamism plays an important role in developing dynamic capabilities and firm performance, and therefore is likely to impact this relationship. Highly dynamic environments are likely to compel firms to develop new products, new processes, or new services. Firms need to harness their HC, including the strategic problem-solving skills, to develop capabilities for gaining an advantage in the volatile market and boosting firm performance. The results found marginal support that environmental dynamism as a moderator positively influenced the managerial analytics HC and firm performance relationship.

Finally, we tested the moderating effect of IT infrastructure quality on the relationship between employee analytics HC and firm performance. We know that organizations that have succeeded in using IT to support knowledge-sharing applications have found that technology platforms influence knowledge-sharing efforts. The IT infrastructure quality often mirrors an organization’s historic progress with the use of IT and tends to influence the success of future technology-based solutions. BDA research has also noted the key role of IT infrastructure as an enabling platform for the success of BDA initiatives; therefore, we anticipated that IT Infrastructure quality as a moderator would strengthen the employee analytics HC and firm performance relationship. The study results found that the moderating influence was marginally supported, and the importance of IT Infrastructure quality is confirmed. Future studies may collect more detailed IT Infrastructure data to evaluate the interaction effect better.

Overall this study brings focuses on the critical role of analytics of human capital for superior firm performance. We find that both managerial analytics HC and employee analytics HC have a significant positive impact on firm performance. The study empirically validates the view that analytics HC of a firm, as manifested by analytics knowledge and experience, represents a key resource that can provide superior firm performance, both in terms of the firm’s net sales growth and market capitalization. We find that firm's strategic change capability partially mediates the relationship between managerial analytics HC and firm performance. Further, the firm's productive cost efficiency capability partially mediates employee analytics HC and firm performance. The empirical validation of these relationships should help scholars to do further research in this area. Also, for managers, it provides strong grounds for developing the analytics skill-sets of their employees and managers to successfully utilize their BDA solutions and get the return on their heavy investments in the BDA initiatives.

Contributions

While, Big data analytics (BDA) has been considered a significant impetus for superior firm performance, many firms adopting BDA find it challenging to gain an advantage from their BDA investments. Management scholars note the need to further understand the factors and mechanisms of BDA success. A review of recent BDA literature found a lack of research on the role of analytics human capital in relation to firm performance. In this dissertation study, I examined the impacts of analytics human capital (HC) on firm performance. Noting the crucial role of managerial skills in business strategy, I further classified analytics HC into managerial and employee analytics HC. The study confirmed the important role of analytics HC in improving the firm performance and identified the firm capabilities that mediate the effects of analytics HC on firm performance.

Previous research has also noted the importance of managers in shaping strategic capabilities, and strategy scholars have also pointed out that management is responsible for strategic change capabilities that may influence firm performance. Prior BDA studies suggest that analytics skills may help managers enhance the strategic change capabilities of the firm by gaining insights from large amounts of consumer and market data. This study empirically validates the insights of the knowledge-based view and firm dynamic capabilities in the BDA context.

As prior studies have found that managerial skills impact strategic change capabilities, and employee skills affect productive efficiency capabilities, the mediating role of these capabilities is investigated. In addition, the moderating influence of environmental dynamism and information technology (IT) infrastructure is also considered. The study results confirm that both managerial and employee analytics HC have a significant positive impact on firm performance. The results also support the partial mediating effect of strategic change capability in the relationship between managerial analytics HC and firm performance.

Further, this study helps to identify mechanisms for organizations to effectively leverage big data to achieve greater productivity and efficiency by testing the mediating role of productive cost-efficiency capabilities between employee analytics skills and firm performance. The partial mediating effect of productive efficiency capability in the relationship between employee analytics HC and firm performance is validated, which confirms that BDA is critical not only for strategy aspects but also the operational business processes of the firm.

The focus of BDA initiatives has been predominantly on big technology investments while often neglecting the development of analytics HC in the firms. This research study highlights the crucial role of analytics HC on firm performance. It provides strong empirical support for firms to develop their managers' and employees' analytics skills to derive business value from their BDA investments. The empirical evaluation of the firm capabilities: strategic-change capability and productive capability, also contribute to research on dynamic and ordinary capabilities. This study is one of the early empirical studies to examine the impacts of analytics human capital on firm performance in the context of Big data analytics and therefore has important implications for both academia and practice in this area.

From a theoretical point of view, the knowledge-based view notes that knowledge resources will increasingly play a defining role in creating firm capabilities and providing superior firm performance. Employee human capital is increasingly gaining importance as a key element to help firms develop new business processes and embed knowledge in the organization. In the age of big data, employees' analytics skills are expected to play a key role in generating superior performance, and the empirical results of this study validate this argument.

This study contributes to the literature on analytics human capital and firm performance in the context of the big data revolution. The study finds that BDA skills can positively influence managers to influence firms' performance. The key role of employee analytics skills has also been confirmed as it directly impacts firm performance and moderates the impact of managerial analytics skills on performance. Another important finding of this study is that employee analytics skills also help enhance firms' efficiency capabilities, partially mediating the relationship between employee analytics skills and firm performance. In the context of BDA human capital, this is one of the first empirical studies confirming the key role played by analytics human capital and provides strong support for continuing investment in BDA human capital initiatives to improve firm performance.

Limitations and Future Research

As with all empirical studies, we recognize several limitations in our study. This study has limitations in terms of cross-sectional data, though predictors and criterion variables were taken from different data sources. Also, we have careful in identifying the research model variables, including the relevant independent, mediating, dependent, and control variables. The hierarchical regression approach helped to assess the explanatory power of each set of variables and was reasonably well suited for this study. At the same time, the use of lagged dependent variables from a separate source than independent variables can also help mitigate reverse causality.

Prior strategy studies have investigated the influence of human capital on a firm's strategic performance in different resource contexts, and currently, Big data presents an important context for such study. While multiple factors influence BDA success, this study was able to develop a parsimonious research model examining a small set of factors. Future studies may build upon this model, including more related factors, and develop an elaborate model. Also, a multi-dimensional measure for analytics Human capital may be used to examine its relationship with firm performance.

For future research, we may suggest using longitudinal data for predictor and performance variables, which allows the researcher to gain the benefits like a field experiment. Further, we acknowledge that our measures of analytics human capital could be seen as another limitation, as using the LinkedIn database is also not free from criticism. More fine-tuned survey-based data may be able to find an interaction between managerial analytics HC and employee analytics HC, and future researchers may consider survey-based measures for analytics HC to assess these measures with multiple dimensions.

Overall, this study does necessary foundational research as it is one of the earliest studies examining analytics human capital in the context of BDA firm performance. Future research may analyze some other related predictor factors, which may also interact with analytics human capital factors. Firm performance can also be measured with a multiple-item measure, including several financial growth parameters. An exploration of social capital interaction and networking effects can be the subject of future research. Considering these avenues, it is evident that this study provides immense opportunities for future research. Big data is a rapidly growing phenomenon with multi-dimensional impacts on firm capabilities and firm performance. This field requires examining a wide range of related factors to ensure effective utilization of large amounts of investment by firms in their analytics initiatives.

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APPENDIX A

LIST OF BIG DATA ANALYTICS SKILLS USED FOR ANALYTICS HUMAN CAPITAL

List of Big Data Analytics Skills used for Analytics Human Capital