Customer Analytics and New Product Performance: The Role of Contingencies

Abstract

Drawing from the Knowledge Based View (KBV) of the firm and Contingency Theory, this paper examines the extent to which the relationship between Customer Analytics (CA) and new product performance is contingent on the strategic fit of CA with certain internal and external contingencies. The paper first conducts a multiple case study based on secondary data analysis. It then undertakes an empirical analysis based on a survey data of 249 high and medium tech firms based in China. We find that while some internal contingencies (such as exploitative learning strategy and market knowledge breadth) negatively moderate the effect of CA on new product performance, others (such as internal capability and knowledge integration mechanisms) mediate its effect on performance. Technological turbulence, as an external contingency, was found to reduce the positive impact of CA deployment on new product performance. This study contributed to the literature by focusing on how several internal and external contingencies of a firm may affect the relationship between CA and new product performance.

1. **Introduction**

Customer Analytics (hereinafter, CA) – or the analytics devoted to the exploitation of customer data to understand their behaviour and preferences – has become very common among businesses (Erevelles, Fukawa, & Swayne, 2016; Johnson, Friend, & Lee, 2017). CA employs descriptive analytics, mining/predictive analytics and machine learning techniques to analyze structured behavioural data (e.g. scanner or sensor data, records, files, and databases) as well as other unstructured data (such as data from videos, images, and audio recordings) (Erevelles et al., 2016; Germann et al., 2014; Wang, Kung, & Byrd, 2018a). CA can help firms to obtain market-based knowledge, improve customer relationship management and customer engagement processes, achieve product (or service) quality improvements, and gain support for new product strategy decisions (Wamba et al., 2017; Wang & Hajli, 2017; Wang et al, 2018a; Wang, Kung, Wang, & Cegielski, 2018b).

There exists a large literature which explores how CA affects new product performance, focusing on the benefits that analytics can generate (Shirazi et al., 2022; Tseng et al., 2023; Zhan et al., 2018; Hajli et al., 2020). Still, most organizations continue to struggle to make progress on their CA initiatives because implementing a CA system can be an expensive and risky undertaking (Watson, 2014; Mortenson, Doherty, & Robinson, 2015; Vidgen et al., 2017). Such mixed evidence on the benefits of analytics suggests more research in this field is needed.

The inconsistences between the potential benefits that CA can offer and the evidence on its actual benefits can be ascribed to the fact that the impact of analytics on new product performance is mostly understood through the lens of the Knowledge Based View (KBV); however, such a theory does not consider the fact that for CA to have a positive impact on new product performance, there has to be a strategic alignment between the external business environment, and its internal processes (Jiang et al., 2018; Vitari and Raguseo, 2020). Recently, the literature on CA and new product performance has started to explore the possibility that the impact of CA is really conditioned by a number of internal factors, whether customer agility (Shirazi et al., 2022), culture (Upadhyay and Kumar, 2020) or absorptive capacity (Tseng et al., 2023); still this research has a limited view on all the contingencies that affect the relationship between new

product performance and customer analytics (Maroufkhani et al., 2022; Olabode et al., 2022; Upadhyay and Kumar, 2020; Vitari and Raguseo, 2020).

Against this background, the main objective of the paper is to identify the contingency factors that may affect the relationship between CA and new product performance. Our starting point is that the inability to manage the *strategic fit* between the use of CA and new product performance lies at the root of a firm's failure to benefit from CA (Maroufkhani et al., 2022; Olabode et al., 2020). To do so, we enrich the Knowledge Based View (hereinafter, KBV) of the firm with the Contingency Theory and investigate the role of contingency factors (both internal and external to the firm) in affecting the relationship between the use of CA and the performance of new products. Eventually, we use the theory to develop a number of hypotheses which enable testing of the extent to which CA deployment *'fits'* with (or is mediated/moderated by) a variety of internal and external contextual contingencies of the focal firm and can support the performance of new products.

There are two main strands to the (contingency) theory, fit-as-moderation and fit-as-mediation. First, the fit-as-mediation view suggests that effective firms adopt organizational elements such as resources, practices and strategies that fit their situations relatively better than the ones that are not effective (De Luca & Atuahene-Gima, 2007; Van de Ven & Drazin, 1984; Venkatraman, 1989). More specifically, in a CA context, the information processing requirements of using Big Data for new product strategy decisions would govern the capabilities needed for the effective processing and integration of information (i.e. internal capability and knowledge integration mechanisms).

Second, the fit-as-moderation view suggests that the firm's performance is attributable to a fit between its strategic behavior and the internal and external contingencies (De Luca & Atuahene-Gima , 2007; Van de Ven & Drazin, 1984; Venkatraman, 1989). In this case, the fit between the use of Big Data through CA for new product strategy decisions, and a firm's situational contingencies such as its learning strategy (i.e. exploitative knowledge strategy), market knowledge structure (i.e. market knowledge breadth) and external environment (i.e. technological turbulence) are likely to affect its new product performance. In line with these two views of the Contingency Theory, we include among internal

contingencies the following factors: a) internal capabilities, b) knowledge integration mechanisms, c) exploitative learning and d) market knowledge breadth while technological turbulence is the external contingency factor.

This paper contributes to the existing literature on CA and New Product Performance in several ways: first, it enriches the prevalent theoretical lens through which the impact of CA on new product performance is understood with insights from the Contingency Theory by showing that alignment to internal and external contingencies matters for CA to have an impact on new product performance. This study builds on previous studies (e.g. Akter et al., 2016; Wamba et al., 2017) by examining the performance implications of CA on new product performance not only from an *IT systems* or *capability* perspective but also from a *knowledge integration* viewpoint. Our study assumes that a firm's strategic fit may account for a considerable proportion of the effect of deploying CA on new product performance.

Second, studies in the NPD area have documented how product innovation performance is hindered by the *strategic misfit* between CA and certain intra-firm contingency factors such as organizational knowledge and learning orientation (e.g. Kyriakopoulos & Moorman, 2004; Yannopoulos, Auh, & Menguc, 2012). Compared to the intelligence obtained through other means, the use of Big Data in the CA process produces knowledge with greater complexity, heterogeneity and dynamism, and thus requires more caution in its implementation. For example, the benefits of Big Data may not be fully realized if firms fail to complement the intelligence obtained through Big Data Analytics (BDA) with learning strategies. For example, the misfit is likely to emerge when customer data with 3Vs is complemented by higher degrees of exploitative learning strategy but with a lack of a more balanced focus involving the exploration and discovery of future customer needs. The study assumes that while achieving a *strategic fit* would enhance a firm's NPD, failing to achieve such fit would diminish it.

Third, previous studies provide evidence that, due to the volatility and immense *volume* of data underpinning the use of BDA, customer or market turbulence, as an external environmental contingency factor, only partially contributes to the effectiveness of using Big Data in NPD (Johnson et al., 2017).

This study further examines how technological turbulence, as an environmental contingency factor and a type of market turbulence, affects the relationship between CA and new product performance relationship. This study suggests, due to the historical and real-time nature of Big Data, foreseeing the recurrent disruptive market changes caused by technological turbulence would challenge the use of CA (Holcombe, 2015). The *misfit* between the use of Big Data and technologically turbulent environments is expected to reduce the impact of CA on NPD performance.

The remainder of the paper is structured as follows. Section 2 discusses the theoretical background and develops the hypotheses. Section 3 focuses on the methodology and the data while Section 4 presents several case-studies on CA and new product performance. Section 5 presents the results from the quantitative analysis while Section 6 focuses on the implications of the findings for theory and practice. Finally, Section 7 offers some concluding remarks.

2. Theoretical Background

CA is a process which is at the crossroads between Big Data and customer behavior analysis (Erevelles et al., 2016). The academic literature treats CA as the science of decision making combined with the management of knowledge extracted from Big Data. In turn, Big Data consists of business internal records (possibly combined with external data) which jointly help to develop behavioral customer insights which can be translated into market advantage (Erevelles et al., 2016; Wang et al., 2018ab). Traditionally, in marketing context, data is used for customer relationship management (CRM) purpose to improve the management of customer lifecycle and interactions, specifically to acquire new customers and retain existing customers (Lamrhari et al., 2022). While pre-Big Data period, CRM was rooted in the utilization of databases with limited data functionality and capabilities, with the emergence of Big Data, firms enhanced their abilities to create more effective and efficient CRM strategies and programmes (Del Vecchio et al., 2022). Nowadays, CRM practice is based on CA deploying Big Data with unprecedented *volume*, *variety*, and *velocity* has revolutionized the way of

gaining customer insights (Erevelles et al., 2016; Johnson et al., 2017)[1]. In an NPD context, Big Data supports the alignment between new product attributes and customer preferences so that new product performance in the market can be achieved (Johnson et al., 2017).

In this context, CA is a type of Big Data Analytics (BDA) which enables generation of customer insights from multiple marketing channels to create superior value for customers (Hossain et al., 2021). Despite the high potential of BDA in general and CA in particular for creating improved customer value, existing research on the role of BDA (or more specifically CA) in the development of innovative new products is still limited (Shirazi et al., 2022). The literature on NPD acknowledges that various factors and contingencies can influence the performance of an NPD activity (Montoya-Weiss and Calantone, 1994). Amongst the limited number of studies which have examined the role of BDA as a firm level factor in new product performance, Ghasemaghaei and Calic (2020) who focused particularly on the effect of different Big Data characteristics on new product (or innovation) performance observed that this effect is mixed. For example, they showed that while variety and velocity of Big Data have a significant effect on new product performance, its volume does not have any significant influence (Ghasemaghaei and Calic, 2020). On the other hand, Shirazi et al. (2022) and Tseng et al.'s (2022) study which focused on BDA capacity perspective documented that the influence of the effective use of data aggregation and analysis tools in new product performance is significant. Shirazi et al. (2022) and Hajli et al.'s (2020) studies further observed that the effective use of data aggregation and data analysis tools generate customer agility which in turn enables firms to achieve improved new product performance. Similarly, Zhan et al.'s (2018) study pointed out that the Big Data driven customer involvement can provide more valuable inputs for NPD. The current study builds on these studies by examining how certain internal and external contingencies to a focal firm may influence the effect of customer data focused BDA in terms of CA on new product performance.

The theoretical foundation of this study is based on the Knowledge Based

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[1] While *volume* represents the size of customer-based data, *variety* relates to the data sources (e.g. various internal and external sources) used to extract such data (Özköse, Arı, & Gencer, 2015). *Velocity*, on the other hand, is about the speed at which new customer data is captured, processed and analyzed.

View (KBV) and Contingency Theory. In the context of KBV, this study defines Big Data as a knowledge-based resource, which enables new value creation for a firm and its customers (Felin & Hesterly, 2007). KBV positions knowledge as a strategic resource that supports managerial problem-solving and decision-making to develop new solutions (Grant, 1996; Felin & Hesterly, 2007; Nickerson & Zenger, 2004). KBV positions knowledge as the strategically most valuable firm resource (Eisenhardt and Santos, 2001; Grant, 1996). However, a key notion of the KBV is that knowledge on its own is not sufficient to achieve sustainable competitive advantage i.e. the firm requires capabilities to apply such knowledge to commercial ends (Cohen & Levinthal, 1990; Grant, 1996; Tsai, 2001) and integrate it among diverse cross functional units (De Luca & Atuahene-Gima, 2007; Grant, 1996). This paper is utilizing the KBV to explain the role of the deployment of CA in new product performance as it considers Big Data as the most significant strategic resource of a firm and the customer intelligence attained through Big Data in the CA process as the most valuable knowledge source for achieving improved performance benefits.

Contingency Theory complements KBV as it assumes that the *strategic fit* between two or more organizational elements (e.g. resource, process, practice, structure, environment, strategy) is central to a firm's performance (Jiang et al., 2018; Symeonidou & Nicolaou, 2017; Van de Ven & Drazin, 1984; Venkatraman, 1989). This study uses Contingency Theory as the complementary theoretical lens to KBV as it enables an overarching framework of a wide range of possible internal and external environmental or situational contingencies of a firm which may explain variations of its performance outcomes. In this sense, the theory allows investigation of how certain internal and external contingencies of the firm may facilitate or demolish its use of Big Data based customer intelligence on its performance.

The existing research still has a limited view on the effect of different contingency factors on the relationship between various big data implementations and performance (Vitari and Raguseo, 2020). As such, limited number of studies have shown mixed evidence on the significance of the effect of certain environmental contingencies on some performance outcomes including new product performance outcomes (Maroufkhani et al., 2022; Olabode et al., 2022; Upadhyay and Kumar, 2020; Vitari and Raguseo, 2020).

These studies have mostly been rooted in the view that it is important to ensure a strategic fit between a firm's internal and external business environment, and its performance outcomes (Jiang et al., 2018; Vitari and Raguseo, 2020). Indeed, besides the availability of a firm's internal environmental contingencies such as its firm level capabilities, some external contingencies such as external stakeholders (e.g. competitors) may influence its adoption of BDA (Maroufkhani et al., 2020; Olabode et al., 2022). There are two main strands to the theory, *fit-as-moderation* and *fit-as-mediation*.

First, the *fit-as-mediation* view suggests that effective firms adopt organizational elements such as resources, practices and strategies that fit their situations relatively better than the ones that are not effective (De Luca & Atuahene-Gima, 2007; Van de Ven & Drazin, 1984; Venkatraman, 1989). More specifically, in a CA context, the information processing requirements of using Big Data for new product strategy decisions would govern the capabilities needed for the effective processing and integration of information (i.e. internal capability and knowledge integration mechanisms).

Second, the *fit-as-moderation* view suggests that the firm's performance is attributable to a *fit* between its strategic behavior and the internal and external contingencies (De Luca & Atuahene-Gima , 2007; Van de Ven & Drazin, 1984; Venkatraman 1989). In this case, the *fit* between the use of Big Data through CA for new product strategy decisions, and a firm's situational contingencies such as its learning strategy (i.e. exploitative knowledge strategy), market knowledge structure (i.e. market knowledge breadth) and external environment (i.e. technological turbulence) are likely to affect its new product performance.

The following section examines the role of Big Data as a knowledge based resource in new product performance by considering internal contingencies of a firm as mediators (i.e. fit-as-a-mediator), and a set of internal and external contingencies as moderators (i.e. fit-as-a-moderator).

2.1. Hypothesis Development
CA[2] allows firms to obtain advanced insights into customer behaviors through

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[2] CA can be of three types: descriptive, predictive and prescriptive techniques (Power, 2013). First, descriptive analytics uses summarization and description of knowledge patterns in real time and historical data using simple statistical methods to make inferences about the future (Power, 2013; Sivarajah et al., 2017). Second, predictive techniques use mathematical algorithms and

various channels (e.g., call center customer interactions vis-a-vis voice, web, text messaging, mobile, video etc.) (George et al., 2014), which in turn helps firms to explore consumers' preferences (Xu, Frankwick, & Ramirez, 2016). When launching new products, CA uses social media analytics, trend discovery, text analytics and data mining to implement behavioral analysis and assess peer impact to enhance the adoption of newly introduced products (Xu et al., 2016)[3].

In addition, manufacturing firms can use CA to make sense of market data to achieve enhanced new product performance (Wang et al., 2016). For instance, Big Data sent by the smart devices may help manufacturers to implement CA to unearth product usage problems, customer needs and preferences, and subsequently enable creation of new product concepts and solutions in an innovative way (Yin & Kaynak, 2015)[4]. Similarly, CA based on smart sensor installations, historical data and communication protocols provides insights into operational or just-in-time maintenance and provide a constant flow of data to optimize workflows and staffing to enable effective product provision (Bughin, Chui, & Manyika, 2015; Lee et al., 2013).

Still, previous research has mixed findings about the usefulness of using Big Data for new product performance (e.g. Johnson et al., 2017). The inconsistent findings can be attributed to the effect of firm-related and environmental contingencies which moderate or mediate the relationship between new product performance and CA.

2.1.1 Mediators: Internal Competencies and Knowledge Integrations mechanisms

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programming, forecasting and statistical modelling to reveal patterns and detect relationships in historical data, and identify future possibilities (Sivarajah et al., 2017; Wang et al., 2016). Third, prescriptive analytics include optimization, simulation, and heuristics-based decision making and uses real time data and mathematical algorithms to determine plausible options for future decisions (Blackburn et al., 2017; Power, 2013; Sivarajah et al., 2017; Wang et al., 2016). The use of these techniques in the CA process can provide insights into the current (i.e. explicit) and latent (i.e. hidden) needs of customers and support new product strategy options.

[3] Eastman Chemical Company collaborated with North Carolina State University and by monitoring the social media feeds, they used CA to support marketing and sales of their 3D printing technology and implemented ongoing product improvements to enhance their market performance (Blackburn et al., 2017).

[4] For example, Big Data on customers captured through sensors and remote app-management software has helped Ford to detect the role of background noise in reducing the software's ability to recognize driver commands, and in turn, enabled the firm to develop and introduce noise cancelling technology software (Erevelles et al., 2016).

Investment in Big Data may fail to pay off if firms are not able to develop the 'hard to imitate' capabilities that allow interpretation of the intelligence obtained from the data (Gupta & George, 2016; Kiron, Prentice, & Ferguson, 2014). Importantly, most of the impact of CA on new product performance is not due to the technology itself but to the internal capabilities of the firm that will allow use of the technology in a distinctive way. For instance, the most common cause of ineffective investment in Big Data is the lack of skills to manage and analyze them (Ross, Beath, & Quaadgras, 2013). Therefore, firms can enhance the chances of exploiting the unique benefits of Big Data when they develop internal capabilities for effectively deploying CA (Manyika et al., 2011). The literature on Big Data suggests there are three types of internal capabilities related to the use of analytics; these include physical or information technology (IT) capabilities, organizational capabilities, and analytics skills (Akter et al., 2016; Wamba et al., 2017).

In this study, we focus on the skills to make effective use of CA tools and techniques to generate customer and market insights from Big Data and address strategy problems for NPD purposes (Germann, Lilien, & Rangaswamy, 2013). Firms have traditionally been maintaining their structured customer data (e.g. demographics, orders, feedback data) within their CRM systems. Yet, since a great deal of customer data exists in an unstructured and semi-structured format, firms can exploit the benefit of using Big Data by developing internal capabilities in deploying CA (Gupta & George, 2016). In this sense, firms need to develop internal capability to manage Big Data to handle routines in a structured (rather than ad hoc) way, consistently with business needs and goals (Wamba et al., 2017). Similarly, the use of CA can fulfill their full potential when the employees have the required know-how to extract and assess intelligence from Big Data (Gupta & George, 2016). Internal capability in acquiring, processing and analyzing Big Data and converting that data into knowledge can provide firms with distinctive insights into changing market trends and unforeseen market opportunities. It also enables distinctive ways of handling the huge amount of complex customer data in a cost-effective manner (Sivarajah et al., 2017), and thereby can help firms to use Big Data to achieve several performance benefits ranging from cost reduction and operation optimization in NPD (Wang et al., 2018a) to improved innovation performance (Erevelles et al., 2016; Johnson et al., 2017). On the other

hand, lack of internal capabilities for CA reduces the odds of exploiting Big Data in NPD. In this way, it also diminishes the opportunities of using CA for achieving unique market benefits.

Knowledge integration mechanisms constitute the formal processes and structures that are used to acquire, interpret and integrate market and other types of knowledge across different functional units within the firm (De Luca & Atuahene-Gima, 2007). In the related literature on absorptive capacity, studies separate potential absorptive capacity (which includes the ability to acquire, assimilate and exploit external knowledge) from realized absorptive capacity that reflects the firm's capacity to leverage the external knowledge that has been absorbed (Zahra & George, 2002). These studies suggest that to be able to apply external knowledge to commercial ends, firms need to first acquire and integrate such knowledge within their diverse functional units (Cohen & Levinthal, 1990; Kostopoulos et al., 2011). Similarly, the market orientation literature emphasizes the significance of disseminating marketing intelligence within diverse functional units of the organization to achieve superior new product performance (Jaworski & Kohli, 1993).

Based on the previous studies, it can be argued that customer intelligence or information obtained from Big Data in the CA process would improve the performance of new products when a firm has established and formalized knowledge integration mechanisms to disseminate the intelligence across diverse functional units (Li & Atuahene-Gima, 2001). Depending on the complexity of information obtained from the data, information sharing among members of the team may become error prone and hard to exploit for the purpose of NPD (De Luca & Atuahene-Gima, 2001; Wang, et al., 2018ab). Hence, the communication of information with a certain level of complexity requires a formalized communication flow among cross functional units through knowledge integration mechanisms (De Luca & Atuahene-Gima, 2007). In general, formal communication of information obtained through CA would encourage the development of innovative new products by cross functional team members who hold both supplementary and complementary knowledge on product and technological domains. However, if such formal communication mechanisms are not successfully employed to integrate knowledge within the firm, the

insights obtained from Big Data would mainly remain secluded within a single unit, limiting their usefulness for product innovation.

In this context, it can be suggested that internal capabilities in CA can explain the role of deployment of CA in the new product performance of Chinese firms. Indeed, previous research has shown the significance of internal capabilities in such analytical functions on decision making efficiency and effectiveness of Chinese firms (Shamim et al., 2019). Similarly, the use of knowledge integration mechanisms can explain how the deployment of CA may impact new product performance. For example, prior research has shown that employees in China, who are characterized by collectivist culture, tend to share less information with outgroup members as compared to employees in the US who carry characteristics of an individual culture (Chow et al., 1999). This implies that in the process of NPD, to benefit from sharing of knowledge attained via CA amongst outgroup members such as across different functional teams, Chinese firms would be better off by using formal knowledge integration mechanisms.

Therefore, we hypothesize that:

Hypothesis 1: **Internal capabilities and knowledge integration mechanisms mediate the effect of the deployment of CA on new product performance.**

2.1.2. *Moderators: the role of exploitative learning and market knowledge breadth*

In NPD, exploitative learning aims at the refinement of existing knowledge for the development of new products (Kang et al., 2007). In particular, exploitative learning uses customer information to identify current market needs and aligns them with current expertise, experience and skills available inside the firm (Kim & Atuahene-Gima, 2010). In the context of Chinese firms, the Confucian heritage, with its emphasis on harmony and incremental progression, fosters a cultural predisposition towards exploitative learning, where refinement and optimization of existing knowledge are highly valued (Lin et al., 2017). This cultural inclination suggests that Chinese firms may inherently prioritize exploitative learning strategies.

An implication of such an exploitation of customer information is that an organization that has an excessive focus on exploitation may eventually suffer

from quicker obsolescence of its products (Levinthal & March, 1993). To avoid this problem, it is necessary to balance out exploitative learning with explorative learning. Explorative learning attempts to discover new possibilities and knowledge to create radically new products (Kim & Atuahene-Gima, 2010; March, 1991). While firms leaning towards exploratory learning search for and utilize complementary knowledge with lower degrees of redundancy or overlap than the ones with a preference for exploitative learning tend to search for and use knowledge with higher degree of similarity or overlap (Knudsen, 2007). Thus, firms adopting an exploitative learning strategy tend to supplement the information obtained from CA with the information on existing customer requirements and preferences acquired through several other means such as customer interactions, customer surveys and conjoint analyses (Ozdemir, Kandemir, & Eng, 2017). However, such a strategic approach to organizational learning is problematic since a certain amount of knowledge complementarity is required to generate new products with a sufficient degree of innovativeness, and thereby to enable improved outcomes (Rindfleisch & Moorman, 2003). So, firms that with low exploitative learning are expected to have a greater tendency to complement their available knowledge with non-redundant information, which may be obtained through Big Data (Ozdemir et al., 2017). However, firms with high exploitative learning are not expected to create new products that are distinctive and have the potential to create a competitive edge. In this respect, an exploitative learning strategy is hypothesized to reduce the potential benefits that can be achieved through the exploration of Big Data in the use of CA and the possibility of thinking 'outside of the box' when developing new products (Ross et al., 2013).

The integration of knowledge across diverse functional units is a costly endeavor (Song & Thieme, 2006). It involves frequent meetings, interactions and debates among NPD team members with expertise and competence in different knowledge domains (Atuahene-Gima & Evangelista, 2000; Brettel et al., 2011). However, the tasks that are simple in nature require much less integration of knowledge than tasks that have a certain degree of complexity (Brettel et al., 2011; Song & Thieme, 2006). The cross-functional integration of knowledge would be most beneficial when the cross functional NPD teams are able to exploit the advantages of their interdependencies and particularly their diversified

knowledge and experiences. Thus, the costs of employing knowledge integration mechanisms to disseminate the intelligence obtained from Big Data is expected to exceed its benefits when NPD team members rely mostly on exploitative learning by merely supplementing their existing knowledge and competencies. In particular, in these situations, the operational costs of cross functional integration of information are likely to exceed the incremental benefits gained from minor product advancements and are unlikely to yield positive returns on investment from the introduction of a new product (Song & Thieme, 2006). In a in highly competitive environments such as Chinese context, exploitative learning has been found to benefit firms (Liu et al., 2020). However, previous studies have shown that when Chinese firms engage in excessive exploitative learning, this may have a diminishing return effect on their performance (Li et al., 2013).

Hence, we propose that:

Hypothesis 2: Exploitative learning negatively moderates the effect of deployment of CA on new product performance.

Hypothesis 2a: Exploitative learning moderates, via knowledge integration mechanisms, the indirect effect of CA on new product performance, such that this mediation effect gradually disappears for firms that use extensively exploitative learning strategies.

Market knowledge breadth represents the scope and diversity of a firm's knowledge base with regards to its customers and competitors (Bao, Xiaoyun, & Zhou, 2012). A firm would have broad market knowledge if it has knowledge on an extensive variety of current and potential customer segments and competitors, and employs an extensive range of parameters to evaluate their behavior (De Luca & Atuahene-Gima, 2007). Breadth of market knowledge may provide firms with opportunities to use knowledge embedded in diverse fields in a more complex and creative manner (Prabhu, Chandy, & Ellis, 2005). However, the breadth of knowledge demands distant (or non-local) search for diversified information bits, and integrating knowledge from across diverse disciplines including the technically complex industries (Katila, 2000; Katila & Ahuja, 2002;

Prabhu et al., 2005). Though effective search and combination of distant knowledge elements may promise path-breaking innovations, bridging these elements is challenging and costly, and thus carries the risk of generating product outputs with little or no commercial value (Miller, Fern, & Cardinal, 2007). For example, previous studies have shown that market knowledge breadth can hurt outputs since firms may not accurately respond to new information that is distinct from their direct experience or local environmental situations (Katila & Ahuja, 2002). It is also suggested that market knowledge breadth may cause a firm to spread its resources too thinly, lose its focal product and technology domain, and thereby fail to exploit externally obtained knowledge in NPD (Prabhu et al., 2005). In the institutional environment of China, where government policies strongly advocate for technological innovation and digitization (Li et al., 2018), firms leveraging niche market knowledge could align more closely with these national priorities, enhancing their use of customer analytics. This alignment is particularly evident in the high-tech sector, where Chinese firms, by concentrating on these specific niches, are able to capitalize on government incentives and regulatory support, leading to more effective and targeted product development strategies. In this sense, it can be claimed that a firm's market knowledge breadth may reduce the value of data-driven facts in its product innovation.

The breadth of market knowledge can enhance the capability to acquire, integrate, analyse and make sense of highly diversified information obtained from Big Data. Some studies suggest that a firm's broader knowledge base with various territories of knowledge has a positive impact on its absorptive capacity because it increases the prospect that external information will relate to what is already known (Cohen & Levinthal, 1990; Zhang, Baden-Fuller, & Mangematin, 2007). In particular, the breadth of market knowledge spanning diverse knowledge domains promises greater scope for identifying and responding to a market opportunity; thus, as the market knowledge breadth increases, internal capability in recognizing, foreseeing and exploiting new and diversified market opportunities hidden in Big Data would also increase. On the other hand, when the breadth of market knowledge is low, the internal capability of the firm to exploit Big Data for pushing performance of new products to a higher level would be limited. Since processing of information associated with fewer

knowledge domains does not require 'hard to imitate' internal capabilities, lower breadth of market knowledge would diminish the mediation effect of internal capability on the relationship between the deployment of CA and new product performance. Hence, firms with lower breadth of market knowledge would incur higher opportunity costs when using internal capability, reducing the indirect effect of CA deployment on new product performance. In competitively and technologically dynamic contexts such as China, it is important to ensure that firms have the required internal capabilities to exploit the benefits of market knowledge breadth. However, it can also be acknowledged that the role of internal capabilities in the relationship between the deployment of CA and new product performance lessens, when the breadth of knowledge reduces.

Previous research suggests that the technological and organizational costs and challenges for integrating a large spectrum of new knowledge and the complexity of its use in NPD may lead to more mistakes in knowledge integration and eventually hurt product innovativeness (Bao et al., 2012; Katila & Ahuja, 2002). Yet, a higher level of market knowledge breadth enables firms to gain familiarity with multiple knowledge elements, which helps them to develop formalized processes to integrate such knowledge across diverse intra-firm functional units for strategic decision-making. For example, integration of complex and diversified information often requires multiple opportunities for assimilating it, including close and frequent interactions and strong ties between actors (Hansen, 1999). Such knowledge sharing practices offer truly innovative ways of combining knowledge by stimulating 'kaleidoscopic thinking', which emerges in a firm with diverse knowledge domains (Zhou & Li, 2012). Therefore, when firms have higher levels of market knowledge breadth, knowledge integration mechanisms become the key instrument for turning highly diversified information obtained from CA into strategies and solutions for supporting improved new product performance. On the other hand, when firms have poor knowledge of the wider market, the importance of knowledge integration mechanisms in the CA deployment and new product performance relationship would reduce. In particular, they would build more on their previous knowledge and the marginal benefits of integrating less diversified and distant information for new product performance would reduce.

Using knowledge integration mechanisms would be particularly important for employees of Chinese firms who tend to share their knowledge with closely knitted social groups rather than with others across the organization who are outside their close networks (Chow et al., 1999). This implies that without the presence of knowledge integration mechanisms, highly diversified knowledge developed through CA may not be effectively shared within Chinese firms to improve new product performance. However, as the diversity of knowledge in terms of the market knowledge breadth reduces, the role of knowledge integration mechanisms in the relationship between CA on new product performance lessens.

Therefore, we suggest that:

Hypothesis 3: **Market knowledge breadth negatively moderates the effect of the deployment of CA on new product performance.**

Hypothesis 3a: **Market knowledge breadth moderates, via internal capability, the indirect effect of the deployment of CA on new product performance, such that this mediation effect gradually disappears for firms with low levels of market knowledge breadth.**
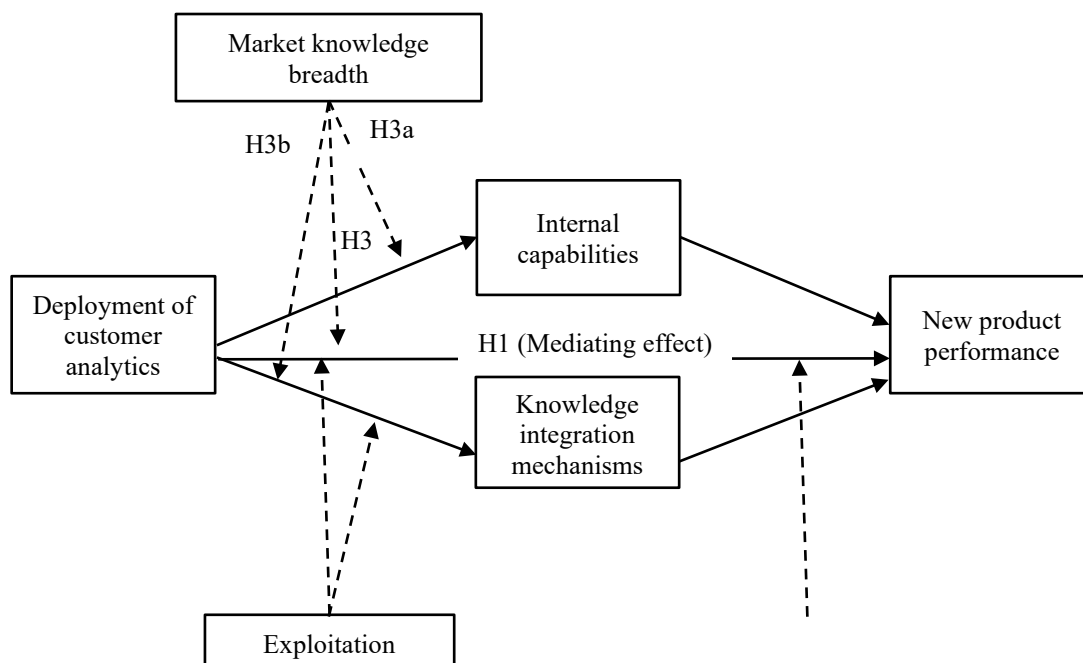
Hypothesis 3b: **Market knowledge breadth moderates, via knowledge integration mechanisms, the indirect effect of the deployment of CA on new product performance. This mediation effect gradually disappears for firms that with low levels of market knowledge breadth.**

Technological turbulence represents the rate of technological change in an industry context (Jaworski & Kohli, 1993). Thus, technologically turbulent environments are characterized by products with short life-cycles and fast technological obsolescence (Song et al., 2005). In the rapidly evolving technological landscape of China, the relevance and applicability of insights derived from CA could be significantly challenged. This high rate of change in particular industries (such as Consumer Electronics) leads to shorter product life cycles and rapid shifts in consumer preferences (Zhou and Li, 2010), making it difficult for firms to rely on CA effectively for new product development (NPD), as customer data and trends may quickly become outdated.

In environments which are technologically turbulent, generating new product success requires information obtained through CA so to have more elements of novelty compared to information acquired under stable environmental conditions (Kaleka & Berthon, 2006). However, CA may not be able to support NPD in environments where technological disruption is common and, as a result, firms may be unable to grasp technological developments or changes in the external environment (Chen et al., 2015; Chen & Lien, 2013). In particular, technologically turbulent environments may limit the usefulness of CA when technological requirements are continuously changing (Harford, 2014; Holcombe, 2015). This creates a strategic misfit between CA and the decision to use it in technologically turbulent environments. Related to this view, studies in NPD suggest that generating product innovation success in technologically turbulent environments necessitates better managerial instincts and co-development with lead users to foresee unforeseen technological occurrences (Grinstein, 2008). Due to these reasons, we expect that Chinese firms which are operating in industries that are characterized by higher levels of technological turbulence, CA may be costly and ineffective for achieving improved new product performance.

Therefore, we hypothesize that:

Hypothesis 4: **Technological turbulence negatively moderates the effect of deployment of CA on new product performance.**

H2   H2a   H4

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                                    ┌──────────────┐
                                    │Technological │
                                    │ Turbulence   │
                                    └──────────────┘
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Figure 1. Conceptual Framework

3. Methodology

3.1 Sample and data collection

3.1.1. Phase I: Multiple Case Study Research

China's unprecedented pace of urbanization has precipitated profound social transformations, leading to diversification in consumer demands and lifestyles that are central to NPD (Wu et al., 2021). Concurrently, the pervasive digitalization of Chinese society, manifest in the ubiquity of mobile internet access and social media usage, offers a rich repository of consumer data, integral for BDA or more specifically CA (Razzaq and Yang, 2023). In addition, The Chinese government has assigned a high strategic priority to the use of Big Data and has encouraged the adoption of CA across a broad spectrum of firms (ICAEW, 2017). These intertwined social phenomena make China an ideal context for examining the impacts of CA on new product performance, reflecting both rapid societal change and advanced technological integration.

First, this study used qualitative multiple case studies which were based on secondary data from various data sources such as company websites, newspaper articles, consultancy reports, industrial publications, and news releases and statistical information attained through certain electronic databases including NEXIS, Euromonitor International and Statista. In this context, the secondary data collection was based predominantly on media and communication sources which constitute a type of archival data source (Barnes et al., 2018). The data analysis included only minor statistical data about companies which were attained from privately available databases (e.g. Euromonitor International). According to Barnes et al. (2018), such sources can provide in-depth information about figures and events such as the case study companies and instances associated with their CA implementations. The case study method was ideal to provide an in-depth examination of a contemporary research phenomenon in its real life context (Yin 1981). Specifically, the case studies were used to gain

insights into the implementations of CA in Chinese manufacturing industries, and complement the findings obtained from the quantitative survey. Judgmental or purposeful sampling strategy was used to select three cases (i.e. Insilico Medicine, COMAC or the Commercial Aircraft Corporation of China, and Huawei) operating in some of the manufacturing industries in China, which constituted the portraits of best practice in BDA implementations in general and application of CA in particular. The data of the case studies was analyzed to build explanations about each case through exploration and identification of the connections between the CA theme and other themes associated with its benefits, challenges and performance implications (Yin, 2013). The analysis of secondary data enabled us to identify the key themes which are important to consider in the context of CA implementations in China (e.g. the roles of internal capabilities and external environment in the deployment of CA). Therefore, the secondary data based multiple case studies have helped us to identify our focal constructs for the survey research or the second phase of this study. In this way, the first phase of the research has provided insights into which contingency factors (both internal and external to the firm) can influence the role of CA deployment in new product performance.

3.1.2. Phase II: Survey Research

Second, the quantitative phase, guided by a structured survey, complements the qualitative insights by offering breadth and generalizability, addressing the comparative limitation of smaller sample sizes in qualitative research (Molina, 2012; Gibson, 2017). Such a methodological design adheres to the principle that integrating qualitative and quantitative data yields a more complete utilization of data and allows for a richer synthesis of information. the study employed self-administered structured, quantitative surveys and the sampling frame of the survey was obtained from the official Chinese National High-Tech Enterprise list, which is held from the Ministry of Science and Technology of the People's Republic of China.

To be included in our sample, a firm has to (1) engage in an NPD activity and (2) have used CA to inform their new NPD decisions in the previous five years. In the initial phase of data collection, randomly selected industrial manufacturing firms were contacted for prescreening questions to identify the

firms that fitted our sample criteria. Following the prescreening process, the structured self-administered surveys were posted to 700 manufacturing firms in China. To encourage participation, the respondents were offered prize incentives. The survey was originally designed in English and subsequently parallel translated into Chinese (Mandarin) by two independent professional translation companies. Subsequently, the parallel-translated surveys were merged into a final draft which was then back translated into English by another independent translator from one of the translation companies. The English version was reviewed by two academics to ensure the accuracy and clarity of the translations. The survey was also pilot-tested with 32 manufacturing firms to eliminate potential ambiguities and further improve the clarity of the questions and face validity of the measurement items. 254 surveys were returned with a response rate of 36%. Of these, only 249 surveys could be used. As reported in Table 1, the sample firms were from several industries that were selected based on the OECD's (2013) definition of high- and medium-high technology industries.

3.2   Survey Variables for Phase II

We developed a series of multi-item measures for our variable. We have therefore either adopted scales that had been previously validated from the existing literature or modified them appropriately to fit our research context. The definitions of the variables are shown in Appendix 1.   The three measurement items for the deployment of the CA construct was adopted from Germann et al. (2014) and used a seven-point Likert-type scale (1=strongly disagree to 7=strongly agree). Based on Germann et al.'s (2013) operationalization, we employed three measurement items to assess internal capability through a seven-point Likert-type scale (1=strongly disagree to 7=strongly agree). The six measurement items for knowledge integration mechanisms were based on the study of De Luca and Athuahene-Gima (2007) and employed a seven-point Likert-type scale (1=never used to 7=very widely used). Exploitative learning was measured through a seven-point Likert-type scale (1=strongly disagree to 7=strongly agree) using ten items, which were based on a study of Yannopoulos et al. (2012).   Market knowledge breadth was measured using a seven-point Likert-type scale (1=strongly disagree to 7=strongly agree) through three items

which were adopted from Zhou and Li (2012). Technological turbulence items were adopted from Jaworski and Kohli's (1993) study and measured using five item statements through a seven-point Likert-type scale (1=strongly disagree to 7=strongly agree). This study focused on the commercial or financial performance of new products. In this context, new product performance was measured through a seven-point Likert-type scale (1=strongly disagree to 7=strongly agree) using four items adopted from Atuahene-Gima and Ko (2001) and Moorman (1995). Finally, we controlled for firm size and industry type. Firm size was measured in terms of the number of employees, while industry type was measured as a categorical variable by asking participants to indicate which category best describes their primary industry.

Table 1. Basic Statistics

		Number of firms	Percentages (%)
Industry type	Aircraft and spacecraft	1	0.4%
	Electrical machinery and apparatus	145	58.2%
	Office, accounting and computing machinery	22	8.8%
	Radio, TV and communications equipment	4	1.6%
	Medical, precision and optical instruments	25	10.0%
	Pharmaceuticals	23	9.2%
	Others	29	11.6%
Firm size	1 to 9 employees	1	0.4%
	10 to 19 employees	1	0.4%
	20 to 49 employees	7	2.8%
	50 to 249 employees	60	24.1%
	250 to 500 employees	69	27.7%
	501 to 1,000 employees	61	24.5%
	1,001 to 2,000 employees	28	11.2%
	2,001 employees and more	21	8.4%

	Others	1	0.4%
Responde nts' role in the firm	Chief Executive Officer	41	16.5%
	Marketing Manager	101	40.6%
	R&D Manager or Chief Engineer	80	32.1%
	Other managers	27	10.8%
Total		249	100.0%

3.3. Reliability and validity of survey data for Phase II

Table 2 presents the means, standard deviations, Cronbach's alphas, the square root of the average variance extracted (AVE), and construct correlations. The Cronbach's alphas (ranging from 0.70 to 0.84) show a satisfactory degree of internal consistency reliability for the measures. Construct reliability was assessed using composite reliability (CR) (Fornell & Larcker, 1981). As shown in Table 3, the CRs range from 0.70 and 0.84 and are all greater than the commonly accepted cutoff value of .70 (Gefen, Rigdon, & Straub, 2011), which demonstrates adequate reliability for the measures. Discriminant validity was first assessed by examining the correlations among the factors. Although there are no firm rules, inter-construct correlations below |0.7| provide evidence of measure distinctness, and thus discriminant validity. No factor correlation is greater than 0.7, which demonstrates discriminant validity (see Table 2). Another way to examine discriminant validity is to compare the Average Variance Extracted (AVE) to the squared inter-construct correlation. When the AVE is larger than the corresponding squared inter-construct correlation estimates, this suggests that the indicators have more in common with the construct they are associated with than they do with other constructs, which again provides evidence of discriminant validity. The data suggests adequate divergent validity of the measures.

To further assess the reliability and validity of the models' seven latent constructs, we conducted a confirmatory factor analysis (CFA) using AMOS 24.0. The fit indices and standardized loadings report are shown in Table 3. The model chi-square was statistically significant (χ^2 (278) = 513.290, p < .05), which indicates that the exact fit hypothesis should be rejected. However, as this test is highly sensitive (Jöreskog & Sörbom, 1986), other measures of goodness-of-fit were also examined. The comparative fit index (CFI) was 0.920, which exceeds the cut-off

value of .80, and the standardized root mean square residual (SRMR) was .0551. The root mean square error of the approximation (RMSEA) was .058, which is less than .08. Thus, we concluded that our data adequately fit the measurement model.

Our data were collected from individual respondents using the same survey instrument, exposing the observed relationships to the threat of common method bias (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). To reduce common method bias, Podsakoff et al. (2003) suggest that structural procedures need to be utilized during the design of the study and data collection processes[5]. We assessed the potential effect of common method bias statistically by conducting three tests. First, Harman's one-factor test (Podsakoff & Organ, 1986) generated eight principal constructs; the un-rotated factor solution shows that the first construct explains only 38.55% of the variance, indicating that our data do not suffer from high common method bias. Second, we performed a partial correlation technique using a marker variable to separate out the influence of common method bias. Following Lindell and Whitney (2001), we used the second smallest positive correlation among measurement items as a proxy for common method bias to adjust the correlations between the principal constructs. The adjusted correlations were only slightly lower than the unadjusted correlations and their significance levels did not change, suggesting that common method bias did not spuriously inflate the construct relationships (Lindell & Whitney, 2001). Finally, we compared correlations among the constructs. The results revealed no constructs with correlations over 0.7, whereas evidence of common method bias ought to have brought about significantly higher correlations (r < .90) (Bagozzi et al., 1991). Consequently, these tests suggest that common method bias is not a major concern in this study.

Table 2. Descriptive statistics and correlations for the study constructs

Constructs	Means	SD	1	2	3	4	5	6	7
Deployment of CA (DCA)	5.16	1.01	**0.7**						

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[5] Following these guidelines, we protected respondent researcher anonymity, provided clear directions, and proximally separated independent and dependent variables (Podsakoff et al., 2003).

Measure	Mean	SD	1	2	3	4	5	6	7
Internal capability (IC)	4.87	0.94	0.55	**0.66**					
Knowledge integration mechanisms (KIM)	5.46	0.99	0.58	0.45	**0.72**				
Exploitative learning (EXPLOIT)	5.30	0.94	0.54	0.35	0.55	**0.70**			
Market knowledge breadth (BREADTH)	5.32	0.98	0.60	0.54	0.65	0.61	**0.72**		
New product performance (NPP)	5.18	1.04	0.48	0.50	0.57	0.51	0.64	**0.75**	
Technology turbulence (TT)	5.31	1.02	0.51	0.48	0.60	0.55	0.69	0.57	**0.76**

Note: Correlations are significant at the 0.01 level (2-tailed). Boldface numbers on the diagonal are the square root of AVEs

Table 3. Confirmatory factor analysis of measures

Measure, source, and items	Factor loading (t-value)	alpha/CR	AVE
Deployment of customer analytics (adopted from Germann, Lilien, Fiedler & Kraus, 2014)		0.74/0.75	0.50
In our firm, we extensively use customer analytics.	0.79 (*)		
Virtually everyone in our firm uses customer analytics-based insights to support decisions.	0.67 (9.63)		
When making decisions, we back arguments with customer analytics-based facts.	0.64 (9.15)		
Internal capability (adopted from Germann, Lilien & Rangaswamy, 2013)		0.70/0.70	0.44
Our employees are very good at identifying and employing the appropriate customer analysis tool and technique given the problem at hand.	0.73 (*)		
Our employees master many different quantitative customer analysis tools and techniques.	0.69 (8.92)		
Our employees can be considered as experts in customer analytics.	0.56 (7.50)		
Knowledge integration mechanisms (adopted from De Luca & Athuahene-Gima, 2007)		0.84/0.84	0.51
Regular formal reports and memos that summarize learning.	0.73 (10.88)		
Information sharing meetings.	0.75 (11.19)		
Face-to-face discussions by cross-functional teams.	0.66 (9.83)		
Formal analysis of failing product development projects.	0.69 (10.29)		
Formal analysis of successful product development projects.	0.74 (*)		

Use of experts and consultants to synthesize knowledge. [a]	-		
Exploitative learning (adopted from Yannopoulos, Auh & Menguc, 2012)		0.76/0.82	0.48
We adhere to existing ideas and methods of solving market and product problems. [a]	-		
We undertake market search activities that we knew we could do well rather than those that may lead to mistakes.	0.75 (*)		
We emphasize current methods and solutions to market problems that build on the company's experience. [a]	-		
We search for market information and ideas that take the company into its existing markets and areas of learning.	0.64 (9.45)		
We undertake information search activities that tap into current experiences of the company.	0.59 (8.79)		
At our company, a strong emphasis is placed on improving efficiency.	0.75 (11.15)		
Our company excels at refining existing technologies.	0.74 (10.99)		
We frequently adjust our procedures, rules, and policies to make things work better. [a]	-		
Market knowledge breadth (adopted from Zhou & Li, 2012)		0.82/0.76	0.51
We possess market information from a diversified customer portfolio.	0.74 (*)		
We have accumulated knowledge of multiple market segments.	0.74 (11.04)		
Our R&D expertise consists of knowledge from a variety of background.	0.66 (9.81)		
New product performance (adopted from Atuahene-Gima & Ko, 2001 and Moorman, 1995)		0.83/0.84	0.56
In the last 3 years, new products/services at my firm generally achieved… … their market share objectives.	0.73 (*)		
… their sales and customer use objectives.	0.75 (11.70)		
… their sales growth objectives.	0.78 (12.16)		
… their profit objectives.	0.68 (10.56)		
Technological turbulence (adopted from Jaworski & Kohli, 1993)		0.80/0.81	0.58
The technology in our industry is changing rapidly.	0.78 (11.36)		
Technological changes provide big opportunities in our industry.	0.78 (11.43)		
It is very difficult to forecast where the technology in our industry will be in the next 2 to 3 years. [a]	-		

A large number of new product ideas have been made possible through technological breakthroughs in our industry.	0.73 (*)		
Technological developments in our industry are rather minor. [a]	-		

Model fit statistics: χ^2 = 513.290 (df = 278, P<0.05); CFI=0.920; IFI=0.921; RMSEA=0.058 [0.050, 0.066]; Standardized RMR = 0.051.

Note: N=249. All factor loadings are significant at p<0.05. Alpha: Cronbach's alpha. CR: Composite reliability. AVE: average variance extracted.

[a] Items were dropped from the scale during the measure purification phase.

[*] Item was equated with 1 to set the scale.

4. Analysis of Case Studies for Phase I

China is becoming one of the most important producers of innovative drugs, which can be attributed to the improved policy environment and establishment of manufacturing facilities by the leading global pharmaceutical companies in China (Atkinson, 2019). Pharma 4.0 concept includes the application of BDA in general and CA in particular to improve R&D cycle times, costs and effectiveness, and production efficiency of pharmaceutical firms (Rowe, 2019; Wang and Chen, 2021). Specifically, it involves CA to improve selection of patients, acquisition of data from targeted users and integration and analysis of patient or user data for decision making (ReleaseWire, 2022). In this sense, the pharmaceutical firms in China are increasingly investing in CA solutions to enhance their innovation performance and competitiveness in the world (Wang and Chen, 2021). Insilico Medicine is a pharmaceutical firm headquartered in Hong Kong with a robotics lab in Suzhou China (Lee, 2023). Due to the presence of contract research organisations in China, in its earlier days Insilico could manage to undertake research without possessing its own wetlab (Chace, 2022). Insilico Medicine directly integrates Big Data based generative AI in its drug discovery for rare diseases.

Importantly, the firm introduced the world's first anti-fibrotic drug generated by its AI-based drug discovery platform, i.e. pharma AI (Zhihua, 2022). The platform uses millions of data samples and multiple data types and through deployment of CA the firm discovers traces of diseases and generates new molecular structures with targeted properties. By using CA induced AI, the company enhances the speed and efficiency in identifying the most relevant patient data for new drug development and anticipation of the performance of new drugs, which in turn reduce the time to market (Hagan, 2023). The

deployment of CA using the patient based Big Data stored in the platform has enabled Insilico Medicine to increase its prospects of success for clinical trials and reduce the risk of drug development failure while finding most innovative solutions to treat several diseases effectively (Philippidis, 2022). It has been observed that Insilico Medicine and other companies using Big Data based AI have reduced the time and costs of drug development by as much as 90% (Chace, 2022; Philippidis, 2022). Alexey Dubovenko, the Product Director of the company's Pandomics platform used for CA purposes to categorize patient groups with improved accuracy, stated that: "At Insilico, we have developed a platform that hands the power of bioinformatics over to the researcher's hands… When designing the tool, we focused on storytelling in data analysis and providing guidance for each step" (CISION PR Newswire, 2020).

Furthermore, CA can be deployed throughout the value chain to identify the requirements of business customers to improve a range of value chain processes ranging from management of supply chains to design of innovative marketing and sales campaigns (Jephcott, 2022). However, the greatest challenge that firms in pharmaceutical industry are facing when implementing Big Data based AI and CA is that they still need to improve their Data Analytics and AI based programming knowledge and skills. In addition, when necessary, they need to ensure that they can enhance their data quality and volume through partnerships with relevant stakeholders which may provide them access to greater degree of specialist knowledge in certain areas of digital technology implementation (Chace, 2022; May, 2003).

Implementation of CA has also become important in other Chinese manufacturing industries such as in aircraft production. The industry has become the largest producers of military drones to equip its own armed forces as well as to grow its export performance (Wodecki, 2023). Importantly, China has exploited its late development advantage in digital technologies as compared to several advanced economies, and thus has benefited from enhanced R&D investment, less intensified innovation risk, reduced market development cost, and accelerated replacement of outmoded technologies with their novel counterparts (Wu and Duan, 2018). As such, it has been more straightforward for China to have progression towards smart manufacturing through the deployment of BDA in general and CA in particular, and other digital

technologies such as Internet of Things (IoT) and AI technologies (Wu and Duan, 2018). COMAC (the Commercial Aircraft Corporation of China), which is a is a state-owned aerospace manufacturer headquartered in Shanghai, China, in its collaboration with Lenovo has benefited from using Augmented Reality (AR) technology which is supplemented with CA in the development and manufacturing of commercial aircrafts. The use of CA and AR technologies have enabled the company to increase product development and manufacturing efficiency and quality while diminishing their costs (Lenovo.com). COMAC has also used other digital technologies to complement its deployment of BDA. For example, it has used 3D printing (or additive manufacturing) in the design and manufacturing of its one of its regional jets, while has plans to continue using 3D printing in increasing number of its products in the future (Qian, 2017). The corporation has also plans to use AI in order to optimize its aircraft designs and continue meeting customer requirements (Nulimaimaiti, 2023). For example, it uses a flight simulator platform through simulation modelling and virtual reality (VR) technology to train pilots and make sense of user experience through CA (Global Times, 2023b). However, the implementation of smart manufacturing including the utilization of AI, 3D printing, AR and IoT technologies, and user driven design through CA also puts manufacturing systems and infrastructure at risk which may be caused by disruptions of wireless communications or internet connectivity. (Marr, 2016). In this context, China still needs to overcome inherent problems grounded in its digital technology infrastructures such as the limitations of its AI talent, deficiency of its knowledge in some core technologies, its funding inequalities, concerns over its market competition and control, and its existing external dependencies (Abadico, 2019).

Similarly, China has developed its digital technology infrastructure in electrical machinery, communications, and electronics industries. Huawei is a Chinese multinational technology firm headquartered in Shenzhen, Guangdong which is operating across these industries. It is a leading global provider of information and communications technology (ICT) infrastructure and smart devices. The firm provides various BDA solutions for several stakeholders. For example, it uses cloud based Fusioninsight data lake and Fusioninsight-Universe BDA Platform to provide solutions for thousands of business customers operating in various industries in more than 60 countries and regions (Huawei,

2022). Importantly, the revenue of Huawei's cloud-based businesses has grown from 3 billion Yuan in 2018 to 20 billion Yuan in 2021 (AskCI Consulting, 2022). This growth can be attributed to the company's high-level competence in creating value for its business customers by supporting them with the implementation of BDA or more specifically CA solutions. For example, Bank of Communications (BOC) has won the Best Big Data Implementation award by building its intelligent data lake solution upon Huawei's Fusioninsight data lake and warehouse. This solution has enabled BOC to generate customer (or user) personas via transactions and interactions with customers (or users), and to implement CA which in turn enhanced the company's rate of customer conversion by 164%. Similarly, the solution has enabled BOC to develop a new CRM system to minimize customer turnover and maximize customer retention (Contify Telecom News, 2022).

Huawei has been positioned as the market leader and driver of customer analytics based solutions which provides its business customers with improved customer insight for marketing and customer service purposes (Targeted News Service, 2017). Indeed, NPD and new product design are some of the key areas that Huawei utilizes CA to gain insights into the market needs and opinions to make key decisions about their future products (Li, 2022). Customer insights attained through CA have enabled the firm to improve its R&D process and significantly reduce the time to market (Huawei.com). As a global firm, when developing new products, Huawei has been implementing an integrated product development approach to ensure that all different functional units of the firm are aware of Big Data on customer requirements that is acquired through customers' use of Huawei products and interactions with the firm. In this sense, the company deploys CA which is based on Big Data about customers collected through multiple channels. Such an approach also enables the firm to make data driven decisions on which products should be introduced to which market (Chenze, 2016). Yet, one of the challenges that the Huawei is facing when deploying BDA and specifically CA for product development purposes is that the firm is facing restrictions of trade in some countries such as the U.S. and data access in regions such as the EU which challenge Huawei's capability to innovate and pursue its technology leadership and dominance in the global market (Shah, 2020). Though Huawei has collaborated with over 5000 European firms in several industries to

provide innovative products and solutions, the EU is concerned about the potential security risks posed by Huawei to their 5G networks, and thus may apply a mandatory ban on the firm's operations in the EU region (Global Times, 2023a). This implies that Huawei will have limited access to customer data which can provide the firm with some in-depth insights on user preferences and behaviours in certain countries and regions. In addition, according to the statements provided by Huawei, the firm is experiencing challenges in employing staff with advanced CA (or more broadly BDA) related skills, which are necessary to be innovative and competitive in its product markets (Huawei.com). Our multiple case analysis demonstrates that CA providing insights into customers has been extensively used by some leading manufacturers in China despite the fact that its implementation is challenged by several factors such as the availability of knowledge and skills in deploying CA (or more broadly BDA).

5. Analysis of Survey Data for Phase II

We first performed a series of multiple regression analyses to test the main effects. The indirect effects were tested by using a macro for SPSS that allows the use of a methodology developed by Hayes (2013). This approach allows testing of the mediation and moderation effects simultaneously (i.e. conditional direct/indirect effects in moderated meditation models) and uses a boot-strapping technique to assess the significance of the indirect effects (Preacher & Hayes, 2008).

5.1. Main effects and mediation effects

Table 4 presents our main results. Model 1 includes four control variables. Model 2 includes all controls and our key independent variable. The deployment of CA is positively associated with new product performance.

The indirect effect of the deployment of CA on new product performance was examined in Model 3a-3c. The deployment of CA has a positive impact on knowledge integration mechanisms, which in turn enhances new product performance. The deployment of CA also has a significant positive effect on internal capability which, in turn, has a significant positive effect on new product performance. The results show that the deployment of CA is not associated with

NPD in Model 3c. The paths describing the effect of the deployment of CA on NPD through knowledge integration mechanisms and internal capability were significant. To test and quantify the indirect effect, we estimated the confidence intervals via bootstrapping (Preacher & Hayes, 2004, 2008). The indirect effect of internal capability is statistically significant (lower level CI [LLCI] = 0.02; upper level CI [ULCI] = 0.15). The same applies to the indirect effect of knowledge integration mechanisms as evidenced by the bias-corrected bootstrapped confidence interval (CI). These results support Hypothesis 1.

Table 4. The results of main and mediation effects

	Model 1	Model 2	Model 3a	Model 3b	Model 3c
Control variables					
Firm size	0.11(2.66)**	0.09(2.38)*	0.12(3.44)***	0.06(1.51)	0.05(1.33)
Firm position	0.28(4.05)***	0.26(3.79)***	0.03(0.57)	0.07(1.12)	0.23(3.60)***
Industry type	-0.19(-0.70)	-0.01(-0.17)	-0.06(-2.30)*	-0.02(-0.88)	0.01(0.53)
Technology turbulence	0.52(10.04)***	0.42(7.16)***	0.40(7.76)***	0.24(4.47)***	0.26(4.15)***
Dependent variables	NPP	NPP	KIM	IC	NPP
Independent variables					
DCA		0.22(3.68)***	0.32(6.11)***	0.35(6.33)***	0.07(1.08)
Mediating variables					
KIM					0.26(3.70)***
IC					0.20(3.03)**
Indirect effect [LLCI; ULCI][a]			0.03[0.02-0.15]		
Indirect effect [LLCI; ULCI][b]			0.04[0.02-0.17]		
N	249	249	249	249	249
R^2	0.393	0.425	0.504	0.372	0.478
F value	39.539***	35.955***	49.42***	28.77***	31.47***

Note[1]: Unstandardized regression coefficients are reported; t-value in parentheses; * $p < .05$; ** $p < .01$; *** $p < .001$ (two-tailed test).
[a] Indirect effect of internal capability (IC)
[b] Indirect effect of knowledge integration mechanisms (KIM)
Note[2]: Deployment of CA (DCA), internal capability (IC), knowledge integration mechanisms (KIM), exploitative learning (EXPLOIT), market knowledge breadth (BREADTH), new product performance (NPP), technology turbulence (TT)

5.2. Moderation effects

A moderated mediation analysis was conducted to test the moderating effect of exploitative learning, market knowledge breadth, and technology turbulence using the methodology suggested by Hayes. To test these relationships, we first mean-centered the variables including the deployment of CA, and exploitative

learning, market knowledge breadth, technology turbulence, and then interacted them (Aiken, West, & Reno, 1991). Second, the significance of the moderated mediation effect was evaluated using the bootstrap confidence intervals. If the bootstrap confidence interval does not include zero, we can confirm that the moderated mediation effect exists. Finally, to probe the nature of the moderated mediation, the conditional direct and indirect effects of the deployment of customer analytics on new product performance was tested using a pick-a-point approach (based on the moderator values of -1 standard deviation, mean and 1 standard deviation) (Rogosa, 1980). The results are presented in Table 5 while the conditional direct and indirect effects of the deployment of CA on new product performance versus the various values of moderators (i.e. technology turbulence, exploitative learning, and market knowledge breadth) are shown in Figure 2. The vertical axis in Figure 2 corresponds to the estimated size of the effect of the deployment of CA on new product performance where 0 denotes no effect.

In Model 1, the interaction between the deployment of CA and exploitative learning shows significant effects on both new product performance (b= -0.13; 95% CI: [-0.23, -0.03]) and knowledge integration mechanisms (b= -0.13; 95% CI: [-0.22, -0.05]). This implies that exploitative learning negatively moderates the effect of the deployment of CA on new product performance supporting hypothesis 2. The conditional direct effect analysis further reveals that the deployment of CA has a positive impact on new product performance for firms with a low level of exploitative learning (95% CI: [0.08, 0.37]). In addition, the index of moderated mediation is significant (b=-0.04, SE =0.02, 95% CI [-0.10, -0.01]). The conditional indirect effect analysis suggests that the relationship of the deployment of CA on new product performance via knowledge integration mechanisms is significant for firms with limited exploitative learning (95% CI: [0.05, 0.27]). However, the relationship of the deployment of CA on NPD via knowledge integration mechanisms is not significant for firms engaging in high levels of exploitative learning (95% CI: [-0.002, 0.19]). As shown in Figure 2(a), both the direct and indirect effects of the deployment of CA on new product performance decrease gradually as firms' level of exploitative learning increases.

In Model 2, regression results suggest that the moderating effect of market knowledge breadth is found to be significant but with a negative sign (b=-0.12; 95% CI: [-0.20, -0.03]). In addition, the results indicate that the conditional effect

of mediation of internal capability is significant at higher (95% CI: [0.04, 0.17]) and moderate levels of market knowledge breadth (95% CI: [0.03, 0.15]), but it is weak when the level of market knowledge breadth was low (95% CI: [0.00, 0.13]). As shown in Figure 2(b), the conditional indirect effects of the deployment of CA on new product performance via internal capability increases gradually as the firm's level of market knowledge breadth increases, in support of Hypothesis 3a. However, in Model 3, the index of moderated mediation is not significant (b=-0.01, SE =0.01, 95% CI [-0.04, 0.01]), rejecting Hypothesis 3b, thus partially supporting Hypothesis 3.

Model 4 shows technology turbulence turns out to be a significant moderator that buffers the relationship between the deployment of CA and new product performance (b=-0.08; 95% CI: [-0.16, -0.01]). Figure 2(C) further reveals that the positive impact of the deployment of CA on new product performance is found when technological turbulence is low (95% CI: [0.10, 0.38]), but not when it is high (95% CI: [-0.09, 0.23]). However, the conditional indirect effect of the deployment of CA on new product performance via internal capability is not significant when technological turbulence is high or low. This implies that technological turbulence is a strong moderator that blunts the impact of the deployment of CA on new product performance. Thus, Hypothesis 4 is supported.

**Table 5. Coefficients of the moderated mediation models**

Model	Independent variables	B	S.E.	T	95% CI Boot Lower	Boot Upper
	Dependent Variable: Knowledge integration mechanisms (R^2=0.44)					
	DCA	0.34	0.06	5.82***	0.23	0.46
	EXPLOIT	0.32	0.06	5.35***	0.20	0.44
	DCA*EXPLOIT	-0.13	0.05	-2.98**	-0.22	-0.05
1	Dependent Variable: New product performance (R^2=0.41)					
	KIM	0.31	0.07	4.41***	0.17	0.46
	DCA	0.11	0.07	1.56 *n.s*	-0.03	0.24
	EXPLOIT	0.27	0.07	3.89***	0.13	0.40
	DCA*EXPLOIT	-0.13	0.05	-2.56*	-0.23	-0.03
	Dependent Variable: Internal capability (R^2=0.39)					
2	DCA	0.33	0.06	5.68***	0.22	0.45
	BREADTH	0.34	0.06	5.44***	0.22	0.46
	DCA*BREADTH	0.08	0.04	1.86†	-0.00	0.16
	Dependent Variable: New product performance (R^2=0.47)					

	IC	0.21	0.07	3.19**	0.08	0.34
	DCA	0.06	0.06	0.86	-0.07	0.18
	BREADTH	0.47	0.07	6.86***	0.33	0.60
	DCA*BREADTH	-0.11	0.04	-2.65**	-0.20	-0.03
3	Dependent Variable: Knowledge integration mechanisms (R^2=0.55)					
	DCA	0.22	0.06	3.97***	0.11	0.32
	BREADTH	0.32	0.07	4.70***	0.18	0.44
	DCA*BREADTH	-0.05	0.04	-1.22 n.s	-0.12	0.03
	Dependent Variable: New product performance (R^2=0.48)					
	KIM	0.16	0.07	2.22*	0.02	0.31
	DCA	0.06	0.06	0.89	-0.07	0.18
	BREADTH	0.37	0.08	4.71***	0.22	0.52
	DCA*BREADTH	-0.07	0.04	-1.60 n.s	-0.15	0.02
4	Dependent Variable: Internal capability (R^2=0.36)					
	DCA	0.38	0.06	6.96***	0.28	0.49
	Technology turbulence (TT)	0.27	0.06	4.58***	0.15	0.38
	DCA*TT	0.03	0.04	0.85 n.s	-0.04	0.10
	Dependent Variable: New product performance (R^2=0.41)					
	IC	0.26	0.07	3.74***	0.12	0.39
	DCA	0.15	0.07	2.35*	0.03	0.28
	TT	0.33	0.07	5.13***	0.20	0.46
	DCA*TT	-0.08	0.04	-2.11*	-0.16	-0.01

Note[1]: † significant at the 0.1 level; * significant at the 0.05 level; ** significant at the 0.01 level; *** significant at the 0.001 level. All control variables (i.e. industry type and firm size) in all models were not significant, except for the effect of firm size on new product performance in Model 4.

Note[2]: Deployment of CA (DCA), internal capability (IC), knowledge integration mechanisms (KIM), exploitative learning (EXPLOIT), market knowledge breadth (BREADTH), new product performance (NPP), technology turbulence (TT)
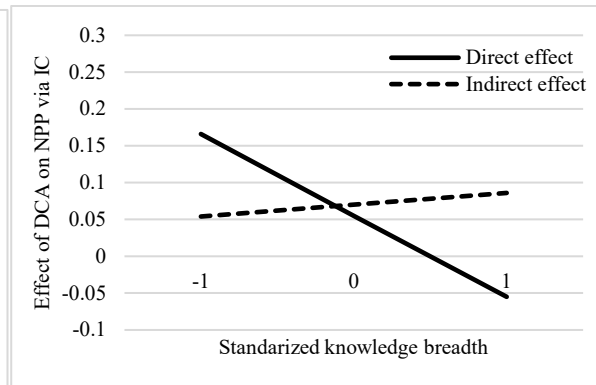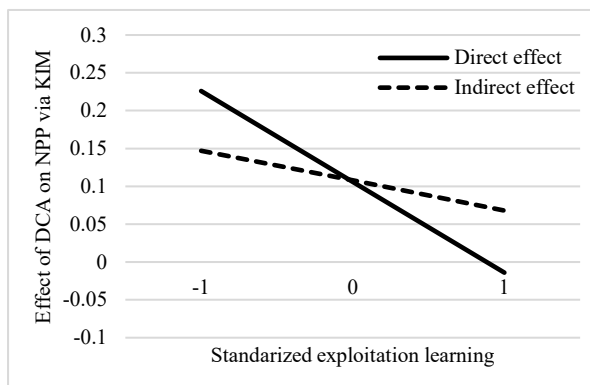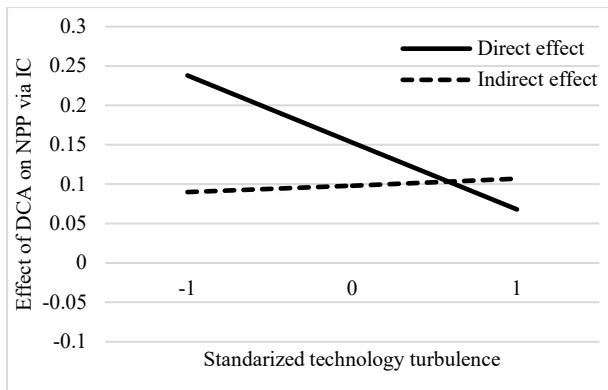
(c) Effect of DCA on NPP via IC versus technology turbulence

Figure 2. Direct and indirect effects of the deployment of customer analytics on new product performance.

6. Discussion

6.1. Theoretical Implications

This study reflects on internal and external environmental factors that may be contingent to the performance implications of using Big Data (Wamba et al. 2020; Vitari and Raguseo, 2020; Sun and Liu, 2021). For investigation purposes, we drew upon the KBV of the firm and contingency theory, to peep into the context of diverse factors that are internally contingent to operationalization of the firm's internal capabilities (Dubey et al. 2021), its knowledge integration mechanisms (Li et al. 2023), its propensity to engage with exploitative learning and market knowledge breadth (Cheng and Shiu, 2023), considering technological turbulence as an example of external contingency (Cao et al. 2009). Our study builds on the available literature that offers a mixed understanding about the use of Big Data for NPD outcomes (Johnson et al., 2017 and Urbinati et al. 2019) by considering Big Data as a valuable tool that supports new products performance, when used through CA. Our case analysis highlights those as deficiencies in knowledge and skills that are important for implementing CA.

When firms use digital technologies for improving their quality and effectiveness with efficiency and reduced costs with lead time, their internal capabilities account for a significant proportion of the relationship between CA and success of new products. Our findings imply that although Big Data may allow firms to achieve higher returns from the introduction of new products, developing a unique and difficult to imitate internal capability to use Big Data

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will provide distinctive benefits (e.g. Akter et al., 2016; Johnson et al., 2017; Wamba et al., 2017). In the Chinese context, internal capabilities have been found to play a significant role in decision making efficiency and effectiveness (Shamim et al., 2019). Similarly, the existing studies have observed that internal capabilities can enable firms to better exploit market opportunities and benefits of Big Data through enhanced efficiency and effectiveness (Sivarajah et al., 2017 ; Erevelles et al., 2016; Johnson et al., 2017; Wang et al., 2018a). In this sense, our findings are consistent with the previous studies which have shown the significance of internal capabilities in using or analyzing Big Data in a variety of performance outcomes.

Integration of knowledge extracted from Big Data has been studied previously by scholars predominantly from IT systems view in the context of interoperability capability (e.g. Wang & Hajli, 2017; Wang et al., 2018a). A few studies have also considered coordination as a type of capability (e.g. Akter et al., 2016; Wamba et al., 2017). However, literature has been silent on the extent to which the ability to integrate knowledge within a firm enhances the value of Big Data, when used for NPD. Our study builds on the previous literature by explaining the important role of knowledge integration mechanisms in the relationship between CA and new product performance. This finding also extends the insights from prior research which has observed that Chinese employees who are characterized by collectivist culture, tend to share less information with outgroup members such as cross-functional team members as compared to US employees who carry characteristics of an individual culture (Chow et al., 1999). Our findings imply that Chinese firms would improve their new product performance by using formal knowledge integration mechanisms in the deployment of CA.

We also explain how exploitative learning during this process, negatively moderates the effect of CA on new product performance. Therefore, we propose that Big Data is likely to combine information during implementation by focusing on both types of knowledge exploitation to gain insights 1) articulated (i.e. existing) customer needs and 2) knowledge exploration to discover unarticulated (i.e. latent) customer needs. It was found that when firms use their CA process for exploitative learning, the opportunity costs of using Big Data to address articulated customer needs would be greater than its benefits (Chen &

Zhang, 2014). An excessive focus on articulated customer needs through higher levels of exploitative learning in the deployment of CA processes would lead to missed opportunities for predicting and designing new product strategies to address latent customer needs and future market trends (Eng and Quaia, 2009). In line with the main tenet of organizational learning theory (Wei, Yi, & Guo, 2014), our findings imply that excessive focus on exploitative learning to recombine new knowledge elements in the realm of a firm's existing knowledge domain and experience may create a competency trap (Levinthal & March 1993), which would eventually diminish the effectiveness of using CA on new product performance.

Our moderated mediation analysis showed that the effect of CA on new product performance via knowledge integration mechanisms is only significant for firms low in exploitative learning and diminishes gradually as firms' level of exploitative learning increase. This finding extends the theoretical assumption that knowledge characteristics such as knowledge ambiguity and specificity constitute the most important predictors of organizational knowledge transfer and integration (De Luca & Atuahene-Gima, 2007; van Wijk, Jansen, & Lyles, 2008). Our results imply that beyond the knowledge generated through Big Data, the level of exploitative learning would determine the extent to which knowledge integration mechanisms support the successful NPD.

Furthermore, market knowledge breadth was found to reduce the effect of the deployment of CA on new product performance. On the other hand, our moderated mediation analysis further suggested that the role of internal capability in the relationship between the deployment of CA and new product performance increases gradually as the firm's level of market knowledge breadth increases. This, in turn, suggests that such capabilities would be most useful when insights generated about current and potential customer segments through Big Data draw from variety of heterogeneous knowledge domains (De Luca & Atuahene-Gima, 2007; Zhou & Li, 2012). Our study contributes to the literature on knowledge management, which suggests that when a firm has diverse knowledge, additional market knowledge acquisition is counterproductive for its product innovation performance (Zhou & Li, 2012). Therefore, we argue that firms capable of exploiting the volume and variety of internal information as organizational knowledge tend to benefit distinctively from the use of Big Data.

The role of knowledge integration mechanisms in the relationship between deployment of CA and new product performance was not supported for firms with higher levels of market knowledge breadth. This implies that the knowledge integration mechanisms do not account for the relation between deployment of CA and new product performance in the context of firms drawing on their knowledge market breadth in NPD (Jin et al. 2019).

Finally, technological turbulence has been found to negatively moderate the effect of the deployment of CA on new product performance. While there were mixed results about how customer turbulence (Johnson et al., 2017) and competitive intensity (Germann et al., 2013) affect the performance outcomes of Big Data analytics, our findings show that technological turbulence has a negative moderating effect on new product performance. This is because as suggested in previous studies, it can be claimed that technological disturbances are more difficult to trace and predict (Abboud and Rogalski, 2021). Thus, compared to other external environmental factors, technological turbulence would be negatively related to new product performance.

6.2. *Managerial Implications*

This study has several managerial implications. First, as suggested by the KBV, manufacturing firms need to think of Big Data as a valuable knowledge resource and use it in the deployment of CA to improve their new product performance. Importantly, in line with the main tenet of the 'fit-as-meditation' view, to achieve superior new product outcomes, firms need to develop hard to imitate internal capabilities and formal mechanisms for integrating knowledge generated through Big Data across diverse intra-firm functional units. For example, to improve the skills of data scientists (or employees implementing CA), firms can provide training on the recent tools and techniques for using Big Data. Besides providing technical training, investing in the improvement of business marketing knowledge of data scientists can facilitate better implementation of CA. In particular, for effective implementations of data analytics, different areas in business marketing such as product development, branding, promotion, customer service, and customer relationship marketing have diverse data and analytics requirements and solutions (Wedel and Kannan 2016). This implies that to develop better insights into customer needs for new products, data analysts

need to develop some domain specific knowledge on data and analytics requirements for conducting rigorous market or customer research and implementing effective product development. Furthermore, firms can organize formalized and regular communication meetings and activities to integrate customer intelligence obtained from Big Data among the team members of their diverse cross-functional units. In these meetings, cross-functional team members such as marketing, engineering and operations team members can develop a common understanding of the knowledge acquired and analyzed through the CA process.

On the other hand, firms need to ensure that they do not use Big Data excessively in their exploitative learning efforts. As suggested by the 'fit-as-moderation' view, when firms use Big Data in the deployment of CA to engage in high degrees of exploitative learning, e.g. with the aim to learn new knowledge closely related to their existing knowledge domain and experiences, its value for new product performance is reduced. For example, in NPD, the value of using Big Data, as opposed to other information sources, is greater if firms use it to explore new insights about potential trends in future markets rather than focusing on the improvement of offerings in the current markets. If firms use a high degree of exploitative learning strategy, they would experience greater time and opportunity costs when employing formal knowledge integration mechanisms to disseminate the information obtained from Big Data in the CA process. The costs of engaging in such mechanisms would gradually reduce as the disseminated information supports lower levels of exploitative learning strategy to develop new offerings without having an excessive focus on current markets, knowledge and experiences. In this context, when firms develop new products with major improvements to meet customer needs which are often hidden, they would be better off by integrating knowledge attained through CA across different functional teams through regular and formalized meetings. On the other hand, when they focus on meeting articulated customer needs by developing new products with minor improvements, integrating CA based knowledge through knowledge integration mechanisms such as formal and regular meetings would be costly to implement.

Internal capability of firms to use Big Data for addressing new product challenges is improved with increase in distinctive skills and knowledge of

employees to use CA tools as techniques. Firms need to ensure that they use Big Data not only for deployment of CA, but also to broaden their market knowledge using their internal capability to achieve improved new product performance. A distinct repository covers organizational knowledge from multiple domains and exploits market intelligence with distinct knowledge elements using data with the *3Vs.* In this context, firms need to use its breadth of market knowledge though its existing organizational repositories to ensure that they can take advantage of their internal capability for NPD purposes in the deployment of CA.

Finally, as suggested by the 'fit-as-moderation' view, firms need to make sure that they do not exclusively rely on the deployment of CA if their market environment is characterized by technological turbulence. For example, firms may complement the use of Big Data about customers attained through CA with other market intelligence means to deal with the challenges of operating in technologically turbulent environments. In such environments, to be able to make more accurate predictions of technological occurrences, Big Data may be used with other means such as lead user involvement (Von Hippel & Katz, 2002), open innovation engagements (Chesbrough & Appleyard, 2007), and involvement of star scientists (Hess & Rothaermel, 2011) in the NPD process. However, it's important to indicate that firms may still consider using Big Data attained for purposes other than understanding customers. For instance, if firms have Big Data about competitive and technological implementations, they can make use of such data through particularly predictive analytics to foresee the emerging trends in technological environments.

6.3.   *Future Research*

This study can be expanded in several ways. First, our study has investigated one type of internal capability related to BDA which focuses on the skills of employees in mastering CA tools and techniques to support business decision-making. Future research can examine how the use of BDA may affect new product performance through diverse types of internal capabilities related to BDA such as analytical capability, decision support capability, predictive capability, interoperability capability, and management capability (Akter et al., 2016; Wamba et al., 2017; Wang & Hajli, 2017; Wang et al., 2018ab).

Second, this study has only focused on formal mechanisms for integrating knowledge across diverse functional units of a firm. For example, research on strategic flexibility suggests that firms can achieve a more dynamic management of resources to adapt dynamic market environments when they build coordination flexibility (Wei et al., 2014). In this sense, informal or flexible mechanisms to integrate knowledge generated through CA may better adapt to the unprecedented *velocity* of Big Data or changing environmental conditions due to the customer and technological turbulence. Thus, future research can examine the relative effects of formal and flexible knowledge integration mechanisms in the performance of CA.

Third, this study has only focused on the moderating effects of exploitative learning and market knowledge breadth as the intra-firm contingency factors. Future studies could also focus on other learning strategies such as the role of exploratory learning and ambidextrous learning in moderating the effect of using Big Data in the CA process on new product performance (March, 1991). Similarly, the effect of certain knowledge characteristics such as knowledge tacitness and specificity, and diverse knowledge structures (both market knowledge breadth and depth) on the performance implications of Big Data analytics could be studied in the future (De Luca & Atuahene-Gima, 2007).

Fourth, this study has not incorporated the effect of intra- and inter-firm NPD collaborations in the relation between the deployment of CA and new product performance. For instance, the extent of such collaborations may support the role of Big Data in predicting the performance of new product introductions. Therefore, future research can investigate how different degrees of cross-functional integration within a firm, and inter-firm collaboration with diverse types of firms for NPD purposes may support the performance outcomes of BDA. The literature on NPD widely agrees that cross functional team integration may amplify NPD effectiveness (Sherman et al., 2005), and collaborations with diverse types of firms may enhance new product performance (Lee et al., 2017), thus they may have a supportive role in the deployment of CA process.

Furthermore, future research may consider developing a new scale for the deployment of CA. The current scales do not incorporate the objective of using Big Data in the deployment of CA. The deployment of Big Data may aim at not

only constructing a description of existing customer segments and their preferences based on certain behavioral dimensions, but also predict the hidden needs of future customers. The objective of gaining insights into both existing and latent customer needs is important for NPD. Addressing needs expressed by customers plays a critical role in the creation of short-term value, whereas, proactive addressing of latent needs of customers aids ongoing value-creation process (Ozdemir et al., 2017). Hence, these different objectives may, in turn, lead to different new product outcomes such as different types of innovation (e.g. radical and incremental innovations), speed-to-market and number of products on the market, which are worth exploring.

Finally, in the analysis of secondary data based multiple case studies, this study has only used archival data from predominantly media and communication (Barnes et al., 2018). However, using some other types of archival data such as internal company records and government research archives would enrich our analysis. Therefore, future research can use different types of archival data when complementing it with data from primary data sources.

7. Conclusions

This study focused on Big Data as a knowledge-based resource useful to firms trying to deploy CA. The investigation reflects on contingency factors that influence new product performance in the context of CA deployment. The findings reveal that the use of Big Data in the deployment of CA through hard to imitate internal capability and formal knowledge integration mechanisms help firms to achieve superior new product performance returns. While high levels of exploitative learning and market knowledge breadth create a strategic misfit by diminishing the effect of the deployment of CA on new product performance, low levels of exploitative learning through knowledge integration mechanisms and high levels of market knowledge breadth using internal capability would enhance this effect. Finally, technological turbulence has been found to reduce the benefits of using Big Data in the deployment of CA on new product performance.

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