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The effect of internet firms' data analytics capability on their innovation speed and innovation quality: A dynamic capability perspective

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THE EFFECT OF INTERNET FIRMS' DATA ANALYTICS CAPABILITY ON THEIR INNOVATION SPEED AND INNOVATION QUALITY: A DYNAMIC CAPABILITY PERSPECTIVE

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I hereby declare that this PhD dissertation is my original work
and it has been written by me in its entirety.
I have duly acknowledged all the sources of information
which have been used in this dissertation.

This PhD dissertation has also not been submitted for any degree
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30 September 2023

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ABSTRACT

With the advent of big data era, data plays a pivotal role in sustaining firms' competitive advantages. Although a few studies have shown that data analytics capability contributes to firms' innovative performance, these studies either focus on general innovative performance or specific types of innovation, such as incremental innovation, radical innovation, and supply chain innovation. In this thesis, I enrich this stream of literature by conducting two studies to further examine the relationship between data analytics capability and innovation speed as well as innovation quality. This thesis consists of two studies. Study 1 is a survey study, in which I investigate the relationship between data analytics capability and innovation speed as well as the boundary conditions for this relationship. Study 2 is also a survey study, in which I explore the relationship between data analytics capability and innovation quality as well as the boundary conditions underlying this relationship. Based on my analyses of a sample of 459 Internet firms, I find that data analytics capability is positively associated with both the speed and quality of innovation. Overall, the two studies in my thesis depict an overarching theoretical framework that links data analytics capability to innovation speed and innovation quality as well as the boundary conditions.

This framework offers a clear picture for researchers and practitioners to understands how to leverage data analytics to drive innovation speed and innovation quality in the digital era.

Keywords: Data analytics capability; Innovation speed; Innovation quality; Survey; Internet firms

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1. INTRODUCTION

With the advent of big data era, data plays a pivotal role in facilitating firms' various performance outcomes, such as competitive advantage (Laguir et al., 2022), market performance (Gupta & George, 2016), decision making quality (Awan et al., 2021), innovation (Mikalef et al., 2019), supply chain agility (Dubey et al., 2018), and operational flexibility (Yu et al., 2021). Research has shown that data matters in numerous contexts, ranging from supply chain (Cetindamar et al., 2022) and healthcare (Behl et al., 2022) to construction (Ngo et al., 2020) and education (Ashaari et al., 2021).

Extant literature mainly builds on dynamic capability theory to investigate the performance implications of data analytics capability, which is defined as firms' capability to leverage quantitative techniques to process data and extract insights from data to improve their decision making (Gupta & George, 2016; Laguir et al., 2022). Although a few studies have shown that data analytics capability contributes to firms' innovative performance (Bhatti et al., 2022; Ciampi et al., 2021; Mikalef et al., 2019; Mikalef et al., 2020a; Wu et al., 2019), these studies either focused on general innovative performance (Wu et al., 2019) or specific types of innovation, such as incremental innovation (Mikalef et al., 2019; Mikalef et al., 2020a), radical innovation (Mikalef et al., 2019; Mikalef et al., 2020a), supply chain innovation (Bhatti et al., 2022), and business model innovation (Ciampi et al., 2021). In this thesis, I enrich this stream of literature by conducting two studies to further examine the relationship between data analytics capability and innovation speed and innovation quality.

Innovation speed and innovation quality have been shown to play a central role in sustaining firms' competitive advantage (Allocca & Kessler, 2006; Haner, 2002; Kessler & Chakrabarti, 1996; Lahiri, 2010; Markman et al., 2005). However, empirical evidence regarding how data analytics capability impacts innovation speed and innovation quality remains absent in the literature. This thesis aims to fill this gap by investigating the effects of data analytics capability on innovation speed and innovation quality as well as the boundary conditions underlying these two relationships. Due to their growing level of digitalization and increased generation of data throughout operations, Internet firms are selected as the research subject in this article.

This thesis consists of two studies. Study 1 is a survey study, in which I focused on the relationship between data analytics capability and innovation speed as well as the boundary conditions for this relationship. Based on my empirical analyses of 459 Internet firms in China, I found that data analytics capability is positively associated with firms' innovation speed. This positive relationship is more pronounced for firms in environment that is characterized by high technological turbulence and strong competitive intensity. However, I did not find a significant moderating effect for market turbulence.

The research method in Study 2 is also survey. Based on my analyses of a sample of 459 Internet firms, I found that data analytics capability positively affects innovation quality. This positive relationship is enhanced when the level of top management support is high and is attenuated when the organizational structure is highly formalized. However, my analysis revealed that centralized organizational structure does not have a significant moderating effect.

Overall, this thesis contributes to the literature on data analytics capability as well as the innovation literature (Mikalef et al., 2019; Mikalef et al., 2020a; Wu et al., 2019). Specifically, whereas prior studies only showed the general relationship between data analytics capability and innovation performance (Bhatti et al., 2022; Ciampi et al., 2021), the two studies in my thesis depict an overarching theoretical framework that links data analytics capability to innovation speed and innovation quality as well as the boundary conditions. This framework offers a clear picture for researchers and practitioners to understands how to leverage data analytics to drive innovation speed and innovation quality in the digital era.

2. LITERATURE REVIEW

2.1 Data Analytics Capability

In the big data era, enormous amounts of complex data are swiftly generated and captured, presenting both opportunities and challenges for firms (Akter et al., 2016; Akter et al., 2020). On the one hand, data has emerged as a key resource and asset for firms to obtain and maintain competitive advantage in the modern economy and society (Gupta & George, 2016; Akter et al., 2020). According to prior research, data can be helpful in multiple ways, including guiding operational decision making (Srinivasan & Swink, 2018), accelerating the innovation process (Wu et al., 2019), promoting value creation (Zeng & Khan, 2019) and so on. However, on the other hand, making full use of the potential value of big data puts forward higher requirements for firms. First and foremost, it is necessary for firms to possess technology and infrastructures that can store, manage and analyze data (Mikalef et al., 2020a). Apart from that, to fully profit from big data, a variety of complementary resources (such as employee's knowledge and skills, organizational structures and processes) are also required (Srinivasan & Swink, 2018).

Against this backdrop, a large number of firms with the aim of transforming big data to commercial value are investing in the development of data analytics capability (Srinivasan & Swink, 2018), which refers to a firm's ability to efficiently assemble, integrate and deploy pertinent resources to derive insightful knowledge from big data (Gupta & George, 2016; Olabode et al., 2022). By enabling firms to quickly obtain, combine, process and analyze data (Li et al., 2022; Mikalef et al., 2020a), data analytics capability has been proven to benefit firms in a variety of ways. In terms of firm performance, it has been shown that operational performance, decision making performance, market performance and many other aspects of performance can be positively influenced by data analytics capability. For instance, building on the organizational information processing theory, Srinivasan and Swink (2018) show that data analytics capability, together with organizational flexibility that enables firms to quickly and efficiently act on insights generated by data analytics, can help firms save operational costs and increase delivery performance. Besides, using a sample of Chinese firms conducting big-data related business, Shamim et al. (2020) propose and validate that firms with data analytics capability tend to make decisions based on data rather than intuition or past experience, which enhances both the accuracy and the speed of decision making. Furthermore, Olabode et al. (2022) conceptualize data analytics capability as a three-dimensional construct (i.e., big data volume, big data variety, big data velocity) and confirm its role in enhancing the market performance.

Regarding innovation, current research has demonstrated that data analytics capability can play an important role in spurring different kinds of innovation, such as incremental and radical innovation, business model innovation, supply chain innovation and so forth. For example, according to Ransbotham and Kiron (2017) and Mikalef et al. (2020b), firms with a higher level of data analytics capability are better equipped to and more likely to generate incremental and radical innovations in their existing products and services. In addition, drawing on a dynamic capability view, Ciampi et al. (2021) show that via shaping the formulation of firms' strategies instead of being subject to them, data analytics capability has a substantial impact on the successful execution of business model innovation. Bhatti et al. (2022) have expanded the investigation of the relationship between data analytics capability and innovation into the realm of supply chain management, suggesting that in the face of technological unpredictability, data analytics capability becomes a crucial determinant for manufacturing firms to implement supply chain innovation.

Taken as a whole, our knowledge of data analytics capability and its outcomes has been significantly improved by the body of studies that have already been done. However, the research on how data analytics capability fosters innovation is generally lacking in comparison to that on general organizational performance. Additionally, the question of whether and how data analytics capability affects the speed and quality of innovation remains unclear. These gaps provide an opportunity for this study to contribute to the growing conversation about data analytics capability.

2.2 Innovation Speed

Organization and management research have the long-standing emphasis on the important role of speed, which is reflected in a number of well-developed strategic viewpoints, such as first-mover strategy, fast-follower strategy, time-based competition and so forth (Hum & Sim, 1996; Kessler & Chakrabarti, 1996). First-mover strategy indicates that a number of benefits comes with being the first one to market a new product or service, such as enhanced profits, more power to control resources, higher brand recognition and customer loyalty (Kerin et al., 1992; Lieberman & Montgomery, 1988). Fast-follower strategy further stresses that through swift following and imitation, fast-followers can not only reduce the cost of product innovation and the risk of failures, but also distance themselves with late comers to create a competitive advantage (Kessler & Chakrabarti, 1996; Robinson et al., 1994). And according to time-based competition, time management is one of the critical determinants of whether a firm can gain strategic advantage, such that those firms who can compress time and boost efficiency across every phase of the product delivery cycle are more likely to succeed in the market (Page, 1993; Stalk, 1988; Stalk & Hout, 1990). All in all, these studies have demonstrated that fast response and action are imperative for firms to establish and maintain an advantageous market position (Kessler & Chakrabarti, 1996; Perlow et al., 2002).

In today's turbulent environment, due to the relentless advancement of technology and the fiercer competition, speed, especially the speed of innovation, is becoming increasingly crucial (Shan et al., 2016; Wang et al., 2021). According to prior research (Vesey, 1991), innovation speed refers to the amount of time that has passed between early development (i.e., new product conception and definition) and ultimate commercialization (i.e., the release of a new product). As a key concept in the innovation literature, a variety of positive outcomes of innovation speed have been underscored in existing research. First and foremost, through various mechanisms, fast innovation speed can eventually result in an increase in organizational performance. For example, Brown and Eisenhardt (1995) reveal that fast-innovating firms can increase their profits and market share by addressing the shifting needs of their customers in time. Research by Kessler and Bierly (2002) implies that firms with faster innovation speed can outperform their rivals and obtain higher returns by promptly analyzing environmental and technological conditions and making timely product adjustments. Shan et al. (2016) demonstrate that accelerating the innovation process enables firms to build industry standards and accumulate brand recognition, which can lead to an increase in market share. In addition to firms' growth and general performance, innovation speed also exerts a positive impact on their innovation performance (Langerak & Hultink, 2006; Zhang et al., 2020), chances of survival (Qin et al., 2017; Schoonhoven et al., 1990).

For its importance, many scholars also analyze some drivers that can speed up innovation in firms. While a conceptual framework proposed by Kessler and Chakrabarti (1996) describes how strategic-orientation factors and organizational-capability factors might affect innovation speed, Verona (1999) develops an agent-resource model to illustrate the impact of different functional and integrative capabilities on innovation speed. Based on a meta-analytic review, Chen et al. (2010) further divide the factors influencing innovation speed into the following four categories: strategy, project, process, and team. More recently, a series of empirical studies have pointed out that entrepreneurial orientation (Clausen & Korneliussen, 2012; Shan et al., 2016), knowledge management (Taherparvar et al., 2014; Zhang et al., 2020), digitization (Cooper 2021; Marion & Fixson, 2021), platform synergy (Wu et al., 2022) and many other factors can also serve as the important antecedents of innovation speed.

In general, the speed of innovation is critical to the survival and development of firms, especially under rapidly changing and highly uncertain context. Therefore, it is imperative to analyze the antecedents that may hinder or promote firms' innovation speed, so as to help them build the capability of rapid innovation and achieve competitive advantage. Despite the fact that numerous determinants have already been examined in existing studies, none of them delves into the key factors in the era of big data. Out of this, I choose to fill this gap by exploring the impact of data analytics capability on innovation speed.

2.3 Innovation Quality

Aside from innovation speed, the quality of innovation is another meaningful dimension of innovation activity, as firms vary greatly in the performance and impact of their innovation outputs (Almeida et al., 2015; Fleming, 2007; Jin et al., 2022). Formally, scholars define this concept as the degree to which firms' innovation achievements (i.e., new products, services, and processes) satisfy consumer demands (Haner, 2002; Lahiri, 2010), which not only indicates a firm's capacity to innovate but also the caliber and level of influence of its innovative outputs (Duan et al., 2022). From the perspective of empirical measure, a range of methods are used to operationalize this variable in the extant research. The most common is the measurement based on the patent information. Take Lahiri (2010) for an example, the total number of citations that each of the firm's patents had received has been used to gauge the quality of a firm's innovation outputs for the reason that a patent that is cited by more future inventors tends to have a bigger impact than those cited by less. In addition, while some scholars utilize the interval between a patent application and its initial citation to assess the quality of innovation (Fisch et al., 2017), others try to distinguish between high-quality and low-quality innovation using the application number of invention patent and utility patent respectively (Hu et al., 2020). Moreover, to encompass as much patent information as feasible into the measurement of innovation quality, some researchers employ the method of principal component analysis (PCA) to integrate various facets of patent information into one index for use (Lanjouw & Schankerman, 2004; Schettino et al., 2013). However, recent studies point out that the patent-based metrics of innovation quality may have several drawbacks (Zhao et al., 2023) and that as an essentially multidimensional concept, it is quite unreliable to measure the quality of innovation by merely one indicator (Higham et al., 2021; Jin et al., 2022). To close this gap, measurement scales for evaluating the firms' innovation quality from multiple angles are developed (Duan et al., 2022). In this thesis, I follow this stream of literature to measure the quality of firm innovation by five survey items (See "Measurement of Variables" part in Study 2 for details).

Due to its potential in increasing the consumer satisfaction and bringing about economic value, the need to focus more on the quality of innovation has been consistently stressed by academics in recent years (Haner, 2002; Makridis & McGuire, 2023; Tseng & Wu, 2007; Wang et al., 2021). However, although innovation has accelerated and multiplied in developing nations like China, the quality of innovation is still dismal (Hu et al., 2017; Hu et al., 2020). To explain this phenomenon, a combination of objective and subjective causes has been put up. First, it might be extremely challenging for innovators to continuously create high-caliber ideas over a long period of time, which would cause the improvement in innovation quality to lag behind the rise in innovation quantity (Almeida et al., 2015). Second, high-quality innovations require more R&D investment and long-term technology accumulation, and are accompanied by higher risks, making it more difficult to be produced compared to those of poor quality (Duan et al., 2022; Hu et al., 2020). Last but not least, some firms might choose to engage in strategic innovation by chasing quantity rather than quality, so as to benefit from the signaling effect of innovation to attract government subsidies, gain tax advantages and more venture capital (Hall & Harhoff, 2012; Hsu & Ziedonis, 2013; Meuleman & De Maeseneire, 2012; Zhao et al., 2023).

In this context, a number of studies regarding the antecedents of innovation quality have been undertaken, aiming to provide relevant insights and practical assistance for firms desiring to truly enhance the quality of their innovation outcomes. Among them, a majority has centered on how external factors impact the quality of firm innovation (Duan et al., 2022; Lahiri, 2010). For instance, Lahiri (2010) discovers that there is an inverted-U shape relationship between firms' geographic distribution of R&D activity and their innovation quality, suggesting that an excessive R&D spread will be detrimental to the quality of innovation. In addition, research by Almeida (2015) has indicated that embedding in a community can lead to an enhancement in the innovation quality through mechanisms including knowledge acquisition and cooperation, whereas over-embeddedness can be counterproductive. Although the diversity of technological resources, intra-organizational linkages, the capability of knowledge management and other internal elements have been discussed in existing studies to have an impact on the quality of innovation, empirical evidence are lacked for these claims (Duan et al., 2022; Lahiri, 2010).

In conclusion, additional research on innovation quality and its internal influencing factors is in much need to help relieve the issue of subpar firm innovation quality. In light of this, my thesis aims to explore whether and how a firm's data analytics capability impacts its innovation quality based on a dynamic capability perspective.

2.4 Environmental Turbulence

The external environment where a firm resides in is thought to have a significant impact on its survival and growth (Droge et al., 2008; Jansen et al., 2006; Tidd, 2001). Therefore, it is necessary for firms to pay close attention to the changes in the environment where they operate and make rapid adjustments if required (Paladino, 2008). This argument has been supported by some classic management theories, such as the contingency theory and the resource-based view (RBV) of the firm. According to the contingency theory, a number of situation factors that can impact organizational behaviors, activities and outcomes should be given more consideration (Flynn et al., 2016; Heirati et al., 2016; McAdam et al., 2019; Wong et al., 2011). Besides, the resource-based view (RBV) of the firm states that firms employ their distinctive resources to pursue expansion opportunities they identified in the external environment (Penrose, 2009). As such, changes in environmental context will greatly influence the value of firms' resources, and consequently, the ability of firms to sustain their competitive advantage (Barney, 1997; Barney et al., 2011). Therefore, in order to succeed, firms must take some measures to swiftly respond to the changing environmental conditions (Barney, 1997; Barney et al., 2011).

In line with this logic, an increasing number of studies have discussed the new opportunities and difficulties encountered by firms due to the environmental changes. On the basis of this, the question of what firms should do to deal with such kind of uncertainty arising from external environment are widely examined. As stated in the research done by Hung and Chou (2013), a turbulent environment may prevent a firm to benefit from accumulated knowledge and cause it to fall victim to competency traps. In this situation, ongoing updating of knowledge base and high flexibility in adapting to environmental changes are the greatest ways for firms to maintain their competitive advantage (Hung & Chou, 2013). Similarly, Lichtenthaler (2009) points out that in a volatile environment where existing products are constantly becoming obsolete, firms are ought to actively gather and absorb outside knowledge, so as to capitalize on the emerging market opportunities. Moreover, Danneels and Sethi (2011) further emphasize that firms must break free from the constraints of their current resources and competencies in order to survive in the tumultuous environment. This assertion is corroborated by the study of Olabode et al. (2022), which reveals that a firm's capacity to switch from its current revenue generation model to a disruptive business model is crucial during periods of changing market conditions.

The studies above demonstrate that the unstable environment places stricter demands on firms, such that firms lacking the requisite capabilities to adapt to a changing environment will progressively fall behind their rivals, whereas those who do so might quickly adjust and seize the new growth possibilities (Wang et al., 2022; Zhong et al., 2022). Consistent with this notion, a large body of researches have postulated and established that environmental factors can play a moderating role in the connection between organizational characteristics and organizational outcomes (Danneels & Sethi, 2011). For instance, research by Haleblian and Finkelstein (1993) indicate that in an environment characterized by difficult-to-predict discontinuities, firms with larger teams can gain advantages, whereas those with high level of CEO dominance may suffer in terms of performance. In addition, Li and Atuahene-Gima (2001) investigate how the link between product innovation strategy and the performance of new technology venture in China is contingent on environmental factors. They find that the effectiveness of these firms' product innovation strategy can be amplified in turbulent environment. And more recently, Alqahtani and Uslay (2020) discover that under fast-changing and highly uncertain market conditions, entrepreneurial marketing turns out to be an optimal strategy that can lead to greater organizational performance.

Following this stream of literature, I take into account in this thesis how environmental turbulence may moderate the relationship between firms' data analytical capability and their innovation speed. According to Jaworski and Kohli (1993), the rate of change and uncertainty in an organization's external environment is referred to as environmental turbulence, which can be further subdivided into three components: market turbulence, technological turbulence, and competitive intensity. While market turbulence describes the degree of change in customer demand and product preference within a firm's marketplace, technological turbulence reflects the fast obsolescence of existing technologies and the unpredictability of technological change (Jaworski & Kohli, 1993). As a powerful source of environmental turbulence, competitive intensity is defined as the degree of rivalry within an industry (Jaworski & Kohli, 1993), which arises from many sources (e.g., resource constraints, lack of growth opportunity) and manifests in a variety of ways (e.g., imitation, promotion competition) (Auh & Menguc, 2005; Chen et al., 2010; Tsai & Yang, 2013). Since distinct sources of turbulence present different chances and risks to firms, it is meaningful to look at the three sub-dimensions separately rather than taking the broad concept of environmental turbulence as a whole (Atuahene-Gima et al., 2006; Danneels & Sethi, 2011). Otherwise, some important fine-grained insights might be obscured (Tsai & Yang, 2013). Out of this, the moderating effects of the three aspects of environmental turbulence are proposed and tested one by one in the present study.

2.5 Organizational Structure

Organizational structure, which is referred to as the mode of distribution and coordination of tasks, duties, and authority within an organization (Galbraith, 2008; Mintzberg, 1979), can exert a broad influence on firms' activities, ranging from strategic decisions (Miller et al., 1988) to interorganizational learning (Lane & Lubatkin, 1998), from information processing (Olson et al., 2005) to knowledge management (Pertusa-Ortega et al. 2010). Additionally, it has been demonstrated that the structure of an organization significantly impacts its innovative activities (Damanpour, 1991; Van de Ven, 1986). Back to 1960s, Sapolsky (1967) has made a case that designing creative and innovative structures to foster organizational innovation is necessary to be ready for a future of fast social and technological change. Following that, Damanpour and Gopalakrishnan (1998) combine elements of environmental change, organizational structure, and innovation adoption to propose that the structural characteristics to promote different types of innovation adoption at different stages under four environmental conditions are different, which deepens the understanding of the organizational structure-innovation link. More recently, the various effects of organizational structure on innovation are covered in a series of empirical research. For instance, Bock et al. (2012) argue that in the process of business model innovation, decentralized decision-making via delegation can simplify the firm structure, thus enhancing managerial attention and augmenting strategic flexibility. What's more, in another study done by Prajogo and McDermott (2014), the structure of small and medium-sized enterprises (SMEs) is shown to have a significant impact on their exploratory and exploitative innovation.

As a multidimensional construct, the organizational structure can be further separated into two aspects: centralization and formalization (Aiken & Hage, 1966; Pennings, 1973). These two dimensions portray the structure of an organization from different facets and can impact firms' innovative activities via distinct mechanisms. Specifically, centralization refers to the degree to which decision-making is concentrated within an organization (Fredrickson, 1986). It may be helpful for firms to carry out innovative activities, but may also hinder this process. According to academics who hold the former position, centralization can encourage innovation since it can clarify responsibilities and make it more efficient to put the innovation decisions into action (Gentile-Lüdecke et al., 2020). However, on the flip side, several scholars suggest that the concentration of power will impede intrafirm communication, organizational members' involvement, as well as the generation, integration, sharing of knowledge, thus jeopardizing firm innovation (Foss et al. 2011; Lee & Choi, 2003; Souitaris, 2001). Likewise, innovation can be impacted both favorably and unfavorably by formalization, which evaluates how much a firm's working procedures, internal processes, and employee behaviors are governed by its rules and regulations (Fredrickson, 1986). On the one hand, formal procedures offer employees with clear and specific action guidelines that can help them integrate and use new knowledge in an efficient and organized manner, which can support and promote innovation (Cordón-Pozo et al., 2006; Okhuysen & Eisenhardt, 2002). On the other hand, innovation may be constrained by formalized organizational structure because it reduces the flexibility necessary to encourage individuals to take risks and come up with creative ideas (Gentile-Lüdecke et al., 2020).

To sum up, organizational structure must be taken into consideration when conducting research related to innovation as it is one of the major influencing factors of firms' innovative activities. For this reason, this study addresses how organizational structure may function as a moderator in the association between data analytics capability and innovation quality. Besides, since there is disagreement in the studies that have previously been conducted regarding what type of structure can foster innovation, and the relationship between firms' organizational structure and their innovation quality has not yet been examined to date, it is anticipated that this study will add some new insights to the organizational structure literature.

2.6 Top Management Support

Top managers are seen to have a considerable impact on the survival and growth of firms because they own the power to formulate strategies, make decisions as well as allocate essential resource (Elenkov & Manev, 2005). According to earlier research (Ifinedo, 2008; Rosenbloom, 2000), the degree to which a firm's top managers provide the necessary assistance, guidance, and resources to internal activities and operating procedures are referred to as top management support. It can act on firm innovation through a variety of mechanisms. First, top management support provides the required resources on which innovative projects can proceed successfully (Rodríguez et al., 2008). In order to generate innovative products and services, firms must pool a range of resources, including funds, technologies, professionals and so forth (Cainelli et al., 2015). However, the available resources of firms are limited (Hite & Hesterly, 2001). Managers can only selectively distribute these precious resources to projects that, after screening and evaluation, are deemed to have potential (Adams et al., 2006). That is to say, merely initiatives with executive backing can get the needed resources to turn into finished goods or services. Without such approval, it won't be possible to put the innovative ideas into practice, and thus cannot bring about improvement in the quality of innovation. Second, top managers can also foster innovation via encouraging and assisting employees. Sometimes, employees may come up with fresh and creative ideas during the course of working (Carnevale et al., 2017; Hellmann, 2007). However, owing to various concerns such as fears of failure, they may not present their innovative ideas to managers, let alone spend time and efforts to refine these ideas (Lin et al., 2023). In this case, the support and incentive provided by top managers can make a difference because they can allay employees' anxieties and spur them to think of novel solutions, which raises the possibility of firms to produce high-caliber innovations (Hsu et al., 2019). Finally, because managers can help set a clear path to achieve innovation targets, rationally schedule relevant resources and capabilities, and promote the synergy of activities within firms, their support is regarded to be one of the key factors for firms to overcome obstacles to implement innovation decisions effectively (Hsu et al., 2019). In summary, top management support is an important factor determining firm innovation. The moderating effect of this variable on the link between firms' data analytic capability and innovation quality is therefore taken into account in my thesis.

3. STUDY 1: DATA ANALYTICS CAPABILITY AND INTERNET FIRMS' INNOVATION SPEED

3.1 Theory and Hypotheses

3.1.1 Data Analytics Capability and Innovation Speed

I contend that firms' data analytics capability can speed up their innovation process. Following prior literature, I divide the innovation process into four stages: idea generation, idea elaboration, idea championing, and idea implementation (Perry-Smith & Mannucci, 2017). Specifically, idea generation refers to a process where employees come up with numerous ideas through brainstorming and other methods. Idea elaboration refers to a process of further development of the generated ideas. Idea championing refers to a process of "selling" the ideas in order to obtain resources from gatekeepers to implement those ideas. Idea implementation refers to a process to transform the idea into concrete new products and services that have commercial value (Capurro et al., 2021; Fisher & Barrett, 2019).

First, data analytics capability increases the speed of idea generation, because it facilitates firms' understanding of customers' needs in a timely manner (Kwon et al., 2014; Mikalef et al., 2020; Wang et al., 2016). Understanding customers' needs is important because the purpose of innovation is to satisfy customers' needs by providing corresponding new products and services (Cui et al., 2005; Tsai & Yang, 2013). In particular, firms can leverage data analytics techniques to analyze customers' data, such as their reviews on products, purchases, and clicks (Bucklin & Sismeiro, 2009; Grover et al., 2018). Based on such analyses, the firms can gain insights regarding what customers need, what customers complain about, and what customers like. Accordingly, they can quickly develop new products and services or update their current products and services, so as to capitalize on the market opportunities (Berman, 2012; Porta et al., 2008). In comparison, if the firms do not possess the capability to analyze customers' data, they are not able to understand and capture the market opportunities timely (Davenport et al., 2001). Consequently, they will be slow movers in the innovation process. Similarly, the firms can also use data analytics methodologies to understand their competitors' products, services, and strategic moves, on the basis of which they can sense the possible opportunities and threats (Ranjan & Foropon, 2021). Then, these firms can rapidly innovate their products and services in order to maintain their competitive advantages relative to their competitors (Simon et al., 2007; Tsai & Yang, 2013).

Second, data analytics capability accelerates the process of idea elaboration and idea championing. On the one hand, data analytics capability can guide the idea elaboration process in that it provides specific directions to refine the generated ideas. High level of data analytics capability helps firms to process a large amount of data rapidly (Ferraris et al., 2019; Wamba et al., 2018; Wang et al., 2018). With the useful information extracted from the data, firms can quickly decide how to optimize the generated ideas (Lozada et al., 2023; Olabode et al., 2022). Besides, the insights generated from data is objective and accurate, which speed up the decision-making process in innovation activities because these insights can resolve conflicts between employees who are involved in the innovation activities (Awan et al., 2021; Janssen et al., 2017). Otherwise, there might be disagreement between employees, which incurs endless discussion and prolongs the decision-making process (Eisenhardt, 1999; Eisenhardt et al., 1997). On the other hand, data analytics capability can help innovators to save time in the idea championing process. In this process, innovators have to demonstrate the potential of their ideas to the gatekeepers, with the objective to gain required resources to convert their ideas to actual products and services (Perry-Smith & Mannucci, 2017). Data analytics capability can speed up this process because "data talks" or data provides convincing evidence to the gatekeeper to believe the potential of innovators' ideas (Ferraris et al., 2019; Korherr et al., 2022). In other words, the innovators can better explicate the value of their ideas based on insights generated from data. With the backup from data, the gatekeepers are more likely to understand and appreciate the value of innovators' ideas. As a result, it shortens the time taken for the innovators to access to the resources.

Finally, data analytics capability can also increase the speed of idea implementation process. During this process, to transfer creative ideas into tangible products and services, the firms conduct intensive research and development (R&D) activities (Perry-Smith & Mannucci, 2017). Accordingly, a large volume of data is generated in the R&D activities, which includes experiment data, manufacturing data, test data, failure analysis data, and so forth (Khanna et al., 2016). Innovators can leverage data analytics capability to mine insights form these datasets, so as to make efficient decisions and move the R&D projects forward (Awan et al., 2021; Mikalef et al., 2019). Besides, innovators might encounter numerous failures in the R&D process (Khanna et al., 2016). For instance, a key metric of a product feature does not work as expected. Then the innovators design some experiments to figure out the root causes of the failures (Thomke, 1998; 2003). Data analytics capability can assist the innovators to quickly analyze the experiment data, so as to identify the causes of failures (Sariyer et al., 2021; Wang et al., 2018). Afterwards, the innovators can take some measures to solve the issues that lead to failures and carry on the R&D projects.

Taken together, I argue that data analytics capability can accelerate the four stages of the innovation process, which increases the overall innovation speed. These arguments lead me to propose that:

Hypothesis 1: Data analytics capability is positively related to innovation speed.

3.1.2 The Moderating Effect of Market Turbulence

Having theorized the main effect of data analytics capability on innovation speed, I now propose that this positive relationship is contingent on three environmental factors: market turbulence, technological turbulence, and competitive intensity. Turbulent market is characterized by frequently changing of customers' needs and preferences (Jaworski & Kohli, 1993; Slater & Narver, 1994), which makes it challenging for firms to predicts and understand what customers will like, need, and purchase. I argue that the positive relationship between data analytics capability and innovation speed is more pronounced for firms in turbulent market.

First, data analytics capability should play a more important role in the idea generation stage, because it can help the firms to predict customers' needs in turbulent market. For firms in turbulent market, data analytics capability enables them to gain a granular understanding of customers' preferences (Akter et al., 2022). With high level of data analytics capability, firms can base on data to understand the trend of customers' needs as well as the preferences for specific groups of customers (Akter et al., 2020). Therefore, data analytics capability helps firms to gain timely insights regarding what products and services are needed in the market, then firms can develop new products and services accordingly to seize the market opportunities (Chen et al., 2016; Matthing et al., 2004). Without such data analytics capability, firms will be "blind" to the current market opportunities, slowing down their innovation pace. In comparison, for firms in stable market, data analytics capability is not so much needed, because firms can straightforwardly observe or understand the current needs in the market (Paladino, 2008). In other words, analyzing data is not necessary in this case. Therefore, the effect of data analytics capability on innovation speed is weakened.

Second, in turbulent market, data analytics capability should be more effective in the idea elaboration stage and idea championing stage. On the one hand, firms can leverage their data analytics capability to understand market opportunities, such that they can fine-tune the generated ideas in the idea elaboration stage (Wang et al., 2018; Zakir et al., 2015). On the other hand, it is difficult for gatekeepers to evaluate the potential of creative ideas in turbulent market, because they are unsure of customers' preferences (Kim, 2016; Spanjol et al., 2011). With high level of data analytics capability, innovators can cite insights distilled from data to support their creative ideas, which can reduce resistance in the idea evaluation by gatekeepers and increase the speed of idea championing process (Wang et al., 2015). In comparison, the role of data analytics capability is attenuated in stable market, where innovators do not have to leverage data analytics to optimize their ideas and back up their ideas in the evaluation process (Li, 2022). Instead, the innovators and gatekeepers can mainly reply on their experience or heuristics to make decisions in this process (Fleck & Weisberg, 2013; Perkins & Rao, 1990; Taylor, 1975).

Third, in idea implementation stage, the effect of data analytics capability should be amplified in turbulent market. In market with high turbulence, the key to maintain competitive advantage is to introduce new products and services to market as soon as possible (Ch'ng et al., 2021; Stalk & Hout, 1990). Firms with high level of data analytics capability can process data generated in the idea implementation process efficiently (Dubey et al., 2021). As a result, these firms can quickly convert the ideas into new products and services. In comparison, the effect of data analytics capability is compromised in stable market, where the rate of new product or new service introduction is not that important, because customers' needs remain unchanged for a long period of time (Calantone et al., 2003; Chen et al., 2012).

In line with these arguments, I hypothesize that:

> ***Hypothesis 2***: Market turbulence positively moderates the positive relationship between data analytics capability and innovation speed, such that the positive relationship between data analytics capability and innovation speed is stronger for firms in high turbulent market.

3.1.3 The Moderating Effect of Technological Turbulence

Technological turbulence represents another dimension of environmental turbulence. Whereas market turbulence refers to the rate of change in customer preference, technological turbulence refers to the speed of technology update in the external environment (Jaworski & Kohli, 1993;

Slater & Narver, 1994). I posit that technological turbulence strengthens the positive relationship between data analytics capability and innovation speed.

First, in technological turbulent environment, firms with decent data analytics capability can sense the technology change immediately, enabling them to response timely to generate innovative ideas by incorporating these technological advancements (Candi et al., 2013; Chen et al., 2018). Through data analytics, firms can understand what new technologies are available on the market and how these technologies can be utilized to upgrade their products and services (Wu et al., 2020). Once firms have a good understanding of the new technologies, they can raise creative ideas accordingly, so as to capitalize on the technological opportunities (Chan et al., 2020; Chaston, 2017). However, if firms do not have such high level of data analytics capability, they will be inert to the technological advancements, thus do not take measures to update their products and services (Dolata, 2009). In comparison, the role of data analytics capability is undermined if technology rarely changes in firms' external environment. In this case, firms can understand the technology change through other channels, such as conferences, newspapers, social media, alliance partners, and venture capitals, instead of data analytics (Almeida et al., 2013).

Second, turbulent technological environment also intensifies the effect of data analytics capability in the idea elaboration stage and idea championing stage. Data analytics capability becomes more effective in accelerating the idea elaboration stage in technologically turbulent environment, because firms can build on insights from data analytics to further optimize their creative ideas. In particular, the insightful knowledge extracted from data analysis provides clear information regarding which new technology to be integrated and how to incorporate in further development of the creative ideas (Ghasemaghaei, 2019). In addition, data analytics also smoothen the idea championing process, because data analytics can yield solid evidence for the gatekeepers to understand the potential of the new technology, thus they are more likely to allocate resources to support the innovators in the commercialization of their creative ideas (Garcia, 2005; Song & Thieme, 2009). In comparison, for firms whose external environment is characterized by slow technology change, data analytics is not essential for them to evaluate the technological opportunities. Instead, firms can rely on other methods to sense and exploit the external technological opportunities, such as recruitment of external experts (Almeida & Kogut, 1999; Zucker et al., 1998) and acquisition of startups (Enkel & Sagmeister, 2020).

Third, in the idea implementation stage as well, data analytics capability becomes more important when technology in the industry is fast-changing. As we argued before, firms with high level of data analytics capability can convert their creative ideas into commercial products and service within a short time window, such that they can appropriate value from the new technologies. Data analytics capability speeds up this process because it drives informed decision making on the basis of data related to the new technologies, which enables these firms to effectively include these new technologies into their new products and services (Awan et al., 2021; Shamim et al., 2020). By contrast, in environment where technologies are changing slowly, the usefulness of data analytics capability is attenuated, since it is straightforward for the firms to sense and seize the external technologies opportunities (Wu et al., 2017).

All in all, these arguments suggest that technological turbulence amplifies the effect of data analytics capability in firms' innovation process. I therefore propose that:

> ***Hypothesis 3***: Technological turbulence positively moderates the positive relationship between data analytics capability and innovation speed, such that the positive relationship between data analytics capability and innovation speed is stronger for firms in environment with high technological turbulence.

3.1.4 The Moderating Effect of Competitive Intensity

Competitive intensity is the third dimension of environmental turbulence, which refers to the degree of competition within an industry (Jaworski & Kohli, 1993). In highly competitive industries, the interfirm competition is cutthroat, thus, firms take every measure to maintain or gain competitive advantages relative to their competitors (Chan et al., 2012; Cui et al., 2005; Tsai & Yang, 2013). In such a scenario, the effect of data analytics capability on innovation speed is enhanced.

First, in highly competitive environment, firms rely more on their data analytics capability to predict customers' wants and needs, such that they can generate new ideas before their competitors do so (Cadogan et al., 2003; Chan et al., 2012; Feng et al., 2019). In other words, data analytics capability helps these firms to gain first mover advantage in the idea generation stage (Kerin et al., 1992; Lieberman & Montgomery, 1988). By contrast, in environment where the level of competition is low, firms may perceive that it is not urgent to innovate (Cadogan et al., 2003), thus data analytics capability plays a weaker role in facilitating firms' idea generation activities.

Second, high external competition also compels the firms to leverage data analytics capability to accelerate their idea elaboration stage and idea championing stage. The mechanism here is similar to what I elaborated above. Competitive pressure enlarges the importance of firms' data analytics capability in the further development of the ideas and the acquisition of relevant resources to support the implementation of these ideas, because if these firms do not quickly innovate and capitalize on the innovative ideas, these firms' competitors will do so, which reduces the competitive advantage for these firms (Kessler & Chakrabarti, 1996; Shan, 1990). In short, data analytics capability is essential for these firms to increase the rate of innovation process in highly competitive environment. In comparison, if firms face low level of competitive pressure, they will be less motivational to conduct data analytics to expedite their innovation process (Olabode et al., 2022).

Third, intensive competition also stimulates the firms to employ data analytics techniques to accelerate the idea implementation process. Specifically, these firms face a situation where if they do not quickly push their innovative products and services to market, it is likely that their competitors will do so (Argyres et al., 2015; Williamson & Yin, 2014). As a result, these firms employ data analytics techniques to speed up the R&D process, such that they can convert their ideas to marketable products and services in a timely manner (El Samra et al., 2023). In comparison, if external environmental competition is low, firms may not have such high motivation to utilize data analytics techniques to expedite their idea implementation process (Olabode et al., 2022).

To summarize, intensive competition increases firms' reliance on data analytics capability to speed up their innovation process, so as to sustain their competitive advantages. Consistent with these arguments, I hypothesize that:

> ***Hypothesis 4***: Competitive intensity positively moderates the positive relationship between data analytics capability and innovation speed, such that the positive relationship between data analytics capability and innovation speed is stronger for firms in environment with high competition intensity.

A research framework of Study 1 is shown in Figure 1.

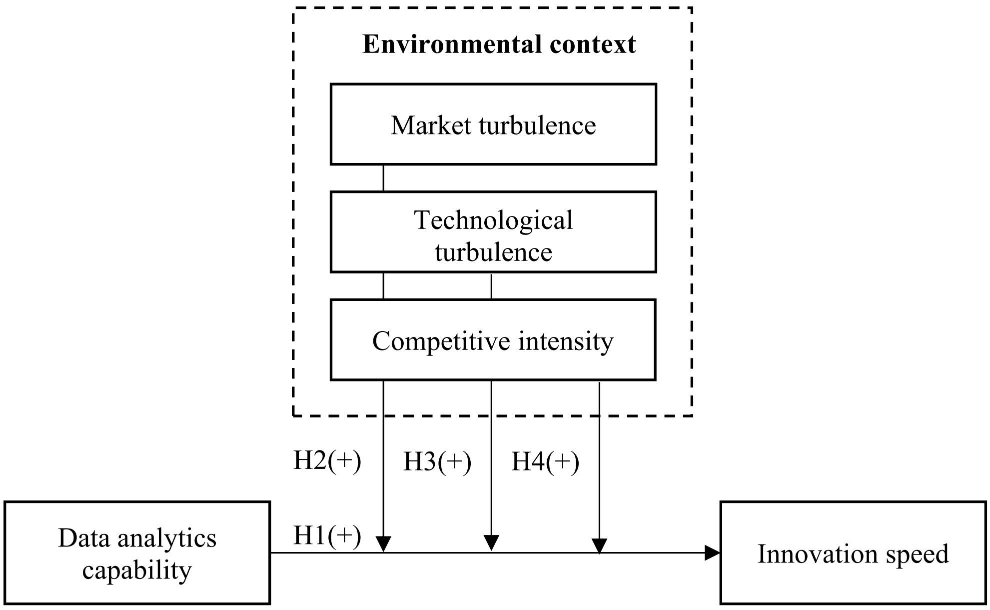

Figure 1. Research framework

3.2 Data and Methods

3.2.1 Sample and Data Collection

The proposed hypotheses were examined using data on a sample of Chinese Internet firms, which was gathered through a self-developed and issued questionnaire. The survey method has been widely adopted in research fields such as psychology, sociology and management because it has the advantage of collecting a sizable sample at a relatively low cost, which can then serve as the foundation for inferring the population and making the empirical results more replicable (Bernard, 2013). For this reason, the survey method was selected as the research approach in this study. In addition, since Chinese Internet firms are on the rise and are actively engaged in acquiring, storing, and analyzing large amounts of user data to drive innovation, it is deemed appropriate to target the Internet firms in China as the research subjects in order to empirically investigate the relationship between data analytics capability and firm innovation speed.

After that, a preliminary English-version questionnaire was developed on the basis of a thorough literature search and reading. Then, considering that the research would be performed in China, the original English questionnaire was translated into Chinese, following by a back-translation procedure to ensure accuracy and consistency (Brislin, 1970). Subsequently, a series of actions were taken to enhance the quality of the questionnaire. First, with the help of three professors owning extensive knowledge and in-depth insights in innovation management and strategic management, a few possible problems stemming from the framing and phrasing of the questions were identified and corrected. Second, five top managers working in different Internet firms were invited to review the measurement scales. The feedback and suggestions provided by them helped me to improve the back-translation consistency and reword several items that were not clear. Third, a pilot test was conducted in 30 Internet firms in Hangzhou, which further assisted me in enhancing the clarity and fitness of the questionnaire. Based on all of these, a questionnaire with clear purpose, complete content and rigorous structure was finalized.

For the data gathering, a list of 1,200 Chinese firms randomly chosen from the directory of information transmission, software and information technology service firms obtained from Qichacha was created[1]. After that, using publicly available contact information (i.e., including email addresses and phone numbers), an online questionnaire was sent out to these firms via emails, along with a cover letter outlining my research goal, assuring them of confidentiality and anonymity, and inviting them to participate in this research. Then, in an effort to boost the response rate to the questionnaire, I tried to contact those firms that hadn't replied three months after the email was sent through phone calls. By employing these techniques, I was able to obtain 482 usable responses throughout the data gathering period (i.e., from May 2022 to December 2022). 23 of which could not pass the manipulation and attention check and were therefore not included in the sample. Overall, 459 firms finished the survey effectively, representing a valid response rate of 38.25% (i.e., 459/1200). Following that, in order to determine whether there is a nonresponse bias, an independent *t*-test was conducted. The results showed no significant differences in firm features and key indicators between the first 115 (25%) and the last 115 (25%) responses in the sample (Armstrong & Overton, 1977), indicating that nonresponse bias was not a serious concern in my research.

[1] Qichacha (https://www.qcc.com/) is a widely utilized corporate information search tool in China. Based on general knowledge, I believe that the firms that are involved in the industry of information transmission, software and information technology on this website can be considered as Internet firms.

Table 1 presents the profile of the 459 effectively responding firms. The sample firms spread across the eastern (29.19%), southern (32.90%), western (16.56%), and northern (21.35%) regions of China, which offers sufficient geographic variety and ensures the representativeness of the sample to a certain extent. Besides, firms of various sizes were contained in my sample. While firms with less than 10 employees accounted for the smallest proportion (0.65%), those with more than 500 employees made up the majority (43.36%). In terms of firm age, it can be found that firms in the sample were relatively young, most of which had been established for less than 6 years (27.23%) or for 6 to 10 years (33.55%).

Table 1. Profile of responding firms (N = 459)

	Frequency	Percentage	Cumulative
Firm size			
< 10	3	0.65%	0.65%
10-50	19	4.14%	4.79%
51-100	59	12.85%	17.65%
101-200	60	13.07%	30.72%
201-300	35	7.63%	38.34%
301-400	35	7.63%	45.97%
401-500	49	10.68%	56.64%
> 500	199	43.36%	100.00%
Firm age			
< 6	125	27.23%	27.23%
6-10	154	33.55%	60.78%
11-15	74	16.12%	76.91%
16-20	42	9.15%	86.06%
> 20	64	13.94%	100.00%
Region			
East	134	29.19%	29.19%
South	151	32.90%	62.09%
West	76	16.56%	78.65%
North	98	21.35%	100.00%

3.2.2 Measurement of Variables

This study intends to examine the impact of data analytics capability on firm innovation speed as well as the boundary conditions for this relationship. To achieve this goal, I identified measurement scales for pertinent constructs from the existing literature and then modified them for application in the context of big data analytics. The following is a detailed description of the variables and corresponding measurement items used in my research. Unless otherwise specified, each survey item was assessed on a 7-point Likert scale (where 1 = strongly disagree, and 7 = strongly agree) and each measure was aggregated from corresponding survey items by taking their arithmetic mean.

3.2.2.1 Dependent Variable

Innovation speed refers to the time elapsed between the conception and definition of a new product and its eventual commercialization (Vesey, 1991). Following Wang and Wang (2012), I included five items to measure this variable: (1) "Our organization is quick in coming up with novel ideas as compared to key competitors"; (2) "Our organization is quick in new product launching as compared to key competitors"; (3) "Our organization is quick in new product development as compared to key competitors"; (4) "Our organization is quick in new processes as compared to key competitors"; and (5) "Our organization is quick in problem solving as compared to key competitors" (alpha coefficient = 0.8569, maximal reliability = 0.6730).

3.2.2.2 Independent variable

Data analytics capability describes a firm's ability to obtain, process, and analyze big data to derive useful insights from it (Gupta & George, 2016; Olabode et al., 2022). It is measured by five items (Laguir et al., 2022;

Srinivasan & Swink, 2018): (1) "Our organization uses advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making"; (2) "Our organization easily combines and integrates information from many data sources for use in our decision making"; (3) "Our organization routinely uses data visualization techniques (e.g., dashboards) to assist users or decision-maker in understanding complex information"; (4) "Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement"; and (5) "Our organization deploys dashboard applications/information to our managers' communication devices (e.g., smart phones, computers)" (alpha coefficient = 0.8551, maximal reliability = 0.7043).

3.2.2.3 Moderating variables

Market turbulence is defined as the degree of change in a firm's customer demand and product preference (Jaworski & Kohli, 1993). The measure of this variable is borrowed from Jaworski and Kohli (1993), consisting of five items: (1) "In our kind of business, customers' product preferences change quite a bit over time"; (2) "Our customers tend to look for new product all the time"; (3) "We are witnessing demand for our products and services from customers who never bought them before"; (4) "New customers tend to have product-related needs that are different from those of our existing customers"; and (5) "We cater to many of the same customers that we used to in the past" (alpha coefficient = 0.8824, maximal reliability = 0.7826).

Also following the practice of Jaworski and Kohli (1993), four items are used to gauge *Technological turbulence*, which evaluates the instability and the rate of technological change in the industry: (1) "The technology in our industry is changing rapidly"; (2) "Technological changes provide big opportunities in our industry"; (3) "A large number of new product ideas have been made possible through technological breakthroughs in our industry"; and (4) "Technological developments in our industry are rather minor" (alpha coefficient = 0.8592, maximal reliability = 0.8226).

Additionally, *Competitive intensity*, which reflects the degree of competition within an industry, was operationalized using six items in line with Jaworski and Kohli (1993): (1) "Competition in our industry is cutthroat"; (2) "There are many 'promotion wars' in our industry"; (3) "Anything that one competitor can offer, others can match readily"; (4) "Price competition is a hallmark of our industry"; (5) "One hears of a new competitive move almost every day"; and (6) "Our competitors are relatively weak" (alpha coefficient = 0.8520, maximal reliability = 0.6274).

3.2.2.4 Control variables

To eliminate other possible explanations for the hypothesized relationship, I controlled for several variables that might influence the dependent variable. These included *Firm size*, measured as the number of employees, as well as *Firm age*, calculated as how many years a firm had been operating. Moreover, *R&D intensity* was taken into consideration, which was measured as the proportion of R&D expenditures to total sales.

Overall, the measurement of our dependent variable, independent variable, moderating variables, and control variables are summarized in Table 2.

Table 2. Measurement of variables

Variable	Measurement
Dependent Variable	

Innovation speed (IS) (Wang & Wang, 2012)	IS1: Our organization is quick in coming up with novel ideas as compared to key competitors. IS2: Our organization is quick in new product launching as compared to key competitors. IS3: Our organization is quick in new product development as compared to key competitors. IS4: Our organization is quick in new processes as compared to key competitors. IS5: Our organization is quick in problem solving as compared to key competitors.
Independent Variable	
Data analytics capability (DAC) (Laguir et al., 2022; Srinivasan & Swink, 2018)	DAC1: Our organization uses advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making. DAC2: Our organization easily combines and integrates information from many data sources for use in our decision making. DAC3: Our organization routinely uses data visualization techniques (e.g., dashboards) to assist users or decision-maker in understanding complex information. DAC4: Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement". DAC5: Our organization deploys dashboard applications/information to our managers' communication devices (e.g., smart phones, computers).
Moderating Variables	
Market turbulence (MT) (Jaworski & Kohli, 1993)	MT1: In our kind of business, customers' product preferences change quite a bit over time. MT2: Our customers tend to look for new product all the time. MT3: We are witnessing demand for our products and services from customers who never bought them before. MT4: New customers tend to have product-related needs that are different from those of our existing customers". MT5: We cater to many of the same customers that we used to in the past.
Technological turbulence (TT) (Jaworski & Kohli, 1993)	TT1: The technology in our industry is changing rapidly. TT2: Technological changes provide big opportunities in our industry. TT3: A large number of new product ideas have been made possible through technological breakthroughs in our industry. TT4: Technological developments in our industry are

	rather minor.
Competitive intensity (CI) (Jaworski & Kohli, 1993)	CI1: Competition in our industry is cutthroat. CI2: There are many 'promotion wars' in our industry. CI3: Anything that one competitor can offer, others can match readily. CI4: Price competition is a hallmark of our industry. CI5: One hears of a new competitive move almost every day. CI6: Our competitors are relatively weak.
Control variables	
Firm size	The number of employees.
Firm age	The number of years since a firm was founded.
R&D intensity	The proportion of R&D expenditures to total sales.

3.2.3 Empirical Models

This study utilized ordinary least squares (OLS) regressions to test the hypotheses. The model shown in equation (1) was used to test Hypothesis 1:

$$Y_i = \alpha_0 + \alpha_1 X_i + \alpha_2 Controls_i + \varepsilon_i \quad (1)$$

where Y_i represents the innovation speed of firm *i*, X_i indicates the data analytics capability of firm *i*, $Controls_i$ indicates a list of control variables, and ε_i is random error term.

The model in equation (2) was used to test the interacting effect in Hypotheses 2-4:

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i \times Z_i + \beta_4 Controls_i + \varepsilon_i \quad (2)$$

where Y_i is the innovation speed of firm *i*, X_i is the data analytics capability of firm *i*, Z_i indicates the corresponding moderating variable in Hypotheses 2-4 (market turbulence in H2, technological turbulence in H3, and competitive intensity in H4), $Controls_i$ indicates a list of control variables, and ε_i is random error term.

3.3 Empirical Results

3.3.1 Reliability and Validity

Before performing the regression analysis, a number of steps were taken to evaluate the reliability and validity of the research data. First, the reliability of the constructs was examined using Cronbach's alpha coefficient (Cronbach, 1951), which measures internal consistency of a set of survey items. It can be seen in Table 3 that the alpha values for variables utilized in this study all exceeded the threshold value of 0.8, suggesting a high level of internal consistency.

Second, since the KMO value was greater than 0.8 and the p-value for Bartlett's test of sphericity was less than 0.001, the exploratory factor analysis (EFA) with varimax rotation was conducted to test construct validity and the factor loadings for each scale. As shown in Table 3, the factor loadings of the measurement items were ranging from 0.5523 to 0.8226, all above the criteria suggested by Hair et al. (2014). Besides, in line with expectations, five factors with eigenvalues bigger than one emerged from the twenty-five items and accounted for 64.8712% of the total variance. This indicated that the designed measurement scales fit well with the theoretical constructs. In summary, the results of EFA proved a relatively good validity of the sample data.

Third, to further check whether the measurements of a construct were consistent with its interpretation, confirmatory factor analysis (CFA) was then implemented. This included tests of model fit indices, convergent validity, and discriminant validity. Table 4 presents the results of different goodness-of-fit indices for the measurement model ($X2/df = 1.7763 < 3$, $RMSEA = 0.0412 < 0.05$, $NFI = 0.9204 > 0.9$, $RFI = 0.9098 > 0.9$, $IFI = 0.9636 > 0.9$, TLI =

0.9585 > 0.9, CFI = 0.9633 > 0.9), from which we can draw a conclusion that this model fit the data well. Next, convergent validity was evaluated by two widely accepted indicators named average variance extracted (AVE) and composite reliability (CR) (Hair et al., 2014), the results of which were displayed in Table 5. As shown, except for competitive intensity, whose AVE value was 0.4901, all other variables' AVE values were higher than 0.5, a threshold recommended by Fornell and Larcker (1981). In addition, the CR values in the present study ranged from 0.8521 to 0.8835, all well above the minimum criteria of 0.7 (Anderson and Gerbing, 1988; Fornell and Larcker, 1981). These findings revealed a high degree of convergent validity. Finally, to examine discriminant validity, the correlations between constructs were compared to the square roots of the AVE values for each construct (on the diagonal). According to Kline (2015), when the absolute values of corresponding inter-construct correlations are less than 0.5 and smaller than the square roots of AVE, the indicators can be assumed to have more in common with the constructs they are associated with than others, which can provide evidence for discriminant validity. As shown in Table 6, all the square roots of the AVE values in this study were higher than the corresponding inter-construct correlations, revealing an adequate divergent validity of the measures.

On the whole, the measurement scales in this paper has high reliability and validity, thus can be used as the basis for subsequent analysis.

Table 3. Reliability test and Factor loading analysis

Measurement items	Cronbach's α	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
		MT	CI	DAC	IS	TT
MT1	0.8824	0.7826				
MT5		0.7719				

Measurement items	Cronbach's α	Factor 1 MT	Factor 2 CI	Factor 3 DAC	Factor 4 IS	Factor 5 TT
MT4		0.7174				
MT3		0.7149				
MT2		0.6756				
CI3			0.6274			
CI4			0.6265			
CI1	0.8520		0.6197			
CI5			0.5668			
CI6			0.5589			
CI2			0.5523			
DAC3				0.7043		
DAC 1				0.6694		
DAC 4	0.8551			0.6487		
DAC 5				0.6476		
DAC 2				0.6289		
IS3					0.6730	
IS1					0.6307	
IS5	0.8569				0.6252	
IS4					0.6205	
IS2					0.5806	
TT4						0.8226
TT3	0.8592					0.7466
TT2						0.7154
TT1						0.6587
Initial eigenvalue		9.0730	2.3462	1.9900	1.6534	1.1552
% of variance		36.2920	9.3848	7.9602	6.6134	4.6207
Cumulative %		36.2920	45.6769	53.6370	60.2504	64.8712

Notes: KMO = 0.9289; Bartlett's test of sphericity, $p < 0.001$.

Table 4. Model fit indices

Model fit indices	X2/df	RMSEA	NFI	RFI	IFI	TLI	CFI
Default model	1.7763	0.0412	0.9204	0.9098	0.9636	0.9585	0.9633
Recommended criteria	< 3	< 0.05	> 0.9	> 0.9	> 0.9	> 0.9	> 0.9

Table 5. Average variance extracted and Composite reliability

Path			Estimate	AVE	CR
DAC	--->	DAC5	0.7562		
DAC	--->	DAC4	0.7000		
DAC	--->	DAC3	0.7790	0.5417	0.8551
DAC	--->	DAC2	0.7134		
DAC	--->	DAC1	0.7286		
IS	--->	IS5	0.7686	0.5452	0.8569

IS	--->	IS4	0.7502		
IS	--->	IS3	0.7378		
IS	--->	IS2	0.7299		
IS	--->	IS1	0.7039		
MT	--->	MT5	0.7565		
MT	--->	MT4	0.7994		
MT	--->	MT3	0.7700	0.6028	0.8835
MT	--->	MT2	0.7739		
MT	--->	MT1	0.7816		
TT	--->	TT4	0.8001		
TT	--->	TT3	0.8182	0.6072	0.8606
TT	--->	TT2	0.7620		
TT	--->	TT1	0.7338		
CI	--->	CI6	0.7246		
CI	--->	CI5	0.6800		
CI	--->	CI4	0.7174	0.4901	0.8521
CI	--->	CI3	0.6803		
CI	--->	CI2	0.6986		
CI	--->	CI1	0.6981		

Table 6. Square roots of AVE and inter-construct correlations

	DAC	IS	MT	TT	CI
DAC	(0.7360)				
IS	0.4939***	(0.7384)			
MT	0.3979***	0.3609***	(0.7764)		
TT	0.4002***	0.3759***	0.2824***	(0.7792)	
CI	0.4405***	0.5271***	0.3460***	0.4210***	(0.7001)

Notes: Square roots of AVE shown on diagonal; *** $p < 0.001$.

3.3.2 Common Method Bias

The single-informant, single-source data gathering strategy used in this work may result in common method bias. To alleviate and assess this issue, ex ante procedural controls and ex post empirical testing were employed. Procedurally, comprehensive explanations about the confidentiality and anonymity of the research were provided to facilitate respondents to deliver accurate and honest answers. Furthermore, approaches such as reverse coding and rational organization of questionnaire structure and ordering were also applied to limit the risk of common method bias (Podsakoff et al., 2003). In terms of empirical tests, three analyses were performed to evaluate the degree of common method bias in the sample data. First, Harman's one-factor test was carried out, the results of which showed that a single unrotated factor only accounted for 36.2920% of the total variance, less than the cutoff point of 50% (Podsakoff et al., 2003). Second, one-way confirmatory factor analysis (CFA) revealed that the one-factor model fit was quite poor itself (X2/df = 8.5281 > 3, RMSEA = 0.1282 > 0.08, NFI = 0.6032 < 0.9, RFI = 0.5672 < 0.9, IFI = 0.6327 < 0.9, TLI = 0.5975 < 0.9, CFI = 0.6310 < 0.9), and much worse than the model fit of the five-factor model (X2/df = 1.7763 < 3, RMSEA = 0.0412 < 0.05, NFI = 0.9204 > 0.9, RFI = 0.9098 > 0.9, IFI = 0.9636 > 0.9, TLI = 0.9585 > 0.9, CFI = 0.9633 > 0.9). Third, the correlation analysis (as shown in Table 6) found no excessively high correlation coefficients between variables, with the highest one being 0.5271. The results of these tests indicated that there was no concerning level of common method bias in this study.

3.3.3 Descriptive Statistics and Correlations

The descriptive statistics and correlations were reported in Table 7, including the means, standard deviations, and correlation coefficients of the variables of interest in this research. As can be seen, the average rate scores of variables measured by 7-point Likert scale were ranging from 4.5874 to 4.7500. The average age of sample firms was 10.7346, and the proportion of total revenues on R&D activities was 27.8475% on average. Regarding the correlations, it can be observed that the independent variable (r = 0.5384) and moderating variables (r = 0.4052 for *Market turbulence*; r = 0.3664 for *Technological turbulence*; r = 0.6518 for *Competitive intensity*) are all positively connected to the dependent variable *Innovation speed*, providing some preliminary evidence for our hypotheses.

Additionally, as some variables had correlation coefficients higher than 0.5, the potential multicollinearity problem was checked by computing the variance inflation factors (VIF). The results showed that VIF values in this research were ranging from 1.0559 to 1.6393, much less than both the common benchmark of 10 and the stricter standard of 5. Hence, multicollinearity was unlikely to be a major threaten in the present study.

Table 7. Descriptive statistics and correlations (N = 459)

	Mean	SD	1	2	3
1.Innovation speed	4.7163	0.8597	1		
2.Data analytics capability	4.6484	0.9366	0.5384	1	
3.Market turbulence	4.5874	0.8880	0.4052	0.4295	1
4.Technological turbulence	4.7500	0.9852	0.3664	0.3649	0.2754
5.Competitive intensity	4.7211	0.8239	0.6518	0.5209	0.4245
6.Firm size	6.0523	2.1047	0.2723	0.2564	0.1240
7.Firm age	10.7364	7.7714	0.0690	0.0806	0.0494
8.R&D intensity	27.8475	14.3495	0.0306	0.0468	0.2079

	4	5	6	7	8
1.Innovation speed					
2.Data analytics capability					
3.Market turbulence					
4.Technological turbulence	1				
5.Competitive intensity	0.4456	1			
6.Firm size	0.2743	0.2596	1		
7.Firm age	0.0766	0.0954	0.2762	1	
8.R&D intensity	0.0696	0.1275	0.0622	-0.0128	1

3.3.4 Main Results

Hierarchical regression analysis was used to test the hypotheses, the results of which were provided in Table 8. Specifically, merely control variables were included in Model 1. On this basis, Model 2 entered the independent variable *Data analytics capability* to investigate the link between data analytics capability and firm innovation speed. And then, Models 3 to 5 were established based on Model 2 to further confirm the moderating effects of market turbulence, technological turbulence, and competitive intensity. In these three models, the interaction terms between *Data analytics capability* and three moderators were added one by one.

Hypothesis 1 predicts that firm's data analytics capability is positively connected with its innovation speed. As shown in Model 2 of Table 8, the coefficient of *Data analytics capability* when regressing on *Innovation speed* was positive and significant at the 0.1% level ($\beta = 0.2030$, $p < 0.001$). Apart from that, additional analysis revealed that for one standard deviation increase in *Data analytics capability* from its mean, the speed of firm innovation increased by 4.03%. These results provided strong support for Hypothesis 1.

Hypothesis 2 posits that market turbulence strengthens the positive relationship between data analytics capability and innovation speed, such that this positive relationship is stronger when a firm experiences significant shifts in the demand for its products and services among customers, and weaker when the consumer demand is generally stable. Since the coefficient of the interaction term between *Data analytics capability* and *Market turbulence* was not significant even at the 10% level ($\beta = 0.0647$, $p > 0.1$), as indicated in Model 3 in Table 8, Hypothesis 2 was not confirmed.

Hypothesis 3 contends that technological turbulence may amplify the positive relationship between data analytics capability and innovation speed. According to the results presented in Model 4 of Table 8, the coefficient of the interaction term between *Data analytics capability* and *Technological* *turbulence* was significantly positive (β = 0.1449, p < 0.001), leading support to this hypothesis. To better illustrate the moderating effect, I plotted the interaction effect in Figure 2 and then estimated the marginal effect. The solid line in Figure 2 illustrated the effect of *Data analytics capability* on *Innovation speed* when *Technological turbulence* is one standard deviation below the mean, whereas the dashed line plotted the situation when *Technological turbulence* is one standard deviation above mean. It can be observed from this figure that, the favorable impact of *Data analytics capability* on *Innovation speed* is more pronounced when *Technological turbulence* is at a higher degree. Consistent with this conclusion, the marginal analysis indicated that when *Technological turbulence* is one standard deviation below the mean, a standard deviation increase in *Data analytics capability* enhanced the *Innovation speed* by just 0.84%. However, when *Technological turbulence* is one standard deviation above the mean, same increase in *Data analytics capability* yielded much more improvement in *Innovation speed* (6.52%). Taken altogether, Hypothesis 3 was supported.

According to Hypothesis 4, competitive intensity can positively moderate the main effect, meaning that firms operating in more competitive industries will see a stronger impact of data analytics capability on innovation speed. The results in Model 5 in Table 8 demonstrated that the interaction of *Data analytics capability* and *Competitive intensity* was significant and positive (β = 0.1166, p < 0.01). Hence, Hypothesis 4 held. Similarly, the interaction effect between *Data analytics capability* and *Competitive intensity* was illustrated and presented in Figure 3. In addition, the marginal effect for this interaction was also checked, which revealed that a standard deviation increase in *Data* *analytics capability* leads to a higher rise in *Innovation speed* when *Competitive intensity* is one standard deviation above the mean (5.19%), as opposed to when the intensity of competition is one standard deviation below the mean (1.95%). Overall, these results reinforced the reliability of Hypothesis 4.

In conclusion, three of the four hypotheses were confirmed in this study. To be specific, data analytics capability indeed exerts a positive effect on firm innovation speed. Besides, it has been established that technological turbulence and competitive intensity positively regulate this relationship. The impact of market turbulence on the association between data analytics capability and innovation speed, however, is unsupported.

Table 8. OLS models predicting Innovation speed

	(1)	(2)	(3)	(4)	(5)
Firm size	0.0440^{**}	0.0342^{*}	0.0329^{*}	0.0266^{+}	0.0314^{*}
	(0.0152)	(0.0148)	(0.0148)	(0.0146)	(0.0149)
Firm age	-0.0029	-0.0028	-0.0025	-0.0017	-0.0022
	(0.0034)	(0.0034)	(0.0034)	(0.0034)	(0.0034)
R&D intensity	-0.0050^{*}	-0.0042^{*}	-0.0043^{*}	-0.0038^{+}	-0.0037^{+}
	(0.0022)	(0.0021)	(0.0021)	(0.0020)	(0.0021)
Market turbulence	0.1596^{***}	0.1056^{*}	-0.1895	0.0966^{*}	0.0979^{*}
	(0.0432)	(0.0416)	(0.2013)	(0.0400)	(0.0408)
Technological turbulence	0.0506	0.0278	0.0245	-0.6272^{***}	0.0274
	(0.0353)	(0.0362)	(0.0362)	(0.1456)	(0.0356)
Competitive intensity	0.5647^{***}	0.4858^{***}	0.4732^{***}	0.4766^{***}	-0.0571
	(0.0444)	(0.0482)	(0.0477)	(0.0473)	(0.2211)
Data analytics capability		0.2030^{***}	-0.0891	-0.5036^{**}	-0.3658^{+}
		(0.0432)	(0.2017)	(0.1617)	(0.2043)
Data analytics capability * Market turbulence			0.0647 (0.0410)		
Data analytics capability * Technological turbulence				0.1449^{***} (0.0315)	
Data analytics capability *					0.1166^{**} (0.0424)

Competitive intensity					
Constant	0.9821***	0.8012***	2.1937*	4.0595***	3.4377**
	(0.2253)	(0.2340)	(0.9868)	(0.7747)	(1.0637)
N	459	459	459	459	459
R^2	0.4658	0.4974	0.5021	0.5225	0.5104

Notes: Standard errors are included in parentheses; + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

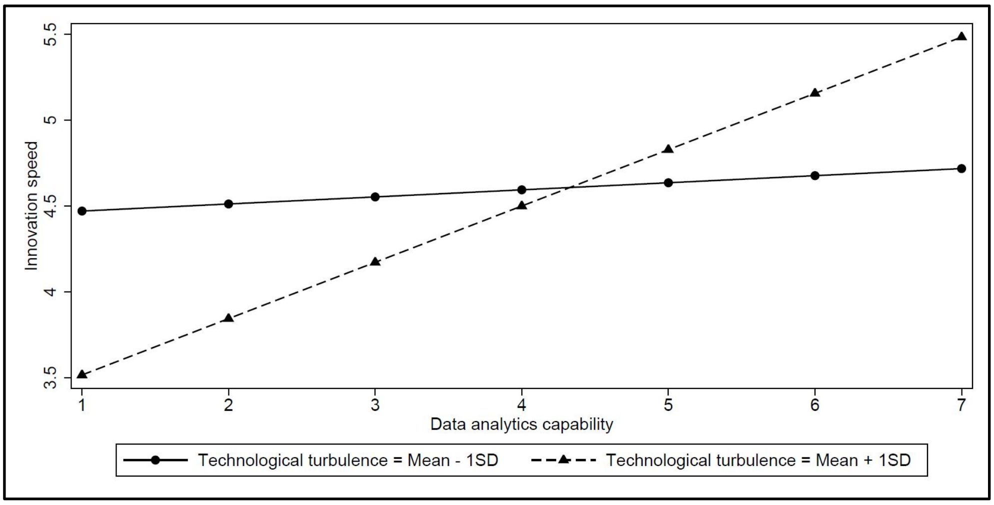

Figure 2. Plot for the interaction between Data analytics capability and Technological turbulence (using Model 4 in Table 8)

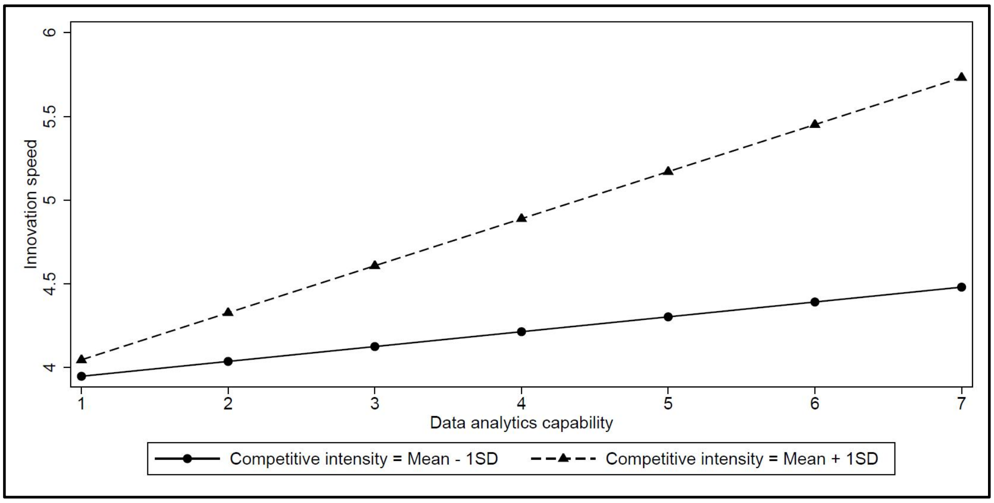

Figure 3. Plot for the interaction between Data analytics capability and Competitive intensity (using Model 5 in Table 8)

3.3.5 Robustness Checks

Two steps were taken to verify the robustness of the results. I began by taking the control variables out of the original model and rerunning the OLS regression because they might affect the empirical results and thus the interpretation of the findings (Becker, 2005; Becker et al., 2016). According to the results presented in Table 9 and the interaction plots demonstrated in Figures 4 and 5, our hypotheses held still after dropping the control variables (H1: $\beta = 0.2189$, $p < 0.001$; H2: $\beta = 0.0660$, $p < 0.1$; H3: $\beta = 0.1521$, $p < 0.001$; H4: $\beta = 0.1243$, $p < 0.01$). Next, I further performed the robustness check by running the regression analysis on three randomly chosen subsamples (90%, 80%, and 70%) following the work of Li et al. (2009) and Xie et al. (2022). As shown in Table 10 and Figures 6 to 11, the results based on the subsamples were consistent with those of the full sample, again corroborating the reliability of the results (90% subsample: H1: $\beta = 0.1857$, $p < 0.001$; H2: $\beta = 0.0791$, $p < 0.05$; H3: $\beta = 0.1473$, $p < 0.001$; H4: $\beta = 0.1312$, $p < 0.01$. 80% subsample: H1: $\beta = 0.1742$, $p < 0.001$; H2: $\beta = 0.1063$, $p < 0.01$; H3: $\beta = 0.1538$, $p < 0.001$; H4: $\beta = 0.1297$, $p < 0.01$. 70% subsample: H1: $\beta = 0.1664$, $p < 0.001$; H2: $\beta = 0.1186$, $p < 0.01$; H3: $\beta = 0.1619$, $p < 0.001$; H4: $\beta = 0.1321$, $p < 0.01$.).

Table 9. Robustness check (Control variables are removed)

	(1)	(2)	(3)	(4)	(5)
Market turbulence	0.1437***	0.0884*	-0.2130	0.0809*	0.0823*
	(0.0412)	(0.0395)	(0.1931)	(0.0381)	(0.0389)
Technological turbulence	0.0687*	0.0395	0.0357	-0.6507***	0.0382
	(0.0344)	(0.0358)	(0.0355)	(0.1391)	(0.0353)
Competitive intensity	0.5778***	0.4890***	0.4756***	0.4779***	-0.0901
	(0.0447)	(0.0484)	(0.0480)	(0.0475)	(0.2190)
Data analytics capability		0.2189***	-0.0795	-0.5255***	-0.3894^{+}
		(0.0441)	(0.1938)	(0.1540)	(0.1987)
Data analytics capability * Market turbulence			0.0660^{+}		
			(0.0393)		
Data analytics capability * Technological turbulence				0.1521***	
				(0.0300)	

Data analytics capability * Competitive intensity					0.1243^{**}
					(0.0415)
Constant	1.0031^{***}	0.7967^{***}	2.2166^{*}	4.2133^{***}	3.6140^{***}
	(0.2192)	(0.2271)	(0.9443)	(0.7348)	(1.0329)
N	459	459	459	459	459
R^2	0.4500	0.4875	0.4925	0.5155	0.5024

Notes: Standard errors are included in parentheses; + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

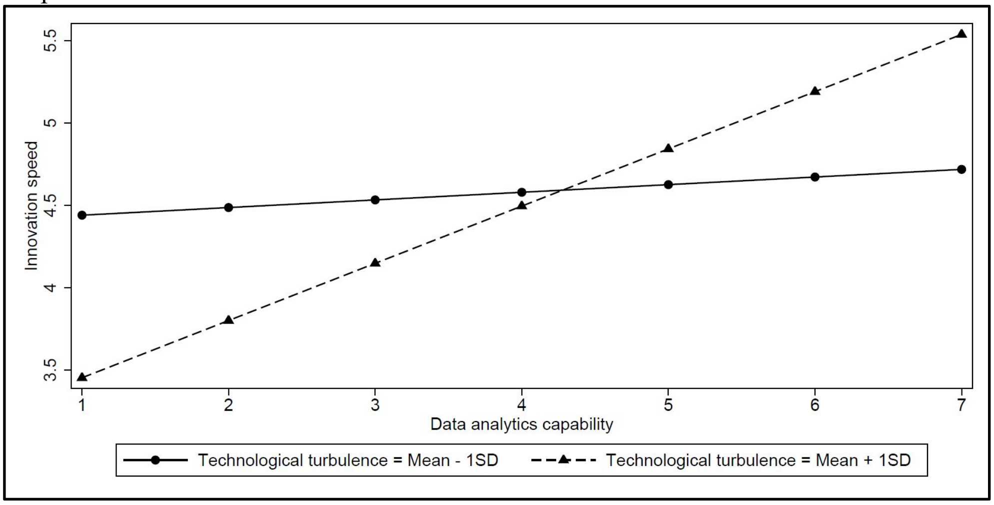

Figure 4. Plot for the interaction between Data analytics capability and Technological turbulence (using Model 4 in Table 9)

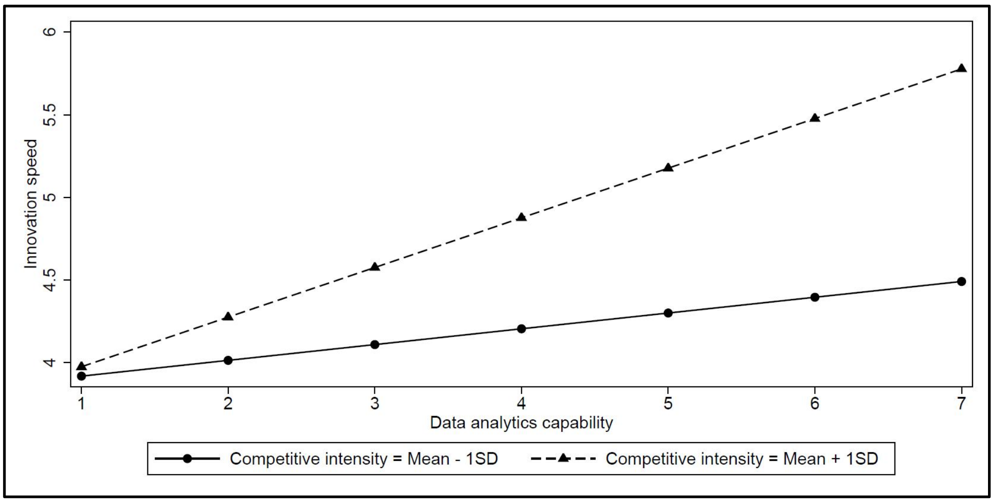

Figure 5. Plot for the interaction between Data analytics capability and Competitive intensity (using Model 5 in Table 9)

Table 10. Robustness check (Randomly selected subsamples)

	(1)	(2)	(3)	(4)	(5)
Panel A: 90% subsample randomly selected from the total sample					
Firm size	0.0446^{**}	0.0356^{*}	0.0344^{*}	0.0279^{+}	0.0331^{*}
	(0.0161)	(0.0156)	(0.0155)	(0.0153)	(0.0157)
Firm age	-0.0026	-0.0023	-0.0020	-0.0011	-0.0016

	(0.0035)	(0.0035)	(0.0035)	(0.0035)	(0.0034)
R&D intensity	-0.0048*	-0.0041+	-0.0043*	-0.0038+	-0.0036+
	(0.0023)	(0.0022)	(0.0021)	(0.0021)	(0.0021)
Market turbulence	0.1412**	0.0922*	-0.2666	0.0837*	0.0835*
	(0.0439)	(0.0429)	(0.1948)	(0.0413)	(0.0419)
Technological turbulence	0.0536	0.0321	0.0284	-0.6318***	0.0312
	(0.0356)	(0.0367)	(0.0366)	(0.1391)	(0.0359)
Competitive intensity	0.5638***	0.4929***	0.4768***	0.4813***	-0.1174
	(0.0453)	(0.0491)	(0.0487)	(0.0482)	(0.2225)
Data analytics capability		0.1857***	-0.1733	-0.5306***	-0.4553*
		(0.0433)	(0.1962)	(0.1585)	(0.2030)
Data analytics capability * Market turbulence			0.0791*		
			(0.0398)		
Data analytics capability * Technological turbulence				0.1473***	
				(0.0306)	
Data analytics capability * Competitive intensity					0.1312**
					(0.0425)
Constant	1.0434***	0.8735***	2.5759**	4.1761***	3.8410***
	(0.2350)	(0.2429)	(0.9587)	(0.7598)	(1.0629)
N	413	413	413	413	413
R^2	0.4696	0.4974	0.5049	0.5247	0.5150
Panel B: 80% subsample randomly selected from the total sample					
Firm size	0.0423*	0.0362*	0.0367*	0.0280+	0.0339*
	(0.0169)	(0.0165)	(0.0163)	(0.0161)	(0.0165)
Firm age	-0.0000	-0.0003	-0.0003	0.0008	0.0003
	(0.0035)	(0.0035)	(0.0036)	(0.0035)	(0.0035)
R&D intensity	-0.0044+	-0.0034	-0.0037+	-0.0034	-0.0029
	(0.0024)	(0.0023)	(0.0022)	(0.0022)	(0.0022)
Market turbulence	0.1217**	0.0782+	-0.3983*	0.0694	0.0694
	(0.0444)	(0.0450)	(0.1789)	(0.0427)	(0.0440)
Technological turbulence	0.0654+	0.0427	0.0365	-0.6457***	0.0407
	(0.0378)	(0.0391)	(0.0386)	(0.1435)	(0.0381)
Competitive intensity	0.5725***	0.5058***	0.4840***	0.4909***	-0.0982
	(0.0458)	(0.0494)	(0.0495)	(0.0487)	(0.2239)
Data analytics capability		0.1742***	-0.3078+	-0.5749***	-0.4575*
		(0.0433)	(0.1787)	(0.1662)	(0.2058)
Data analytics capability * Market turbulence			0.1063**		
			(0.0374)		

Data analytics capability * Technological turbulence				0.1538^{***} (0.0319)	
Data analytics capability * Competitive intensity					0.1297^{**} (0.0428)
Constant	1.0149^{***}	0.8433^{**}	3.1070^{***}	4.2955^{***}	3.7771^{***}
	(0.2647)	(0.2728)	(0.9033)	(0.8116)	(1.0943)
N	367	367	367	367	367
R^2	0.4739	0.4995	0.5129	0.5297	0.5182
Panel C: 70% subsample randomly selected from the total sample					
Firm size	0.0437^{*}	0.0388^{*}	0.0398^{*}	0.0322^{+}	0.0345^{+}
	(0.0179)	(0.0175)	(0.0173)	(0.0170)	(0.0176)
Firm age	-0.0016	-0.0014	-0.0016	-0.0003	-0.0008
	(0.0036)	(0.0036)	(0.0037)	(0.0037)	(0.0037)
R&D intensity	-0.0040	-0.0030	-0.0036	-0.0035	-0.0028
	(0.0025)	(0.0024)	(0.0023)	(0.0023)	(0.0023)
Market turbulence	0.1048^{*}	0.0637	-0.4768^{*}	0.0527	0.0505
	(0.0485)	(0.0495)	(0.1864)	(0.0469)	(0.0484)
Technological turbulence	0.0594	0.0333	0.0271	-0.7103^{***}	0.0357
	(0.0431)	(0.0454)	(0.0444)	(0.1461)	(0.0439)
Competitive intensity	0.5951^{***}	0.5359^{***}	0.5119^{***}	0.5275^{***}	-0.0826
	(0.0489)	(0.0514)	(0.0518)	(0.0498)	(0.2325)
Data analytics capability		0.1664^{***}	-0.3721^{*}	-0.6189^{***}	-0.4807^{*}
		(0.0456)	(0.1794)	(0.1657)	(0.2148)
Data analytics capability * Market turbulence			0.1186^{**} (0.0379)		
Data analytics capability * Technological turbulence				0.1619^{***} (0.0319)	
Data analytics capability * Competitive intensity					0.1321^{**} (0.0443)
Constant	1.0217^{***}	0.8376^{**}	3.4073^{***}	4.5196^{***}	3.8744^{***}
	(0.2895)	(0.3010)	(0.9375)	(0.8312)	(1.1547)
N	321	321	321	321	321
R^2	0.4885	0.5119	0.5281	0.5451	0.5317

Notes: Standard errors are included in parentheses; + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

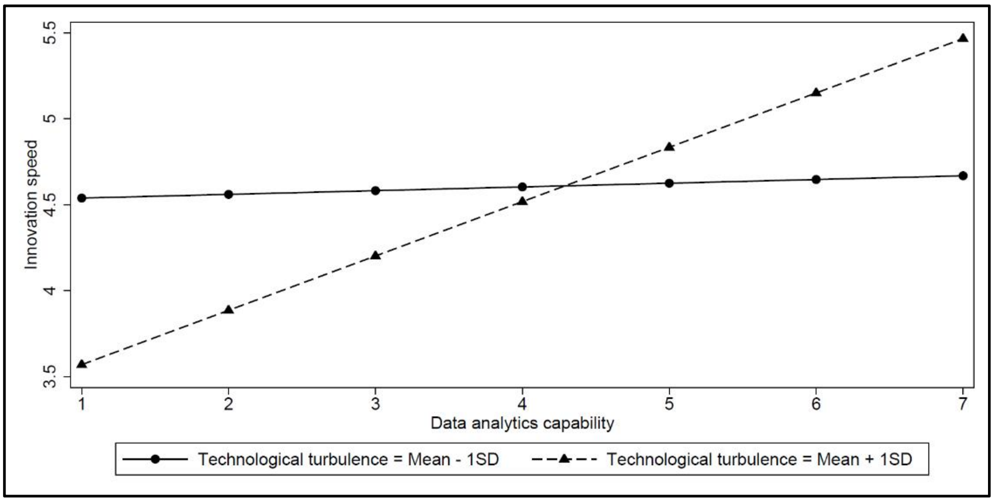

Figure 6. Plot for the interaction between Data analytics capability and Technological turbulence (using Model 4 in Panel A of Table 10)

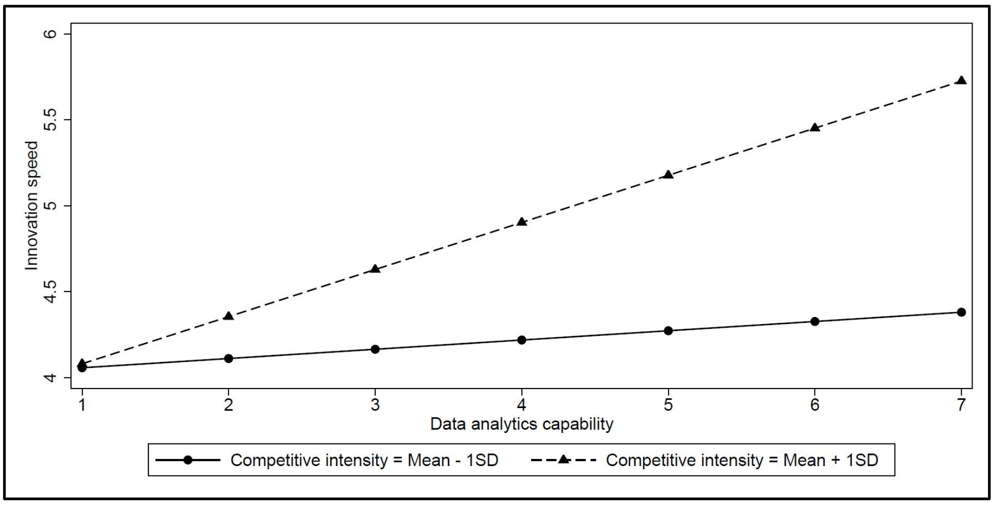

Figure 7. Plot for the interaction between Data analytics capability and Competitive intensity (using Model 5 in Panel A of Table 10)

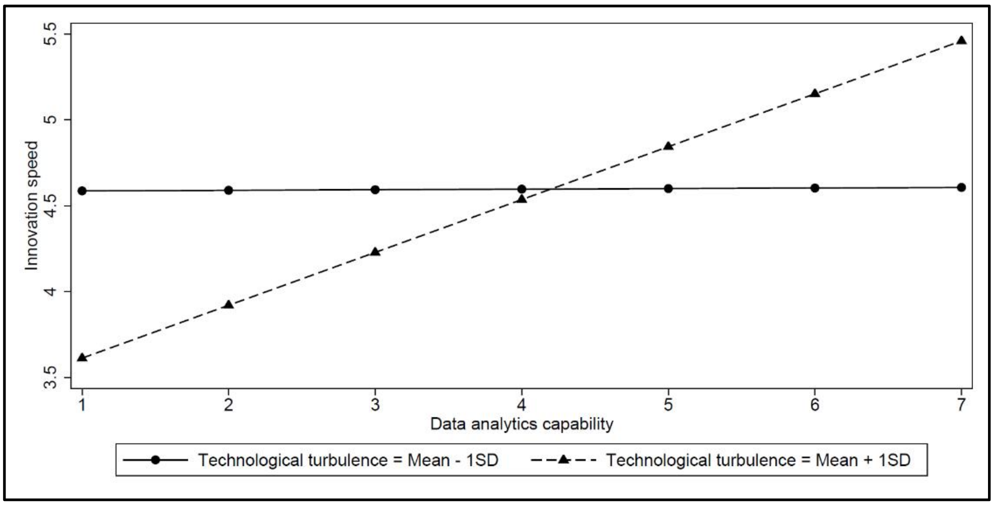

Figure 8. Plot for the interaction between Data analytics capability and Technological turbulence (using Model 4 in Panel B of Table 10)

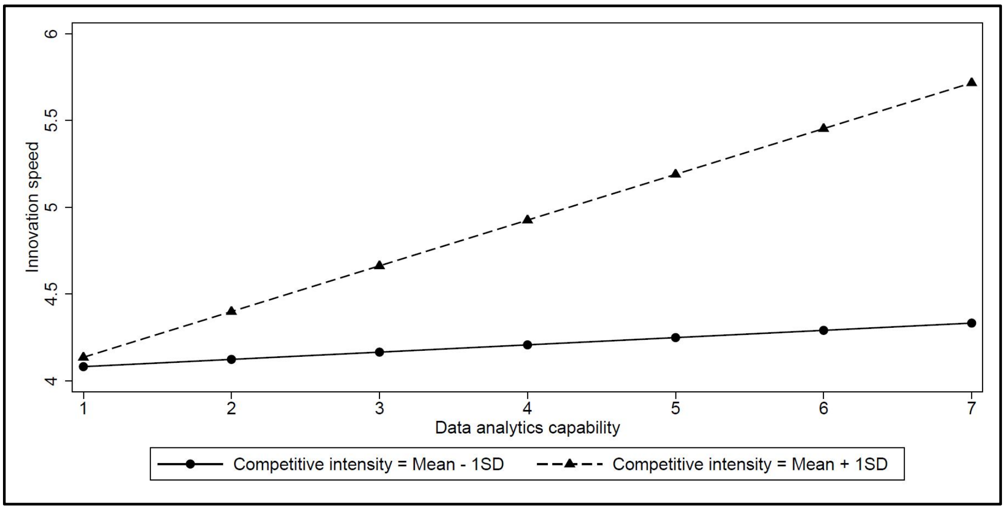

Figure 9. Plot for the interaction between Data analytics capability and Competitive intensity (using Model 5 in Panel B of Table 10)

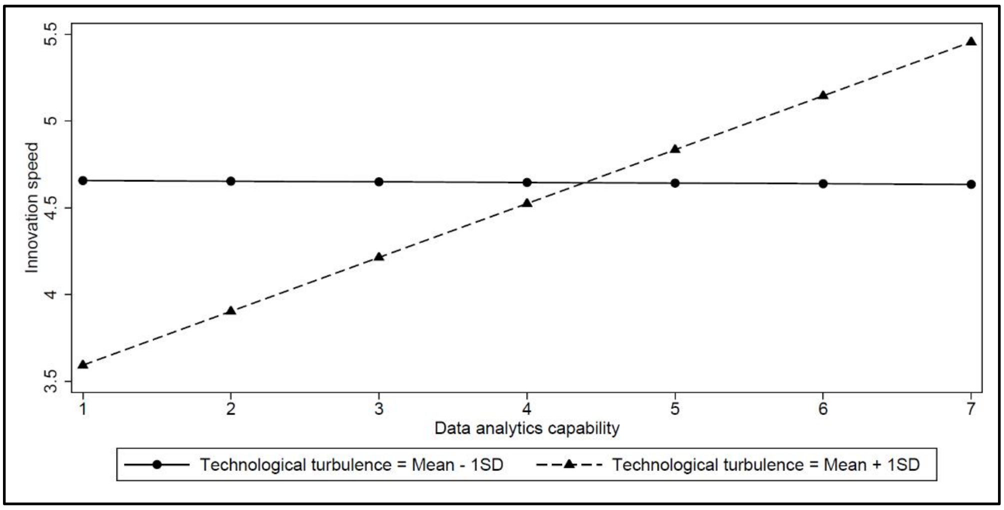

Figure 10. Plot for the interaction between Data analytics capability and Technological turbulence (using Model 4 in Panel C of Table 10)

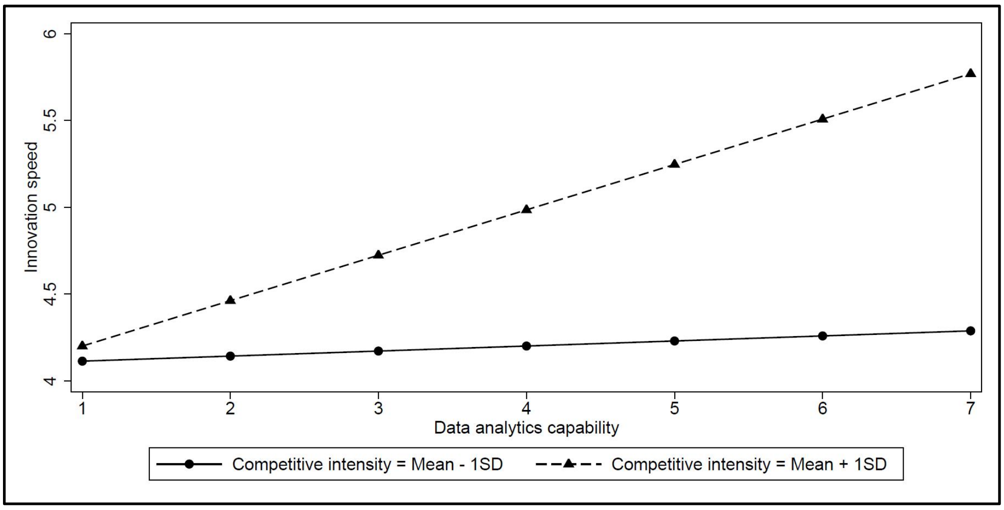

Figure 11. Plot for the interaction between Data analytics capability and Competitive intensity (using Model 5 in Panel C of Table 10)

4. STUDY 2: DATA ANALYTICS CAPABILITY AND INTERNET FIRMS' INNOVATION QUALITY

4.1 Theory and Hypotheses

4.1.1 Data Analytics Capability and Innovation Quality

Innovation quality refers to the extent to which firms' products and services can satisfy customers' needs (Haner, 2002; Lahiri, 2010). I posit that firms' data analytics capability increases their innovation quality for two reasons.

First, in the digital era, customers' needs, wants, expectations, and pain points are embedded in the data that they generated on the digital platforms, such as online reviews, purchase, views, and clicks (Bucklin & Sismeiro, 2009; Grover et al., 2018). However, it is not straightforward for firms to understand what customers need from the data, because the data is large, unstructured, and dispersed (George et al., 2016; Ren et al., 2017). In order to extract valuable insights regarding customers' needs from the data, the firms should possess decent level of data analytics capability to process and analyze the data (McAfee et al., 2012). For firms with high level of data analytics capability, they can gain sophisticated understanding of customers' preferences by applying state-of-the-art techniques in their data analytics (Hossain et al., 2020). Accordingly, they can delve into the data and gain an in-depth understanding of what customer want currently and even in the future (Shuradze et al., 2018). The understanding of customers' needs is essential because it provides clear directions for the firms to upgrade their current products and services or develop new products and services (Liu et al., 2020). And it is these new products and services that can better fulfill customers' needs since the update or development of these products and services directly draw insights generated from analysis of customers' data. In comparison, firms with low level of data analytics capability are not able to understand customers' needs from their data, thus their innovation in products and services might not be in the right direction to satisfy their customers' needs (Christensen et al., 2016).

Second, data analytics capability facilitates high-quality decision making in the process of new products and services development. In the development of new products and services, firms generate a large amount of diverse data, such as experiment data and test data (Mahajan & Wind, 1992; Thomke, 1998). The data is usually unstructured and dispersed in different databases or documents, which creates obstacles for R&D employees to integrate and run analyses (Boutellier et al., 1998; Gunasekaran, 1999). This is less of an issue for firms with high level of data analytics capability because these firms can employ advanced data analytics methodologies to combine the fragmented datasets and efficiently process and analyze the data to gain valuable insights (Jahani et al., 2023). As a result, these insights can help R&D employees to make high-quality decisions (Ghasemaghaei & Calic, 2019). These decisions are diverse and can touch every aspect of R&D process, such as what the root cause is for some problems and how to improve the performance of product features. However, for firms with low-level of data analytics capability, they may have difficulty to assemble data from various sources and conduct effective analysis (Jha et al., 2020). Therefore, the quality of their decision making is compromised, as it is not based on rigorous data, but instead of personal experience, which could be biased (Liedtka, 2015; Tversky & Kahneman, 1974).

These arguments lead me to propose that:

Hypothesis 1: There is a positive relationship between data analytics capability and innovation quality.

4.1.2 The Moderating Effect of Centralization

Organizational structure plays a significant role in affecting firms' innovation activities (Damanpour & Gopalakrishnan, 1998; Damanpour & Aravind, 2012; Sapolsky, 1967). Prior research suggests that organizational structure is a multidimensional construct (Fredrickson, 1986; James & Jones, 1976). In the present study, I focus on two dimensions of organizational structure: centralization and formalization, as a number of prior studies have shown that these two dimensions have substantial impact on firms' innovation activities (Gentile-Lüdecke et al., 2020; Zmud, 1982). I assert that centralized organizational structure can weaken the positive relationship between data analytics capability and innovation quality.

First, in firms with highly centralized organizational structure, although data analytics capability helps the firms to detect customers' needs, it might be hard for these firms to leverage these insights to promote innovation quality. This happens because decisions in such firms are made by a few employees with high power, which reduces creative idea generation from other employees (Rhee et al., 2017). These employees are discouraged to propose new ideas because they perceive that their ideas might be evaluated negatively or rejected by the decision makers (Scarffe et al., 2022). This is evidenced in prior research that hierarchy can suppress the voice from individuals who have low level of power (Milliken et al., 2015; Pfrombeck et al., 2023). In addition, the decision made by the decision makers may be suboptimal, because they may not fully understand the insights extracted from the data (Joseph & Gaba, 2020). In comparison, in firms with decentralized organizational structure, a large number of employees can base on insights generated from data to formulate creative ideas (Darvishmotevali, 2019). Then, they can discuss with other employees and collectively evaluate the potential of the ideas and select the ideas with the high potential (Keum & See, 2017). Therefore, decentralized organizational structure can amplify the positive effect of data analytics capability on innovation quality since it encourages more employees to generate new ideas and thus increase the possibility of the emergence of higher quality ideas (Pertusa-Ortega et al., 2010).

Second, in the development of new products and services, decentralized organizational structure is more effective for firms to leverage the potential of data analytics capability to realize high quality innovation as well. As I illustrated above, employees use data analytics techniques to analyze dispersed and fragmented datasets generated in the R&D process. Ideas might be generated at any time during this process and decisions must be made accordingly in these cases (Bröring et al., 2006; Kijkuit & Van Den Ende, 2007). Decentralized organizational structure is advantageous in such cases, because it gives autonomy for employees to make their decisions, such that this structure not only encourages idea generation, but also increases the chance of high-quality ideas in the R&D process (Richardson et al., 2002). In comparison, in the case of centralized decision making, employees have little autonomy to make decision in the R&D process, thus they are less motivated to raise new ideas based on data analytical results (Hage & Aiken, 1967; Wally & Baum, 1994). Even though they come up with their ideas, these ideas might not be adopted by the key decision makers. Consequently, the usefulness of data analytics is comprised in firms with decentralized organizational structure.

Taken together, I propose that:

> ***Hypothesis 2***: Centralization negatively moderates the positive relationship between data analytics capability and innovation quality, such that the positive relationship between data analytics capability and innovation speed is weaker for firms with highly centralized organizational structure.

4.1.3 The Moderating Effect of Formalization

Firms with high level of formalization is characterized by a number of predefined rules and procedures to guide decision making (Gibson et al., 2019; Podsakoff et al., 1986; Vlaar et al., 2007). I contend that formalization undermines the positive relationship between data analytics capability and innovation quality.

First, in firms with high level of formalization, the existence of large number of rules may hinder the effective analyses of customers' data (Hirst et al., 2011). This is mainly because data analytics is a flexible process, in which employees who run the data analytics are required to use different software, algorithms, and methodologies to gain deep insight of the data (Dubey et al., 2018; 2021). Besides, different combinations of methods need to be used by employees to analyze different datasets. If these employees employ a formal analytical procedure to run the analytics for all the datasets without considering their difference, the quality of analytical results might be discounted or might be even wrong, because the real insights hidden in the data are not extracted. By contrast, for firms with less formalized structure, employees have high degree of flexibility to decide which methods to use for the data analyses (Nasurdin et al., 2006). As a result, they can distill useful information from different datasets, which can provide valuable input for their decision making in the innovation process.

Second, based on the similar logic that I explicated above, formalized organizational structure can also undermine the usefulness of data analytics capability in the development of new products and services. Since the data generated in the R&D process is highly fragmented and dispersed, formal rules would constrain employees to creatively leverage diverse data analytics techniques to process different datasets (Acar et al., 2019). As such, the information they extract from data using formal procedures is shallow and less likely to be insightful, which can eventually reduce the quality of innovation. In comparison, a less formalized organizational structure can encourage R&D employees to flexibly use required methodologies to analyze different dataset, which helps them to extract diverse and valuable insights from these datasets, enhancing the quality of their innovation.

In summary, I posit that formalized organizational structure diminishes employees' flexibly to fully unpack the potential of data analytics capability in innovation activities. I therefore propose that:

> ***Hypothesis 3***: Formalization negatively moderates the positive relationship between data analytics capability and innovation quality, such that the positive relationship between data

analytics capability and innovation speed is weaker for firms with highly formalized organizational structure.

4.1.4 The Moderating Effect of Top Management Support

In addition to organizational structure, I theorize that top management support can enhance the positive association between data analytics capability and innovation quality.

First, top managers can provide necessary support for the analyses of customers' data (Chen et al., 2015; El-Haddadeh et al., 2021; Gunasekaran et al., 2017). For example, they can provide training for employees so as to sharpen their skills in data analytics or help them master the state-of-the-art data analytics techniques (e.g., machine learning, big data analytics). In addition, top managers can also provide financial resources to purchase advanced software to support the data analyses (Barbosa et al., 2018; Popovič et al., 2018). Research has shown that data analyses will be more effective with mature business data analytics software (Delen & Demirkan, 2013). Besides, top managers can also provide headcounts to hire more employees owning expertise in data analytics, increasing firms' chance to fully utilize their data resources to support their innovation activities (Greer et al., 1999; Simons, 1991). Finally, top managers can also provide relevant resources for employees to implement the insights gathered from data, which make the new products and services responsive to customers' needs (Hornsby et al, 2002; Qian et al., 2013). In comparison, the resource that is provided to data analytics activities will be limited if there is little top management support. Consequently, the effect of data analytics on firms' innovation quality will be discounted.

Second, top managers can also provide the needed support in the development of new products and services (Bonner et al., 2002). Specifically, they can not only deploy more human resources to analyze customers' data, but also provide more financial resources to implement insights gained from data in the new products and services (Barbosa et al., 2018; Gupta & George, 2016). In addition, they can provide guidance and make high-quality decisions based on information distilled from data, such that employees can incorporate what they suggested in the product and service innovation (Laguir et al., 2022). Finally, managers can coordinate the activities between different teams and departments, such that the ideas generated from data can be effectively implemented in new products and services (Zhou, 2013). In comparison, if the level of support from top managers is low, although employees can conduct data analyses and extracts insights from it, the implementation of these insights would be challenging due to coordination issues or resource constraints (Michel & Hambrick, 1992; Rao & Drazin, 2002).

To summarize, I assert that top managers can provide necessary resources to support data analyses in firms' innovation activities, which amplifies the usefulness of data analytics in firms' product or service innovation. In line with this logic, I hypothesize that:

> ***Hypothesis 4***: Top management support positively moderates the positive relationship between data analytics capability and innovation quality, such that the positive relationship between data analytics capability and innovation speed is stronger for firms with high level of top management support.

A research framework of Study 2 is shown in Figure 12.

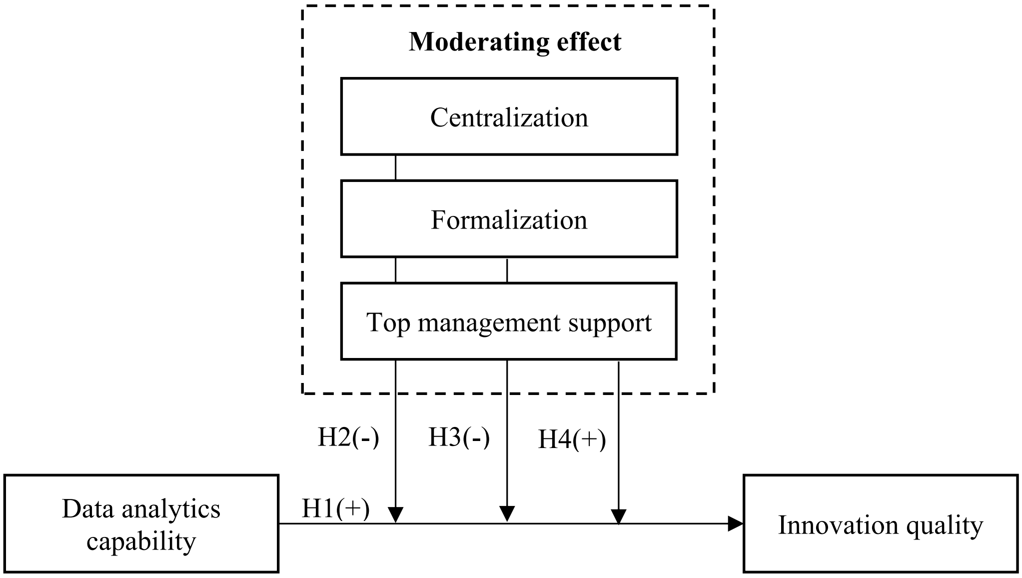

Figure 12. Research framework

4.2 Data and Methods

4.2.1 Sample and Data Collection

The proposed hypotheses were examined using data on a sample of Chinese Internet firms, which was gathered through a self-developed and issued questionnaire. The survey method has been widely adopted in research fields such as psychology, sociology and management because it has the advantage of collecting a sizable sample at a relatively low cost, which can then serve as the foundation for inferring the population and making the empirical results more replicable (Bernard, 2013). For this reason, the survey method was selected as the research approach in this study. In addition, since Chinese Internet firms are on the rise and are actively engaged in acquiring, storing, and analyzing large amounts of user data to drive innovation, it is deemed appropriate to target the Internet firms in China as the research subjects in order to empirically investigate the relationship between data analytics capability and firm innovation quality. The findings from this study may also be instructive for academics looking at big data analytics and innovation in other research settings.

After establishing the research methodology and object, a preliminary English-version questionnaire was developed on the basis of a thorough literature search and reading. Then, considering that the research would be performed in China, the original English questionnaire was translated into Chinese, following by a back-translation procedure to ensure accuracy and consistency (Brislin, 1970). Subsequently, a series of actions were taken to enhance the quality of the questionnaire. First, with the help of three professors owning extensive knowledge and in-depth insights in innovation management and information systems, a few possible problems stemming from the framing and phrasing of the questions were identified and corrected. Second, five top managers working in different firms were invited to review the measurement scales. The feedback and suggestions provided by them helped me to improve the back-translation consistency and reword several items that were not clear. Third, a pilot test was conducted in 30 Internet firms in Hangzhou, which further assisted me in enhancing the clarity and fitness of the questionnaire. Based on all of these, a questionnaire with clear purpose, complete content and rigorous structure was finalized.

For the data gathering, a list of 1,200 Chinese firms randomly chosen from the directory of information transmission, software and information technology service firms obtained from Qichacha (i.e., a widely utilized corporate information search tool in China) was created. After that, using publicly available contact information (i.e., including email addresses and phone numbers), an online questionnaire was sent out to these firms via emails, along with a cover letter outlining my research goal, assuring them of confidentiality and anonymity, and inviting them to participate in this research. Then, in an effort to boost the response rate to the questionnaire, I tried to contact those firms that hadn't replied three months after the email was sent through phone calls. By employing these techniques, I was able to obtain 482 responses throughout the data gathering period (i.e., from May 2022 to December 2022). 23 of which could not pass the manipulation and attention check and were therefore not included in the sample. Overall, 459 firms finished the survey effectively, representing a valid response rate of 38.25% (i.e., 459/1200). Following that, in order to determine whether there is a nonresponse bias, an independent t-test was conducted. The results showed no significant differences in firm features and key indicators between the first 115 (25%) and the last 115 (25%) responses in the sample (Armstrong & Overton, 1977), indicating that nonresponse bias was not a serious concern in my research.

Table 11 presents the profile of the 459 effectively responding firms. As can be observed, the sample firms spread across the eastern (29.19%), southern (32.90%), western (16.56%), and northern (21.35%) regions of China, which offers sufficient geographic variety and ensures the representativeness of the sample to a certain extent. Besides, firms of various sizes were contained in my sample. While firms with less than 10 employees accounted for the smallest proportion (0.65%), those with more than 500 employees made up the majority (43.36%). In terms of firm age, it can be found that firms in the sample were relatively young, most of which had been established for less than 6 years (27.23%) or for 6 to 10 years (33.55%).

Table 11. Profile of responding firms (N = 459)

	Frequency	Percentage	Cumulative
Firm size			
< 10	3	0.65%	0.65%
10-50	19	4.14%	4.79%
51-100	59	12.85%	17.65%
101-200	60	13.07%	30.72%
201-300	35	7.63%	38.34%
301-400	35	7.63%	45.97%
401-500	49	10.68%	56.64%
> 500	199	43.36%	100.00%
Firm age			
< 6	125	27.23%	27.23%
6-10	154	33.55%	60.78%
11-15	74	16.12%	76.91%
16-20	42	9.15%	86.06%
> 20	64	13.94%	100.00%
Region			
East	134	29.19%	29.19%
South	151	32.90%	62.09%
West	76	16.56%	78.65%
North	98	21.35%	100.00%

4.2.2 Measurement of Variables

To investigate the effect of firm's data analytics capability on innovation quality and the boundary conditions for this link, measurement scales for pertinent constructs were identified from the existing literature and then modified to fit the research context of big data analytics. The following is a detailed description of the variables and corresponding measurement items used in this research. Unless otherwise specified, each survey item was assessed on a 7-point Likert scale (where 1 = strongly disagree, and 7 = strongly agree) and each measure was aggregated from corresponding survey items by taking their arithmetic mean.

4.2.2.1 Dependent variable

Innovation quality refers to the extent to which firms' products and services satisfy their consumers' demands (Haner, 2002; Lahiri, 2010). Following the work of Lahiri (2010) as well as Wang and Wang (2012), I included five items to measure this variable: (1) "Our organization does better in coming up with novel ideas as compared to key competitors"; (2) "Our organization does better in new product launching as compared to key competitors"; (3) "Our organization does better in new product development as compared to key competitors"; (4) "Our organization does better in processes improving as compared to key competitors"; and (5) "Our organization does better in management improving as compared to key competitors" (alpha coefficient = 0.8355, maximal reliability = 0.6552).

4.2.2.2 Independent variable

Data analytics capability describes a firm's ability to obtain, process, and analyze big data to derive useful insights from it (Gupta & George, 2016; Olabode et al., 2022). It is measured by five items (Laguir et al., 2022; Srinivasan & Swink, 2018): (1) "Our organization uses advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making"; (2) "Our organization easily combines and integrates information from many data sources for use in our decision making"; (3) "Our organization routinely uses data visualization techniques (e.g., dashboards) to assist users or decision-maker in understanding complex information"; (4) "Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement"; and (5) "Our organization deploys dashboard applications/information to our managers' communication devices (e.g., smart phones, computers)" (alpha coefficient = 0.8551, maximal reliability = 0.6918).

4.2.2.3 Moderating variables

The degree of concentration of the power to make decisions and assess actions is referred to as *Centralization* (Fredrickson, 1986). In the present study, it was measured by inquiring at which hierarchical level are decisions normally made within organizations. Operationally, respondents were asked to rate on a scale of 1 to 7, with 1 representing lower-level employees and 7 representing top managers. Borrowing from Pertusa-Ortega et al. (2010), eleven typical and significant organizational decisions were listed in the questionnaire: (1) "Decisions about work conflicts"; (2) "Decisions about overtime"; (3) "Decisions about employee recruitment"; (4) "Decisions about job assignment"; (5) "Decisions about machinery"; (6) "Decisions about worker layoffs"; (7) "Decisions about order priority"; (8) "Decisions about employee numbers"; (9) "Decisions about working methods"; (10) "Decisions about staff selection"; and (11) "Decisions about production plans" (alpha coefficient = 0.9163, maximal reliability = 0.6891).

Also following the practice of Pertusa-Ortega et al. (2010), five items were used to gauge *Formalization*, which assesses the degree to which firm's working practice, internal operations, and employee behaviors were constrained by its rules and regulations (Fredrickson, 1986). Specifically, in the questionnaire, respondents were asked to what extent was their organization regulated in the following aspects: (1) "Regulations on procedures"; (2) "Regulations on the monitoring of work development"; (3) "Monitoring of employees"; (4) "Rules of behavior"; and (5) "Resources to ensure compliance with rules" (alpha coefficient = 0.8680, maximal reliability = 0.6588). A rating scale of 1 to 7 was also utilized for this question, with 1 being low degree and 7 denoting high degree.

Additionally, *Top management support*, which evaluates the extent to which big data analytics is supported by executives, was operationalized using four items in line with Soliman and Janz (2004): (1) "Our top management is willing to invest funds in big data analytics"; (2) "Our top management is willing to take risks involved in the utilization of big data analytics"; (3) "Our top management is interested in big data analytics in order to gain competitive advantage"; and (4) "Our top management considers the use of big data analytics as strategically important" (alpha coefficient = 0.8278, maximal reliability = 0.6796).

4.2.2.4 Control variables

In order to eliminate other possible explanations for the hypothesized relationship, several variables that might influence the dependent variable were controlled in this study, including *Firm size*, measured as the number of employees, as well as *Firm age*, calculated as how many years a firm had been operating. Moreover, *R&D intensity* was taken into consideration, which was measured as the proportion of R&D expenditures to total sales.

Overall, the measurement of the dependent variable, independent variable, moderating variables, and control variables are summarized in Table 12.

Table 12. Measurement of variables

Variable	Measurement
Dependent Variable	
Innovation quality (IQ)	IQ1: Our organization does better in coming up with novel ideas as compared to key competitors.
(Lahiri, 2010; Wang & Wang, 2012)	IQ2: Our organization does better in new product launching as compared to key competitors.

	IQ3: Our organization does better in new product development as compared to key competitors. IQ4: Our organization does better in processes improving as compared to key competitors. IQ5: Our organization does better in management improving as compared to key competitors.
Independent Variable	
Data analytics capability (DAC) (Laguir et al., 2022; Srinivasan & Swink, 2018)	DAC1: Our organization uses advanced analytical techniques (e.g., simulation, optimization, regression) to improve decision making. DAC2: Our organization easily combines and integrates information from many data sources for use in our decision making. DAC3: Our organization routinely uses data visualization techniques (e.g., dashboards) to assist users or decision-maker in understanding complex information. DAC4: Our dashboards give us the ability to decompose information to help root cause analysis and continuous improvement". DAC5: Our organization deploys dashboard applications/information to our managers' communication devices (e.g., smart phones, computers).
Moderating Variables	
Centralization (COS) (Pertusa-Ortega et al., 2010)	At what level are the following decisions typically made in our organization? (1 = Lower level employees; 7 = Top managers) COS1: Decisions about work conflicts. COS2: Decisions about overtime. COS3: Decisions about employee recruitment. COS4: Decisions about job assignment. COS5: Decisions about machinery. COS6: Decisions about worker layoffs. COS7: Decisions about order priority. COS8: Decisions about employee numbers. COS9: Decisions about working methods. COS10: Decisions about staff selection. COS11: Decisions about production plans.
Formalization (FOS) (Pertusa-Ortega et al., 2010)	To what extent is our organization regulated in the following aspects? (1 = Low degree; 7 = High degree) FOS1: Regulations on procedures. FOS2: Regulations on the monitoring of work development. FOS3: Monitoring of employees. FOS4: Rules of behavior. FOS5: Resources to ensure compliance with rules.

Top management support (TMS) (Soliman & Janz, 2004)	TMS1: Our top management is willing to invest funds in big data analytics. TMS2: Our top management is willing to take risks involved in the utilization of big data analytics. TMS3: Our top management is interested in big data analytics in order to gain competitive advantage. TMS4: Our top management considers the use of big data analytics as strategically important.
Control variables	
Firm size	The number of employees.
Firm age	The number of years since a firm was founded.
R&D intensity	The proportion of R&D expenditures to total sales.

4.2.3 Empirical Models

Ordinary least squares (OLS) regression was utilized to test the hypotheses. The model shown in equation (1) was used to test Hypothesis 1, and the equation (2) was used to test the interacting effect in Hypotheses 2 to 4:

$$Y_i = \alpha_0 + \alpha_1 X_i + \alpha_2 Controls_i + \varepsilon_i \qquad (1)$$

$$Y_i = \beta_0 + \beta_1 X_i + \beta_2 Z_i + \beta_3 X_i \times Z_i + \beta_4 Controls_i + \varepsilon_i \qquad (2)$$

where Y_i is the innovation quality of firm *i*, X_i is the data analytics capability of firm *i*, Z_i indicates the corresponding moderating variable in Hypotheses 2-4 (centralization in H2, formalization in H3, and top management support in H4), $Controls_i$ indicates a list of control variables, and ε_i is random error term. The coefficient α_1 in equation (1) and the coefficient β_3 in equation (2) are two of the most concerned parameters in this research.

4.3 Empirical Results

4.3.1 Reliability and Validity

A number of tests were performed to check the reliability and validity of the measurement model. First, the reliability of the constructs was examined using Cronbach's alpha coefficient (Cronbach, 1951), which evaluates internal consistency of a set of survey items. Due to the fact that the alpha values for variables utilized in this study ranged from 0.8278 to 0.9163 (as shown in Table 13), all above the threshold value of 0.8, the reliability and internal consistency of the variables could be confirmed.

Second, factor loading analysis was conducted to verify the validity of measurement items. It can be seen in Table 13 that five factors with eigenvalues bigger than one emerged from a sum of thirty items, which collectively explained 61.0049% of the total variance. In addition, all of the scales were loaded on their corresponding constructs, with their factor loadings above the practical criteria of 0.5 recommended by Hair et al. (2014). These results indicated that the variables in the present study had strong scale validity.

Third, goodness-of-fit indices were used to check the overall fit of the measurement model. Considering that some indices might be sensitive to sample size (Gerbing & Anderson, 1992), a variety of fit indices were tested in this paper, the results of which were presented in Table 14. As shown, all values were well above (below) their minimum (maximum) thresholds (Hair et al., 2014), which demonstrated a solid model fit.

Fourth, two indicators, average variance extracted (AVE) and composite reliability (CR), were used to evaluate the convergent validity. According to prior research, the recommended cutoff point of AVE value was 0.5, whereas the CR value ought to be higher than 0.7 (Anderson & Gerbing, 1988; Fornell & Larcker, 1981). As shown in Table 15, the AVE values in this study varied from 0.4995 to 0.5685, with the CR values all well above the minimum criteria (i.e., ranging from 0.8279 to 0.9164), providing strong evidence for a good convergent validity.

Fifth, discriminant validity was assessed by comparing the square roots of AVE with the inter-construct correlations. When a measurement model's discriminant validity is strong, the correlations between constructs should be lower than the square roots of AVE (Bagozzi & Yi, 1988). The results in this study met the requirement aforementioned, as reported in Table 16, demonstrating an adequate divergent validity of the measures.

Taken altogether, it can be concluded that the variables in this research had relatively good reliability and validity, such that the measurement scales fit well with the theoretical constructs.

Table 13. Reliability test and Factor loading analysis

Measurement items	Cronbach's α	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
		COS	DAC	FOS	IQ	TMS
COS11		0.6891				
COS9		0.6842				
COS1		0.6766				
COS5		0.6691				
COS7		0.6564				
COS2	0.9163	0.6487				
COS6		0.6460				
COS3		0.6439				
COS4		0.6325				
COS10		0.6218				
COS8		0.5978				
DAC3			0.6918			
DAC1			0.6581			
DAC5	0.8551		0.6485			
DAC4			0.6266			
DAC2			0.5609			
FOS1				0.6588		
FOS5				0.6496		
FOS2	0.8680			0.6482		
FOS3				0.6395		
FOS4				0.6154		
IQ1	0.8355				0.6552	

Measurement items	Cronbach's α	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5
		COS	DAC	FOS	IQ	TMS
IQ3					0.6308	
IQ4					0.5974	
IQ5					0.5757	
IQ2					0.5531	
TMS1	0.8278					0.6796
TMS4						0.6451
TMS3						0.6140
TMS2						0.5843
Initial eigenvalue		11.2963	2.6874	1.7419	1.3758	1.2000
% of variance		37.6544	8.9579	5.8065	4.5860	4.0001
Cumulative %		37.6544	46.6124	52.4188	57.0049	61.0049

Notes: KMO = 0.9510; Barlett's test of sphericity, $p < 0.001$.

Table 14. Model fit indices

Model fit indices	X2/df	RMSEA	NFI	RFI	IFI	TLI	CFI
Default model	1.5069	0.0334	0.9166	0.9081	0.9702	0.9670	0.9700
Recommended criteria	< 3	< 0.05	> 0.9	> 0.9	> 0.9	> 0.9	> 0.9

Table 15. Average variance extracted and Composite reliability

Path			Estimate	AVE	CR
DAC	--->	DAC5	0.7445		
DAC	--->	DAC4	0.7057		
DAC	--->	DAC3	0.7731	0.5418	0.8552
DAC	--->	DAC2	0.7312		
DAC	--->	DAC1	0.7243		
IQ	--->	IQ5	0.7118		
IQ	--->	IQ4	0.7574		
IQ	--->	IQ3	0.6911	0.5052	0.8359
IQ	--->	IQ2	0.7258		
IQ	--->	IQ1	0.6643		
COS	--->	COS5	0.7163		
COS	--->	COS4	0.6613		
COS	--->	COS3	0.6967		
COS	--->	COS2	0.7013		
COS	--->	COS1	0.7110		
COS	--->	COS6	0.7115	0.4995	0.9164
COS	--->	COS7	0.7098		
COS	--->	COS8	0.6986		
COS	--->	COS9	0.7370		
COS	--->	COS10	0.6728		
COS	--->	COS11	0.7530		
FOS	--->	FOS5	0.7537	0.5685	0.8682

FOS	--->	FOS4	0.7519		
FOS	--->	FOS3	0.7520		
FOS	--->	FOS2	0.7494		
FOS	--->	FOS1	0.7630		
TMS	--->	TMS4	0.7763	0.5463	0.8279
TMS	--->	TMS3	0.7430		
TMS	--->	TMS2	0.6996		
TMS	--->	TMS1	0.7357		

Table 16. Square roots of AVE and inter-construct correlations

	DAC	IQ	COS	FOS	TMS
DAC	(0.7361)				
IQ	0.4564***	(0.7108)			
COS	-0.3577***	-0.3770***	(0.7068)		
FOS	-0.4561***	-0.4621***	0.4408***	(0.7540)	
TMS	0.5736***	0.4447***	-0.3936***	-0.4075***	(0.7391)

Notes: Square roots of average variances extracted (AVE) shown on diagonal; *** $p < 0.001$.

4.3.2 Common Method Bias

Because the data on independent and dependent variables were obtained from same source and self-reported by a single informant, common method bias might be a concern to this study. In order to alleviate this problem, several program controls were implemented during the stage of research design and data collection, including protecting anonymity, proximally separating independent and dependent variables, balancing the order of items, reversing coding and so on (Podsakoff et al., 2003). In addition, I also used a series of post hoc measures to make sure that the data was not confounded by common method bias. To begin with, Harman's one-factor test (Greene & Organ, 1973) was used to determine whether the data was prone to possible bias or not. The unrotated factor solution indicated that no factor accounted for 50% or more of the variance, with the highest one being 37.6544%. This showed evidence for a lack of a common factor that could individually explain most of the variance, meaning that there was no serious common method bias in the present research. To verify this conclusion, I took a further step to run a one-way confirmatory factor analysis (CFA) where all items were loaded on a common method factor (Yildiz et al., 2019). The results showed that the model fit was quite poor (X2/df = 5.9061 > 3, RMSEA = 0.1035 > 0.08, NFI = 0.6654 < 0.9, RFI = 0.6406 < 0.9, IFI = 0.7053 < 0.9, TLI = 0.6821 < 0.9, CFI = 0.7040 < 0.9), which again confirmed that common method bias was not a significant threat in this study.

4.3.3 Descriptive Statistics and Correlations

Table 17 reports the summary statistics and correlations among the variables utilized in this study. It showed that the mean value of 7-point ratings on innovation quality was 4.7913, while the assessment of data analytics capability was 4.6484 on average. In terms of three moderating variables (i.e., centralization, formalization, and top management support), their average scores were 3.2014, 3.1359, 4.6917 respectively. Furthermore, while data analytics capability (r = 0.5402) and top management support (r = 0.4978) were positively correlated with innovation quality, the correlation between innovation quality and centralization (r = -0.5165), and the correlation between innovation quality and formalization were negative (r = -0.5692). These results were consistent with the basic expectation.

Table 17. Descriptive statistics and correlations (N = 459)

	Mean	SD	1	2	3
1.Innovation quality	4.7913	0.8002	1		
2.Data analytics capability	4.6484	0.9366	0.5402	1	
3.Centralization	3.2014	0.7940	-0.5165	-0.4482	1
4.Formalization	3.1359	0.8873	-0.5692	-0.5121	0.5733
5.Top management support	4.6917	0.9489	0.4978	0.5903	-0.4674
6.Firm size	6.0523	2.1047	0.2554	0.2564	-0.2637
7.Firm age	10.7364	7.7714	0.1464	0.0806	-0.0295

8.R&D intensity	27.8475	14.3495	0.0877	0.0468	-0.1060
	4	5	6	7	8
1.Innovation quality					
2.Data analytics capability					
3.Centralization					
4.Formalization	1				
5.Top management support	-0.4377	1			
6.Firm size	-0.2538	0.2388	1		
7.Firm age	-0.1520	0.0430	0.2762	1	
8.R&D intensity	-0.0740	0.0465	0.0622	-0.0128	1

4.3.4 Main Results

In prior to running the regression analysis, the variance inflation factors (VIF) were used to evaluate the multicollinearity issue. Since all VIF values were lower than 2 (ranging from 1.0138 to 1.7777), multicollinearity was not a major concern in this study. After that, stepwise regression was conducted, with the regression results presenting in Table 18. Model 1 included only the control variables. Then, to empirically examine the connection between data analytics capability and firm innovation quality, the independent variable *Data analytics capability* was added in Model 2. Further, with the aim of testing the moderating effects, the interaction terms between *Data analytics capability* and three moderators (i.e., *Centralization*, *Formalization*, and *Top Management support*) were separately incorporated in Models 3 to 5.

Hypothesis 1 claims that data analytics capability contributes to firm innovation quality. As shown in Model 2 of Table 18, the coefficient of *Data analytics capability* was significantly positive (β = 0.1839, p < 0.001), leading support to this hypothesis. Next, a further step was taken to check the magnitude for this effect. The results indicated that a standard deviation increase in *Data analytics capability* resulted in 3.59% rise in *Innovation quality*, suggesting that data analytics capability was an economically meaningful predictor of innovation quality.

Hypothesis 2 predicts that centralization attenuates the positive relationship between data analytics capability and innovation quality, such that data analytics capability is less crucial to the quality of innovation in centralized organizations, compared to decentralized ones. As can be seen in Model 3, despite being negative, the coefficient of the interaction term between *Data analytics capability* and *Centralization* was not significant at the 10% level (β = -0.0802, $p > 0.1$). Thus, Hypothesis 2 was not supported.

Hypothesis 3 asserts that formalization weakens the positive association between data analytics capability and innovation quality, representing that data analytics capability can be more effective in improving innovation quality when it is combined with a non-formalized organizational structure. It can be seen in Model 4 that the coefficient of the interaction term between *Data analytics capability* and *Formalization* was negative and significant at the 5% level (β = -0.1106, $p < 0.05$), suggesting that Hypothesis 3 was basically verified. Furthermore, the marginal effect analysis was conducted to confirm this finding even further, which showed that for firms whose *Formalization* was one standard deviation below the mean, a standard deviation increase in *Data analytics capability* enhanced *Innovation quality* by 5.18%. However, for firms whose *Formalization* was one standard deviation above the mean, a same amount of increase in *Data analytics capability* yielded much less improvement (1.62%). For a more explicit way to show this conclusion, the interaction effect between *Data analytics capability* and *Formalization* was illustrated in Figure 13, in which the solid line plotted this effect when *Formalization* was one standard deviation below the mean, whereas the dashed line plotted the same relationship when *Formalization* was one standard deviation above the mean. Overall, these findings provided strong support for Hypothesis 3.

According to Hypothesis 4, top management support enhances the beneficial impact of data analytics capability on the quality of innovation, such that data analytics capability contributes more to innovation quality when stronger support from top managers is present. Since the coefficient of the interaction term between *Data analytics capability* and *Top management support* was positive and significant at the 1% level ($\beta = 0.0814$, $p < 0.01$), as indicated in Model 5 in Table 18, Hypothesis 4 was well supported. To better illustrate this moderating effect, the effect size was also checked. It turned out that increasing *Data analytics capability* by one standard deviation from its mean gave rise to a far more noticeable boost for firms whose *Top management support* was one standard deviation above the mean (4.97%), in contrast with firms whose *Top management support* was one standard deviation below the mean (2.12%). The interaction effect between *Data analytics capability* and *Top management support* plotted in Figure 14 was in line with this finding, where the solid line plotted the situation when *Top management support* was at a lower degree (i.e., one standard deviation below the mean), while the dashed line plotted the circumstance when *Top management support* was at a higher level (i.e., one standard deviation above the mean). Taken altogether, Hypothesis 4 held.

In summary, this study identifies a positive relationship between a firm's data analytics capability and the quality of innovation, with formalization and top management support acting as two moderators of this interaction. Specifically, while formalization attenuates the positive relationship between data analytics capability and the quality of innovation, top management support enhances it.

Table 18. OLS models predicting Innovation quality

	(1)	(2)	(3)	(4)	(5)
Firm size	0.0153	0.0098	0.0069	0.0053	0.0066
	(0.0149)	(0.0146)	(0.0146)	(0.0145)	(0.0144)
Firm age	0.0072*	0.0072*	0.0075*	0.0076*	0.0072*
	(0.0034)	(0.0033)	(0.0034)	(0.0034)	(0.0033)
R&D intensity	0.0016	0.0017	0.0020	0.0016	0.0020
	(0.0021)	(0.0020)	(0.0020)	(0.0020)	(0.0021)
Centralization	-0.2004***	-0.1823**	0.1903	-0.1692**	-0.1615**
	(0.0590)	(0.0598)	(0.2831)	(0.0617)	(0.0621)
Formalization	-0.2913***	-0.2401***	-0.2347***	0.2692	-0.2364***
	(0.0465)	(0.0483)	(0.0492)	(0.2387)	(0.0473)
Top management support	0.2104***	0.1342**	0.1249**	0.1305**	-0.2324+
	(0.0391)	(0.0421)	(0.0422)	(0.0412)	(0.1365)
Data analytics capability		0.1839***	0.4396*	0.5231**	-0.2000
		(0.0508)	(0.1949)	(0.1651)	(0.1419)
Data analytics capability * Centralization			-0.0802		
			(0.0579)		
Data analytics capability * Formalization				-0.1106*	
				(0.0484)	
Data analytics capability * Top management support					0.0814**
					(0.0287)
Constant	5.1433***	4.4598***	3.2792**	2.8538**	6.0776***
	(0.3366)	(0.4139)	(1.0138)	(0.9464)	(0.6566)
N	459	459	459	459	459
R^2	0.4339	0.4600	0.4661	0.4729	0.4727

Notes: Standard errors are included in parentheses; + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

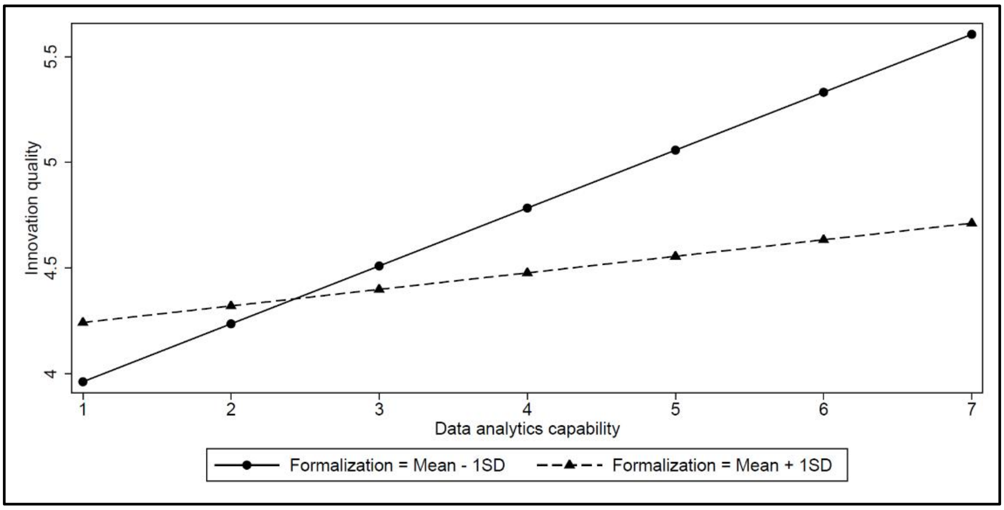

Figure 13. Plot for the interaction between Data analytics capability and Formalization (using Model 4 in Table 18)

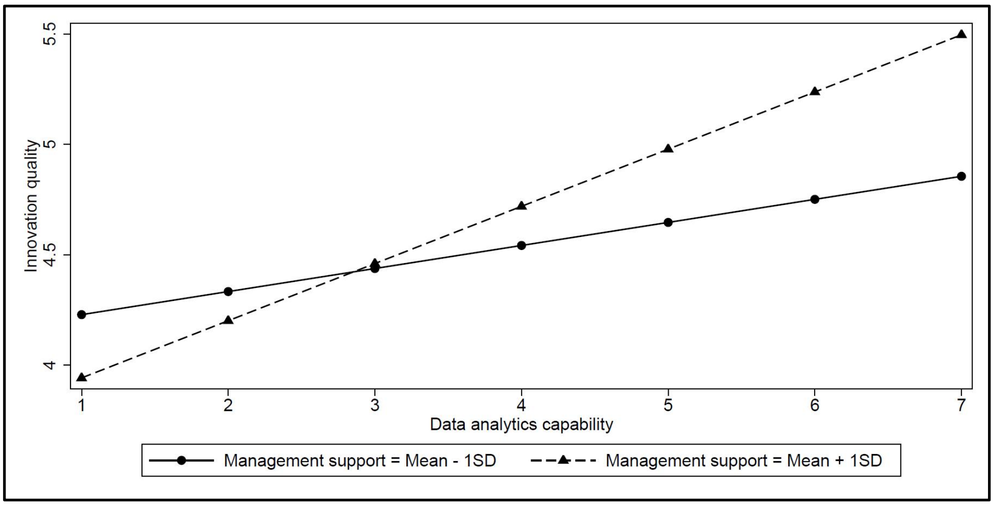

Figure 14. Plot for the interaction between Data analytics capability and Top management support (using Model 5 in Table 18)

4.3.5 Robustness Checks

In order to corroborate the reliability of the results, robustness test was first conducted by running regression models in which the control variables were removed. The rationale behind this action was that the inclusion of control variables may become a potential source of bias in regression analysis (Becker, 2005; Becker et al., 2016). For this reason, the OLS regressions were reran after dropping three controls, the results of which were reported in Table 19, with the interaction plots displaying in Figures 15 and 16. As shown, the empirical outcomes explained in the Main results section remained unchanged (H1: β = 0.1880, p < 0.001; H2: β = -0.0790, p > 0.1; H3: β = -0.1119, p < 0.05; H4: β = 0.0820, p < 0.01). Subsequently, following the work of Li et al. (2009) and Xie et al. (2022), regression analysis was performed on randomly selected subsamples that made up 90%, 80%, and 70% of the entire sample. The OLS regression results based on these three subsamples were shown in panels A, B, and C of Table 20 respectively, and the interaction diagrams were displayed sequentially in Figures 17 through 22. As can be seen, the results based on the subsamples were in line with those of the complete sample, further supporting the validity of the findings (90% subsample: H1: β = 0.1856, p < 0.001; H2: β = -0.0776, p > 0.1; H3: β = -0.1092, p < 0.05; H4: β = 0.0785, p < 0.01. 80% subsample: H1: β = 0.1775, p < 0.01; H2: β = -0.0725, p > 0.1; H3: β = -0.0943, p < 0.1; H4: β = 0.0718, p < 0.05. 70% subsample: H1: β = 0.1736, p < 0.05; H2: β = -0.0775, p > 0.1; H3: β = -0.1058, p < 0.05; H4: β = 0.0706, p < 0.05.).

Table 19. Robustness check (Control variables are removed)

	(1)	(2)	(3)	(4)	(5)
Centralization	-0.2030***	-0.1826**	0.1853	-0.1671**	-0.1611**
	(0.0582)	(0.0595)	(0.2855)	(0.0620)	(0.0620)
Formalization	-0.3091***	-0.2552***	-0.2498***	0.2601	-0.2508***
	(0.0460)	(0.0485)	(0.0496)	(0.2419)	(0.0475)
Top management support	0.2139***	0.1344**	0.1248**	0.1299**	-0.2352^{+}
	(0.0395)	(0.0428)	(0.0428)	(0.0418)	(0.1398)
Data analytics capability		0.1880***	0.4393*	0.5301**	-0.1993
		(0.0523)	(0.1966)	(0.1674)	(0.1451)
Data analytics capability * Centralization			-0.0790		
			(0.0581)		
Data analytics capability * Formalization				-0.1119*	
				(0.0489)	
Data analytics capability * Top					0.0820**
					(0.0293)

management support					
Constant	5.4068***	4.6713***	3.5036***	3.0205**	6.2928***
	(0.3148)	(0.4127)	(1.0384)	(0.9699)	(0.6774)
N	459	459	459	459	459
R^2	0.4254	0.4529	0.4589	0.4662	0.4658

Notes: Standard errors are included in parentheses; + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

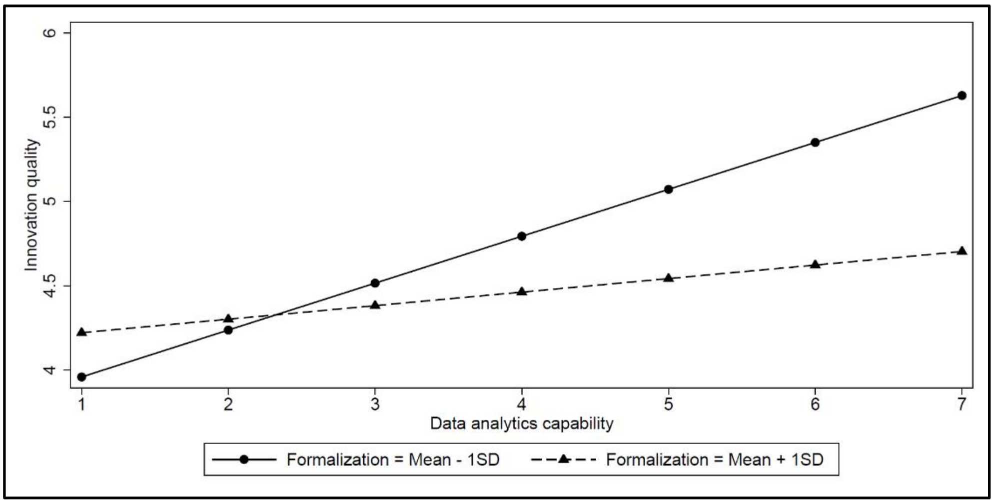

Figure 15. Plot for the interaction between Data analytics capability and Formalization (using Model 4 in Table 19)

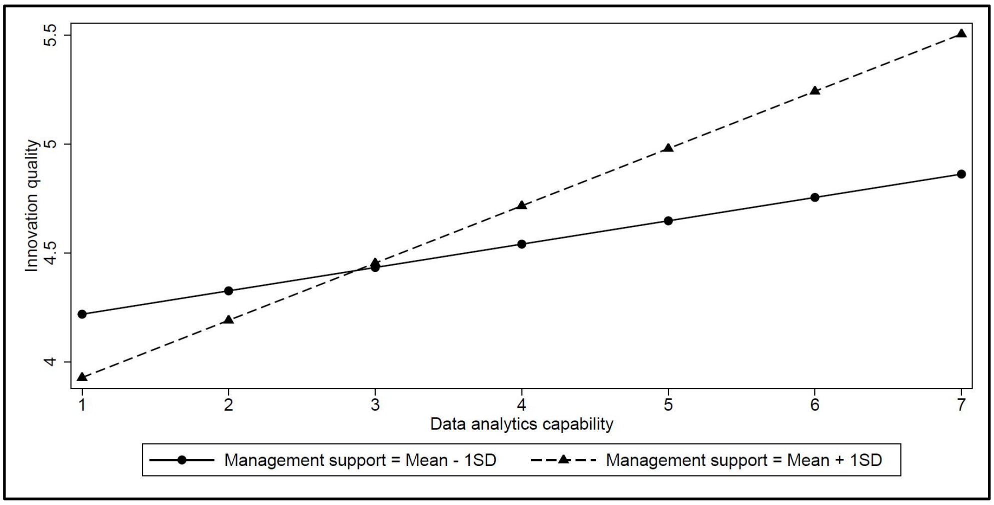

Figure 16. Plot for the interaction between Data analytics capability and Top management support (using Model 5 in Table 19)

Table 20. Robustness check (Randomly selected subsamples)

	(1)	(2)	(3)	(4)	(5)
Panel A: 90% subsample randomly selected from the total sample					
Firm size	0.0131	0.0075	0.0047	0.0031	0.0046
	(0.0159)	(0.0155)	(0.0155)	(0.0154)	(0.0153)
Firm age	0.0068+	0.0070*	0.0073*	0.0075*	0.0068*
	(0.0035)	(0.0034)	(0.0035)	(0.0036)	(0.0034)

R&D intensity	0.0025	0.0026	0.0028	0.0023	0.0028
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Centralization	-0.2019***	-0.1828**	0.1768	-0.1697**	-0.1627*
	(0.0601)	(0.0608)	(0.2825)	(0.0631)	(0.0633)
Formalization	-0.2792***	-0.2303***	-0.2251***	0.2710	-0.2273***
	(0.0471)	(0.0491)	(0.0499)	(0.2431)	(0.0481)
Top management support	0.2025***	0.1245**	0.1156**	0.1207**	-0.2279
	(0.0402)	(0.0436)	(0.0437)	(0.0426)	(0.1395)
Data analytics capability		0.1856***	0.4326*	0.5210**	-0.1852
		(0.0533)	(0.1947)	(0.1693)	(0.1460)
Data analytics capability * Centralization			-0.0776 (0.0579)		
Data analytics capability * Formalization				-0.1092* (0.0494)	
Data analytics capability * Top management support					0.0785** (0.0293)
Constant	5.1561***	4.4754***	3.3379**	2.8913**	6.0374***
	(0.3484)	(0.4272)	(1.0126)	(0.9695)	(0.6808)
N	413	413	413	413	413
R^2	0.4243	0.4517	0.4580	0.4652	0.4644
Panel B: 80% subsample randomly selected from the total sample					
Firm size	0.0147	0.0114	0.0092	0.0079	0.0082
	(0.0164)	(0.0161)	(0.0161)	(0.0160)	(0.0159)
Firm age	0.0087*	0.0085*	0.0085*	0.0089*	0.0084*
	(0.0038)	(0.0037)	(0.0038)	(0.0038)	(0.0036)
R&D intensity	0.0029	0.0032	0.0034	0.0029	0.0034
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0022)
Centralization	-0.2117***	-0.2003**	0.1355	-0.1905**	-0.1829**
	(0.0620)	(0.0625)	(0.2914)	(0.0644)	(0.0651)
Formalization	-0.2617***	-0.2154***	-0.2128***	0.2171	-0.2130***
	(0.0477)	(0.0497)	(0.0501)	(0.2429)	(0.0488)
Top management support	0.2038***	0.1256**	0.1178*	0.1218**	-0.1970
	(0.0427)	(0.0469)	(0.0468)	(0.0459)	(0.1432)
Data analytics capability		0.1775**	0.4081*	0.4678**	-0.1616
		(0.0546)	(0.2012)	(0.1688)	(0.1501)
Data analytics capability * Centralization			-0.0725 (0.0602)		
Data analytics capability * Formalization				-0.0943+ (0.0496)	
Data analytics					0.0718*

capability * Top management support					(0.0300)
Constant	5.1040***	4.4818***	3.4267**	3.1211**	5.9174***
	(0.3652)	(0.4356)	(1.0328)	(0.9685)	(0.6993)
N	367	367	367	367	367
R^2	0.4233	0.4496	0.4553	0.4606	0.4610
Panel C: 70% subsample randomly selected from the total sample					
Firm size	0.0113	0.0088	0.0063	0.0045	0.0054
	(0.0173)	(0.0169)	(0.0170)	(0.0169)	(0.0168)
Firm age	0.0076+	0.0076+	0.0076+	0.0079+	0.0076*
	(0.0039)	(0.0039)	(0.0040)	(0.0040)	(0.0038)
R&D intensity	0.0034	0.0037	0.0040+	0.0032	0.0038
	(0.0024)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Centralization	-0.2113**	-0.2024**	0.1574	-0.1921**	-0.1844**
	(0.0639)	(0.0644)	(0.2981)	(0.0666)	(0.0672)
Formalization	-0.2595***	-0.2202***	-0.2175***	0.2694	-0.2194***
	(0.0506)	(0.0522)	(0.0525)	(0.2619)	(0.0513)
Top management support	0.2133***	0.1341**	0.1259*	0.1328**	-0.1855
	(0.0448)	(0.0498)	(0.0495)	(0.0487)	(0.1497)
Data analytics capability		0.1736**	0.4190*	0.4943**	-0.1591
		(0.0583)	(0.2040)	(0.1778)	(0.1554)
Data analytics capability * Centralization			-0.0775		
			(0.0613)		
Data analytics capability * Formalization				-0.1058*	
				(0.0530)	
Data analytics capability * Top management support					0.0706*
					(0.0310)
Constant	5.0900***	4.5048***	3.3812**	2.9873**	5.9300***
	(0.3822)	(0.4520)	(1.0517)	(1.0217)	(0.7288)
N	321	321	321	321	321
R^2	0.4222	0.4478	0.4547	0.4617	0.4594

Notes: Standard errors are included in parentheses; + p < 0.10, * p < 0.05, ** p < 0.01, *** p < 0.001.

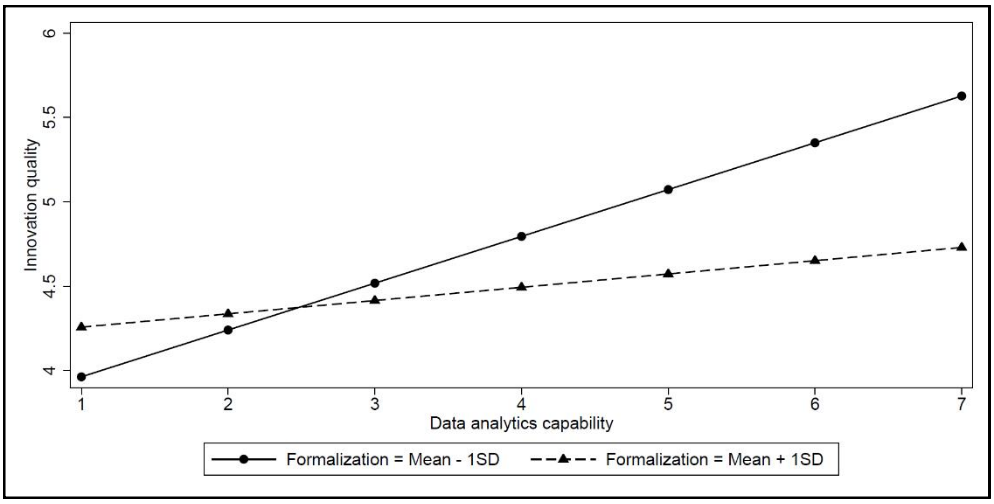

Figure 17. Plot for the interaction between Data analytics capability and Formalization (using Model 4 in Panel A of Table 20)

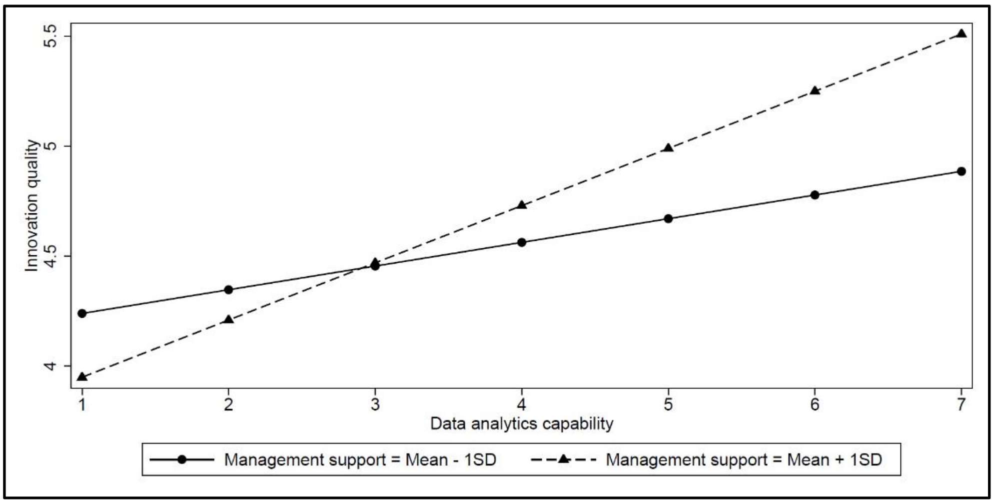

Figure 18. Plot for the interaction between Data analytics capability and Top management support (using Model 5 in Panel A of Table 20)

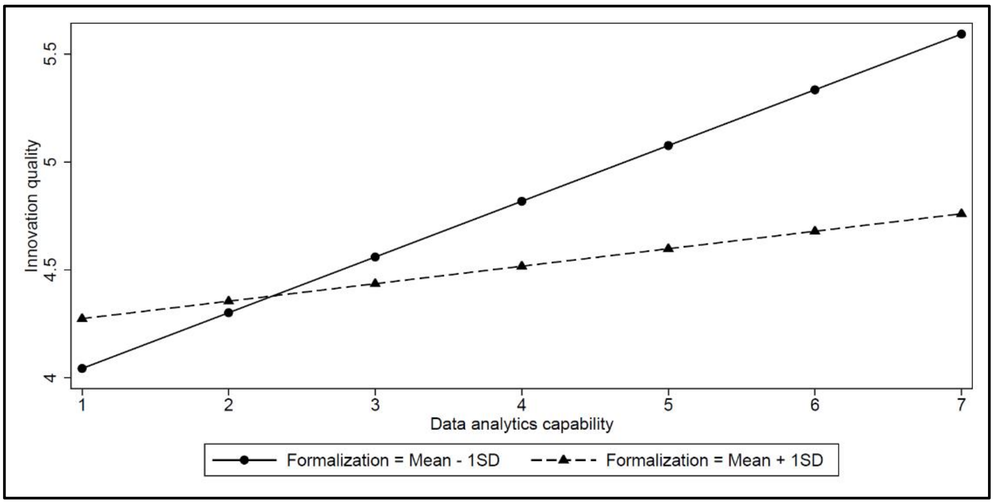

Figure 19. Plot for the interaction between Data analytics capability and Formalization (using Model 4 in Panel B of Table 20)

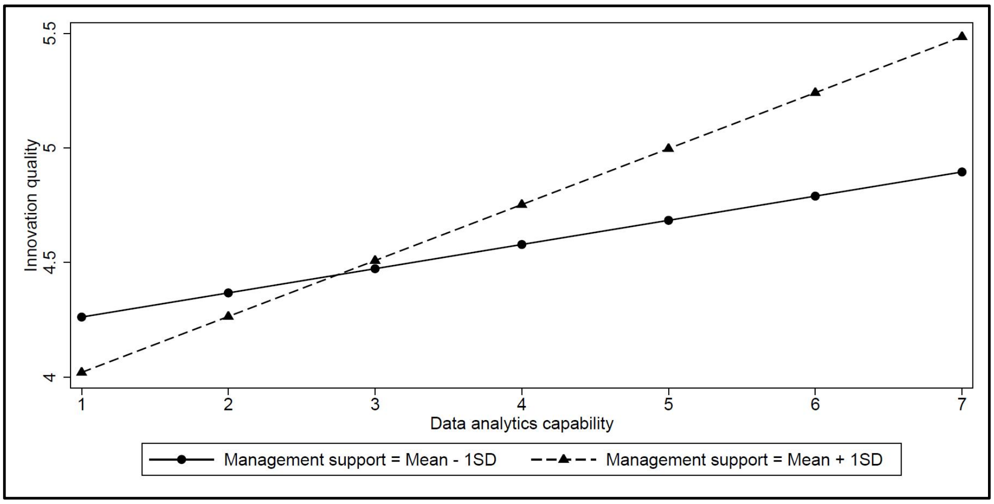

Figure 20. Plot for the interaction between Data analytics capability and Top management support (using Model 5 in Panel B of Table 20)

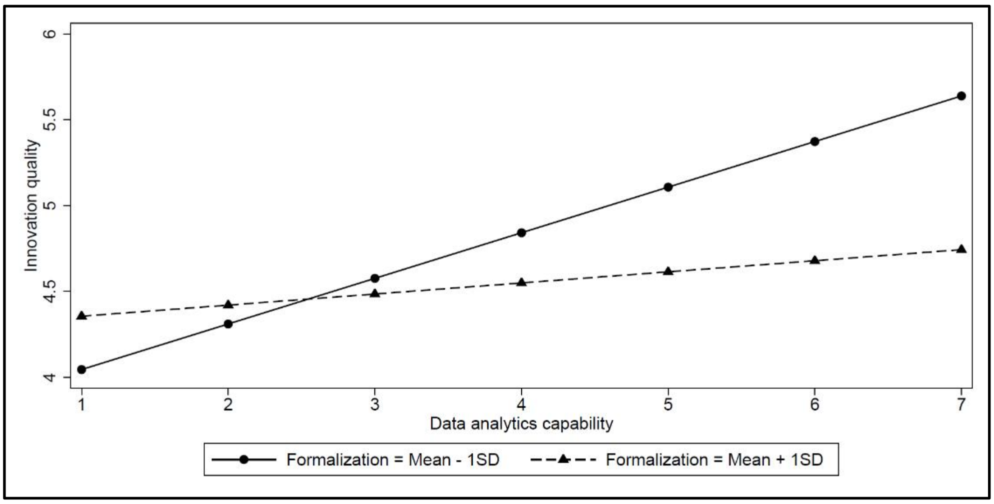

Figure 21. Plot for the interaction between Data analytics capability and Formalization (using Model 4 in Panel C of Table 20)

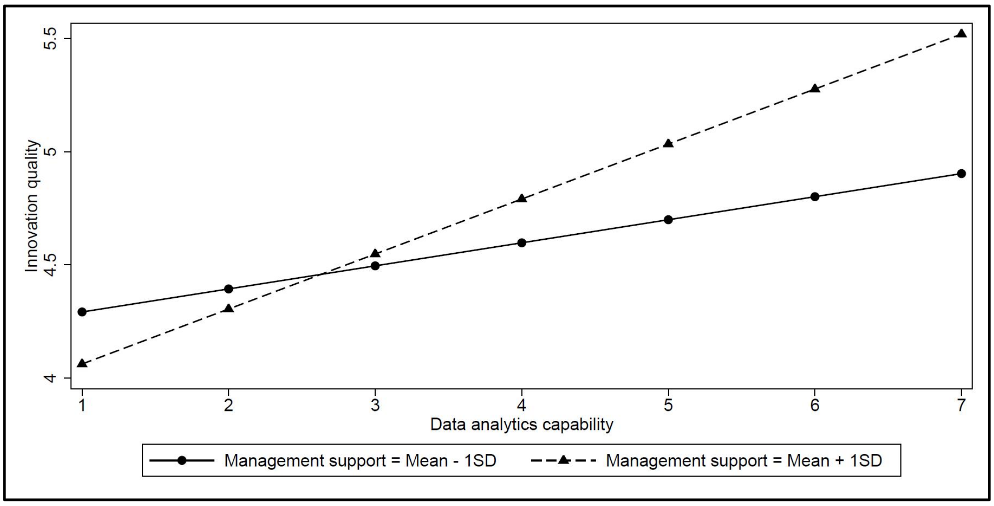

Figure 22. Plot for the interaction between Data analytics capability and Top management support (using Model 5 in Panel C of Table 20)

5. DISCUSSION AND CONCLUSION

5.1 Discussion and Conclusion for Study 1

Data analytics capability has become essential in the age of big data because it enables firms to mine the value of large amounts of complex data instead of being confused by them. In line with this, a variety of benefits of data analytics capability have been verified by earlier studies, including boosting market performance and operational performance (Gupta & George, 2016), spurring business model innovation (Ciampi et al., 2021) and so forth. However, the question of whether and how data analytics capability influences innovation speed has received less attention. To address this issue, the survey method was adopted in this paper to collect data from Chinese Internet firms, after which the hierarchical regression analysis was performed to empirically assess the association between these two variables. The results indicate that a firm's data analytics capability can speed up its innovation process and that this relationship depends on the environmental conditions. Specifically, in an environment with frequent technological upgrades and fiercer competition, the impact of data analytics capability on firms' innovation can be amplified.

Overall, this study contributes to the existing research in four fronts. First, this study adds to the dynamic capability theory by suggesting that data analytics capability, as a kind of dynamic capability, can enhance firms' innovation speed via assisting them in timely sensing environmental changes, quickly seizing emerging technological and market opportunities, and continuously transforming their resources with a relatively clear direction (Mikalef et al., 2021; Torres et al., 2018; Wamba et al., 2017). Second, this research demonstrates that apart from general innovation performance, firms' data analytics capability can also play an important role in accelerating their innovation process, which adds to the body of knowledge on the outcomes of data analytics capability. Third, by identifying data analytics capability as a key precursor for firms to expedite innovation, current studies on innovation speed has been enriched. Fourth, the moderating effects of three aspects of environmental turbulence (i.e., market turbulence, technological turbulence, and competitive intensity) in the relationship between data analytics capability and innovation speed are examined in the present study, which not only deepens our understanding of the conditions under which data analytics capability can better come into play, but also complements the literature highlighting the need to pay more attention to the impact brought up by external environment to firms.

The current research also yields some meaningful practical implications. First, more attention and efforts should be allocated to the development of data analytics capability since it can speed up innovation, which is one of the major determinants of a firm's competitive edge. It should be highlighted, nonetheless, that building an effective data analytics capability is not an easy task for most firms. It encompasses a variety of resources, including tangible resources, human knowledge and skills, and intangible resources, and calls for a high level of coordination among managers, staffs, and the entire organization. In order to complete this task, managers must first shift their perceptions and recognize that data analytics capability is more than just performing data analysis on raw datasets obtained from multiple sources. Instead, it is a key arrangement tied to corporate strategy. Following that, a number of actions should be taken to smooth the process of adopting and implementing data analytics within firms, so as to achieve increased value from such initiative. To begin with, the resources needed for data infrastructure and technology development must be guaranteed, which is the cornerstone of data gathering, processing, and analysis. Thereafter, employees need to be trained to master the skills of data analysis and establish the mindset of data-driven decision-making. Further, an organizational structure with high level of flexibility, an organizational culture that make decisions based on data, and ongoing organizational learning are all necessary. These suggestions are pertinent given that numerous firms in the real business world do not actually own strong data analytics capability, and it is quite challenging for them to truly transform big data into commercial value. The second implication regards the four stages of firms' innovation process: idea generation, idea elaboration, idea championing, and idea implementation. Depending on the traits of each stage, multiple actions can be performed to accelerate the overall pace of innovation. For the idea generation stage, on the one hand, more incentives (e.g., monetary awards, honor) should be provided to stimulate new creative ideas. On the other hand, firms should foster a supporting and encouraging atmosphere where staff members can freely propose ideas without any fear of repercussion. Regarding the stage of idea elaboration, affording employees the proper authority and freedom to further explore their ideas, and supporting cross-departmental cooperation and communication are thought to be conducive to facilitate idea polishing. In addition, if possible, firms can conduct digital experimentations with a small randomly selected sample of their users during the idea championing phase. As doing so can get real customer feedback in a quick and low-cost manner, thereby hastening the evaluation of innovative ideas. And in the stage of idea implementing, the necessary capital and resources should be offered promptly and all parties involved, including R&D personnel and product operators, need to be efficiently coordinated. Third, the contingency role of environmental turbulence enlightens managers to employ data analytics capability to monitor and identify changes in client needs, technology advancements, as well as the competitive landscape. In fact, it is a common topic that firms must be aware of changes in their external environment, yet doing so successfully is highly challenging. And the advent of big data era makes it harder than ever for firms to precisely spot environmental trends since changes are occurring more frequently and unpredictably. As demonstrated in this study, a certain amount of support for resolving this issue can come from the development of data analytics capability. Thus, in order to sustain competitive edge in such a turbulent environment, firms can follow the aforementioned recommendations to first build then continuously mature their data analytics capability.

This research is not without shortcomings, which constitutes feasible directions for future studies. First, while existing researches, including my study, has confirmed the benefits of data analytics capability from multiple perspectives, there is still a lack of insights into how firms can actually reap such values. To contribute to this end, future study can employ methods such as case studies to open up the mechanism and process through which data analytics capability leads to positive consequences. This can offer managers more straightforward instructions on how to fully utilize and profit from big data. Second, understanding the factors that promote or inhibit firms from developing data analytics capability is an important area for future research considering that many firms are still in the early stages of doing so. Third, factors such as data privacy, data security, and data governance that may affect both the usage of data analytics and the firm innovation process are not included in this study but may be discussed in subsequent studies. Fourth, due to the data limitations, neither the industry heterogeneity nor the potential endogenous issues caused by reverse causality and omitted variables are well addressed in the present research. Further studies should take these problems seriously if data permits.

5.2 Discussion and Conclusion for Study 2

In addition to striving to increase the quantity and speed of innovation, practitioners urge greater focus on the quality of innovation outcomes. Consistent with this, scholars have done extensive exploration on the issue of how to improve firms' innovation quality and are awaiting further contributions in this area. In response to the aforementioned appeal, the impact of data analytics capability on innovation quality is empirically tested in this study based on data from Chinese Internet firms. Moreover, drawing on the literature on organizational structure and top management support, some boundary conditions of the interaction between these two variables are also investigated. The findings of this study demonstrate that firms' data analytics capability can play an important role in enhancing their innovation quality and that while such benefit can be magnified with more support obtained from top managers, it will diminish as a result of increased degree of formalization.

In general, several theoretical advancements are made in this study. First, this study points out that data analytics capability is one of the critical elements in enhancing innovation quality in the digital age, because it can direct the development of new products and services through identifying consumer demands, and also aid in decision-making throughout the R&D process. This finding provides a relevant and significant contribution to the discussion in extant studies about how to raise the caliber of firms' innovation outputs. Second, by stating and validating that formal organizational structure hinders employees' flexibility to fully utilize the potential of data analytics capability in innovative activities, this study adds to existing research on the relationship between organizational structure and innovation. Third, the body of literature that emphasizes the important role of top management support is enriched by this research, where the resources and support provided by executives are found to be essential for data analytics capability to play a role in boosting innovation quality.

Additionally, this study offers several practical implications for managers. First and foremost, in order to improve the quality of innovation, managers need to recognize the value of data resources and harness their potential through the development of data analytics capability. As we mentioned before, in the digital age, customers' needs and wishes are embedded in the data they produce on digital platforms, such as views, clicks, and online reviews. However, it is not easy to mine these demands accurately and timely from vast, complicated, and scattered data. In this case, data analytics capability becomes increasingly crucial because it enables firms to derive useful insights from big data. Firms should, therefore, increase their investment in developing data analytics capability, so as to acquire an advantage over rivals by better identifying and fulfilling customers' needs. Second, the design of organizational structure and provision of management support should be incorporated in order to fully utilize the insights obtained from data analytics. To be specific, managers need to build a flexible structure that favors autonomy and creativity among employees. Moreover, top managers, who are in charge of the allocations of resources, need to guarantee the necessary human and financial resources to implement insights gained from data in the development of new products and services.

There are certain limitations in this study, which point out directions for future research. First of all, the sample of this study only consists of Chinese Internet firms, which may restrict the generalizability of the conclusions. Due to the fact that the adoption and application of big data analytics is a global phenomenon, future research can explore and examine the relationship between data analytics capability and innovation quality based on samples from other countries, or consider the impact of national-level factors on this relationship. Besides, samples across a broad range of industries can also be employed because in today's big data era, data analytics technology and skills are imperative for a lot of industries, including manufacturing, health and so on. Second, merely the moderating effects of organizational-level factors on the connection between data analytics capability and innovation quality are taken into account in this study. To better understand the boundary conditions of the interaction between the two, subsequent studies can look into some environmental or industry features. Third, it would be of interest to see if the quality of innovation serves as a mediator between data analytics capability and firm performance, or whether there are missing intermediary mechanisms in the process of data analytics capability affecting innovation quality. Fourth, the cross-sectional nature of survey data deserves attention since it can only reveal the correlations rather than causality. To solve this issue, future study can gather longitudinal data from questionnaires across multiple time periods or use dynamic panel data.

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