Master's Thesis of Engineering

Exploring big data analytics capabilities of organizations

Big data analytics capability and mature knowledge utilization

지식의 성숙도와 혁신 성과의 관계에서 조직의
빅데이터 분석 역량의 매개 효과에 관한 연구

2020 년 8 월

서울대학교 대학원

협동과정 기술경영경제정책전공

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이 논문을 공학석사 학위논문으로 제출함

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이희라의 공학석사 학위논문을 인준함

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Abstract

While the era of big data has emerged, theoretical research on how it contributes to a firm's knowledge utilization remains limited. We consider it to assist in promoting the effective utilization of mature knowledge. We examine the mediating effect of big data analytics (BDA) capability on the effect of knowledge maturity as well as the direct effect of knowledge maturity on a firm's overall innovation performance. We identify that knowledge maturity can support a firm's ability to create novel innovations and that BDA capability strengthens the positive impact of knowledge maturity by interacting with the relation between knowledge maturity and innovation. Overall, the results suggest that organizations with mature knowledge are more capable of utilizing knowledge by leveraging their BDA capability.

Keywords: *Big Data Analytics Capability, Innovation, Knowledge Maturity, Explicit Knowledge Maturity, Tacit Knowledge Maturity.*

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Chapter 1. Introduction

1.1 Study Background

As the big data revolution rapidly emerges, a large volume of unconventional data sources has become accessible. This new phenomenon has created an optimum environment in which various industries can exploit extensive, real-time data across many business fields. Following this trend, a call for big data analytics (BDA) capabilities has intensified throughout the industries. The ability to address, process, and analyze a vast amount of data has begun to establish itself as a core value for diverse business areas. The emergence of big data has transformed the existing operational and managerial structure into a data-driven operations and management system. For instance, Business Intelligence (BI) systems have facilitated the adoption of a broader array of data analytics tools for processing operational data (Brynjolfsson et al., 2011). Indeed, the rising concept of "reality mining," developed by streams of data from mobile devices, vehicles, factory automation systems, and numerous wearable devices (Eagle et al., 2006; Eagle et al., 2008), necessitates the advancement of data analytics intelligence essential to yielding maximum profit from the big data.

Theories built on information technology (IT) literature have led to studies on BDA. Brynjolfsson (1993) introduced the phenomenon of the "productivity paradox of IT," which explains that a positive correlation between firms' IT-relevant investments and economy-wide productivity might be reversed at a certain point (Brynjolfsson,1993). However, several previous IT literature empirically examined the positive relationship between IT-enabled knowledge capabilities and firm innovation and developed a consistent theoretical rationale for their positive relationship (Joshi et al., 2010). shown consistent results. It has been empirically proven that data analytics assets and capabilities enable firms to enhance their performance (Brynjolfsson and McElheran, 2016; Müller et al., 2018). Wu et al. (2020) confirmed that the data analytics capabilities among firms' inherent capabilities complement the improvement of process-oriented business practices and diverse recombination of knowledge to generate innovation. Overall, this finding suggests that BDA capability has beneficial effects on a firm's innovation performance.

1.2 Purpose of Research

Although previous studies have examined the effect of BDA investments on a firm's innovation performance, the underlying mechanism of how BDA affects innovation has been unidentified. In this paper, we argue that understanding BDA's precise mechanism for innovation creation is among the critical elements for mature knowledge utilization. To examine these research subjects, we attempt to identify how BDA capability mediates the relationship between matured knowledge utilization and a firm's overall innovation performance. We first test the positive effects of BDA capabilities on matured knowledge utilization and then extend the research on the effects of matured knowledge utilization by dividing it into two types of knowledge: explicit and tacit.

To investigate our research model, we constructed a firm-level dataset of 159 pharmaceutical firms. As a way to measure each firm-level BDA capability, we followed the prior study (Wu et al., 2020) and used web-scraped employee profiles data from focal firms on LinkedIn. Considering the distribution of the dataset, we adopted the Tobit regression model for analyses. The results confirm that our proposed hypotheses are supported.

There has been an enormous demand for adopting BDA across most industries, but there exists a lack of theoretical understanding of its effectiveness and use. The conclusion of our study theorizes BDA's practical contribution to knowledge utilization, providing implications for practitioners to understand the value of BDA deeply. Furthermore, it contributed theoretically and methodically to understand the characteristics of matured knowledge utilization.

Chapter 2. Literature Review

2.1 Big Data Analytics (BDA) as a Firm Capability

2.1.1 Resource based view of BDA

The Resource-Based View (RBV) of competitive advantage has been deemed a fundamental theory explaining how firms hold a superior position in the industry. The RBV suggests extensive subjects such as how firms' resources are integrated and applied, what factors lead to sustainability in the development of competitive advantage, and where intra-firm and inter-firm heterogeneity are from (Peteraf, 1993). Peteraf's work (1993) has contributed to coalescing studies that are seemingly disjointed and disunited in the previous relevant researches. This research is built upon four theoretical foundations of competitive advantage that present the conditions required for firms to sustain competitive advantages; *resource heterogeneity, ex-post limits to competition, imperfect resource mobility, and ex-ante limits to competition* (Peteraf, 1993). The assumption of *resource heterogeneity* implies that the distinctiveness in the set of firms' resources helps them reap profits in the market. That is, the uniqueness in their resources contributes to reinforcing the capability of sustaining a competitive advantage. Thus, analyzing the origin of such heterogeneity in resources and capabilities is a crucial component in outperforming potential competitors (Helfat and Peteraf, 2003). Nevertheless, the mere achievement of resource heterogeneity does not assure a long-term competitive advantage.

To acquire sustained competitive advantage, there must *be resource heterogeneity* inherent in the set of resources, but there must also be protective barriers to restrict ex-post competition. As an illustration, property rights act as an official barrier for deterring ex-post competition (Rumelt, 1987). This safe protective barrier is one of the fundamental conditions that impose *ex-post limits to competition* and maintain a competitive advantage, which emphasizes the significance of constructing solid safety devices to attain a sustainable competitive advantage. Thus, it is critical to deepening the understanding of what forces competitors to be discouraged in jumping into a competition and how these forces can be deployed as restrictions to ex-post competitions. According to Peteraf (1993), *imperfect imitability* and *imperfect substitutability* are two primary factors to prevent competition from arising. These conditions as limits to ex-post competition imply that allowing competitors to imitate the existing resources or produce alternative resources can lead to overheated competition. Thus, retaining resources that are not easy to copy and cannot be replaced is essential for a company to maintain its long-term competitive advantage.

In a similar vein, *imperfect resource mobility* has emerged as another fundamental means for preserving competitiveness. Resources with the trait of being imperfectly mobile indicate resources that are not easy to be traded and exclusive to firm-specific needs (Peteraf, 1993). Resources with secure imperfect mobility are regarded as to have a more significant effect when combined with other various assets rather than to be used in isolation. These resources thus have the characteristics that can have the greatest effect when they are integrated and recombined with internal resources. Therefore, imperfect mobility is a critical factor that allows firms to have a competitive advantage in continued growth. Finally, to attain a sustainable competitive advantage, the *ex-ante limits to the competition* are also an essential condition to be fulfilled. This condition indicates that although firms need to protect their gained competitive advantage against competitors, before that, the market itself must not be over-heatedly competitive in the first place.

A resource-based view (RBV) specifies fundamental differences between resources and capabilities; if resources are a concept that includes both tangible and intangible assets, Capabilities are considered subsets of non-transferable resources inherent in the organization, which is leaned toward the goal of increasing productivity of other resources (Barney and Arikan, 2001). Besides, as a sub-concept of resources, capabilities play a major role in increasing productivity by efficiently reconfiguring various resources. Namely, capabilities are the value that a company must possess in harnessing resources to enhance productivity, and a valuable resource to advance to maintain its dominant position in the competition. The big data analytics capabilities (BDAC) are said to be “the next frontier for innovation, competition, and productivity” (Manyika et al., 2011). Obviously, as the new phenomenon of big data has become a rising interest in both academia and industry and it can make a big impact across a wide range of fields including science and technology, the ability to analyze it has become one of the critical competencies in terms of competitive advantage (Ann Keller et al., 2012; Fosso Wamba et al., 2015). Akter et al. (2016) reviewed the foundations of RBV to conceptualize big data analytics capabilities(BDAC) for each foundation of RBV. This research accepted the VRIO framework besides the RBV of resources. The VRIO framework involves the underlying assumption that only firms retaining valuable, rare, imperfectly imitable, and appropriately organized resources can pay off (Amit and Schoemaker, 1993; Barney et al., 2001).

In this paper, applying the VRIO framework to big data analytics capabilities argues that only valuable, rare, imperfectly imitable, and organized capabilities can contribute to strengthening performance in the data economy (Akter et al., 2016).

2.1.2 BDA as a firm capability

Recently, industries have been experiencing unprecedented access to extensive data of all kinds and the expansion of data storage capacity. The availability of new types of data, as discussed by Schroeck et al. (2012), has allowed the unlimited acquisition of higher volumes of information for diverse uses. For instance, various types of data—such as a customer's social media activity, clickstream data, RFID tags, web browsing patterns, consumer sentiment, and mobile phone usage—have been easily obtainable from all parts of firm activities (Tambe, 2014; Liu, 2014; Müller et al., 2018). These enable firms to capitalize on different data sources and promote innovative practices by transforming the existing decision-making process into one capable of proposing optimal data-driven solutions. For the retail industry, vendors can utilize clickstream data to identify a consumer's preference patterns and predict market response and possible performance in real-time (Liu, 2014).

Furthermore, credit card companies suffered from time-consuming data analytics processes, rendering them incapable of reflecting market movements in real-time. Quick deployment of "ready-to-market" databases and the adoption of a faster data analytics system played a significant role in providing personalized and optimized offers that reflected consumer responses (Davenport, Barth, and Bean, 2012). Most healthcare firms have recently attempted to leverage big data infrastructure and relevant human capital to lower operational expenditures and enhance data analysis efficiency (Liu, 2014).

Manufacturing and operations management is a principal sector in which data analyzing capabilities have been utilized to boost innovative performance.

Since the emergence of big data, the value of big data analytics (BDA) has proliferated, and the BDA capabilities have begun to emerge as “a major differentiator between high-performing and low-performing organizations” (Liu, 2014, p. 40). The new phenomena derived from big data has become of greater interest to both academia and industry and made a massive impact on a wide range of fields, including science and technology. For many companies, the ability to analyze BDA has become a critical competency in terms of competitive advantage (Ann Keller et al., 2012; Fosso Wamba et al., 2015).

BDA capability is best defined as the ability to process, analyze, and transform data to elicit useful information from large and diverse forms of data (Wu et al., 2020). Prior literature has underscored the importance of BDA capability as “the next frontier for innovation, competition, and productivity” (Manyika et al., 2011). The BDA capability allows firms to obtain unique and applicable business insights through effective data management (Kiron et al., 2014). It also accelerates the process and analysis of the large volume of trace data generated by digital records of activities on social media or websites in combination with extensive BDA technologies (e.g., text analytics, web analytics, social media analytics) (Lehrer et al., 2018). Thus, firms should develop it as a new essential competency so that maximum leverage of these new types of data can be applied.

As BDA capability emerges as a new research area, BDA literature gives an increased focus on empirical studies investigating the impact of data-driven decision-making (DDD) and BDA capability on innovation and productivity growth. Brynjolfsson et al. (2011)

found that DDD can promote productivity, suggesting that a firm's DDD capability is its vital asset that a firm must hold and sustain (Brynjolfsson and McElheran, 2016). The analysis of the influence that big data investments can exert on innovation demonstrates that they are positively associated with the enhancement of productivity (Tambe, 2014). The application of BDA can significantly support a firm's capability to generate new ideas from existing search spaces and increase their innovation performance (Müller et al., 2018; Wu et al., 2020).

The BDA literature has further strengthened its theoretical basis as well as empirical research of BDA. For instance, Akter et al. (2016) reviewed the foundations of a resource-based view (RBV) to conceptualize BDA capability according to each foundation of RBV and introduced the value, rarity, imitability, organization (VRIO) framework. The VRIO framework involves the underlying assumption that firms retaining valuable, rare, imperfectly imitable, and appropriately organized resources can pay off (Amit and Schoemaker, 1993; Barney et al., 2001). In this paper, it argues that only valuable, rare, imperfectly imitable, and organized BDA capabilities can enhance innovative performance in the data economy (Akter et al., 2016). While BDA's effect can vary between firms, recent BDA literature has proven that BDA capability acts as an enabler for increased innovation performance to a variety of business operations. Namely, there is no doubt that BDA capability is essential for firms to establishing themselves as leaders in the latest market trends and gaining a competitive edge in the current environment, in which access to vast amounts of data has increased.

2.1.3 BDA history – case literatures

Since the emergence of big data, the value of BDA has proliferated, and the BDA related capabilities have begun to emerge as a new study interest accordingly. In particular, as the scope of application related to BDA has rapidly expanded, studies that used to be limited to case-oriented research have focused on empirical studies investigating the impact of BDA on innovation and productivity growth. First of all, it is necessary to look into a paper regarding data-driven decision-making (DDD), a concept that has a significant functional and practical correlation with BDA. Brynjolfsson et al. (2011) used a detailed survey data of 179 publicly traded firms in the US that include questions developed in previous IT-related studies and self-developed questions to identify the effect of data-driven decision making (DDD). The result indicates that DDD has a positive impact on their productivity. By demonstrating the link between DDD and productivity, it suggested that DDD capabilities are another vital asset that firms must hold in the great count.

Moreover, Trabucchi & Buganza (2019) performed a case study analysis regarding data-driven innovation. This paper is regarded as meaningful in showing a comprehensive view of the relationship between data and innovation by examining various previous studies that demonstrated the relationship between data and innovation. Looking at the analysis results, the view that data is a by-product of innovations such as the Internet of Things was dominant in a variety of studies used in the analysis.

Tambe (2014) analyzed the effect of big data investment on a firm's productivity growth by using the LinkedIn skills database. It took a firm's Hadoop investment as a proxy for its big data investment since Hadoop investments have been seen as essential technological investments within diverse industries (e.g., see Dumbill 2012, Bertolucci 2012). This paper proved that Hadoop investments have a positive association with enhanced productivity levels in data-intensive industries. However, it also emphasized that there could be a possible trade-off between the benefits of big data technologies and costs incurred by acquiring and retaining relevant expertise. Wu et al. (2019) examined the effect of data analytics capabilities on innovation by adopting detailed firm-level data and natural language processing methods. This paper indicated that data analytics capabilities are more associated with process-related improvement and more likely to be efficacious in innovation that is sourced from an existing knowledge base rather than creating entirely new innovations. This heterogeneity depending on the formation of base knowledge is attributable to the fact that there is still a shortage of data and the limit of a search when creating entirely new innovation.

Notwithstanding, these results are consistent with its argument that the adoption of data analytics is beneficial to enhance existing processes and generate new ideas from existing search spaces. Finally, Müller et al. (2018) also empirically estimated the relationship between big data analytics and firm performance. Not only did it prove the general effect of BDA assets on generating innovation, but it has also proven that the effect of BDA assets is more substantial in IT intensified and highly competitive industries.

While big data analytics can vary between firms, recent BDA literature has proven that BDA is complementary to a variety of business operations and processes, enabling firms to generate innovative ideas. In consequence, it is of profound importance for firms to capitalize on BDA assets and be aware of how to benefit from their BDA investment. Namely, there is no doubt that BDA capability is an essential capability for firms to establish themselves as leaders in the latest market trends and gain an edge in competition these days when access to vast amounts of data has increased.

2.1.4 Knowledge and innovation performance

Cohen & Levinthal (1990) highlighted that external knowledge is a vital source of information for generating innovation at various organizational levels. Previous literature placed considerable emphasis on leveraging external sources of information in creating novel innovations (Leonard-barton, 1995; Keil, 2002; Kang & Kang,2009). Not only do external sources of knowledge contain embodied and tangible forms of technologies, but they also encompass a wide range of disembodied and non-codifiable know-how (Howells, 1996). Howells (1996) defined this form of non-codified, disembodied know-how, obtained from an informal and unstructured learning environment, as “tacit knowledge.”

Tacit knowledge is an aggregate of long-term learning and trial-and-error experiences, highly dependent on individual cognition and intuition (Nonaka & Takeuchi, 1995; Mascitelli, 2000; Cavusgil et al., 2003). To illustrate, the accumulated know-how of master craftsmen is a staple product of dedicated experience and practice in their fields, and their expertise is developed through "learning by doing," "learning by using," and "learning to learn" (Howells, 1996, p. 94). However, tacit knowledge cannot be directly transmitted. It can be embodied and formalized by forms of "explicit knowledge," such as patents, licenses, or research contracts (Howells, 1996). This interaction between tacit and explicit knowledge is referred to as "knowledge conversion," which is realized through the complementarity and interaction effect between tacit and explicit knowledge (Nonaka, 1994; Nonaka and Von Krogh, 2009).

In today's rapidly changing and competitive market, the primary source for sustainable competitive advantage is knowledge acquisition and utilization. Since strengthening competitive advantage is a core value for firms' sustainable management, effective knowledge utilization is fundamental for sustaining successful business operations (Sveiby, 1997). Many previous researchers have suggested that innovation is the creation of new ideas that are promoted by the recombination of old ideas. This indicates that innovation is the product of incorporating existing knowledge elements that were developed and applied in the past (Capaldo, Lavie, & Petruzzelli, 2017). Hartmann & Gemünden (2004) posited that innovative and novel ideas require creativity to promote them and that such creativity stems from an informal, intangible set of experiences or learning environments. When utilizing knowledge to evolve it into innovation, tacit knowledge acts as a crucial element since the creativity vital to innovation is derived from intangible pools of experience (Alwis, Hartmann, & Gemünden, 2004). Furthermore, the interplay of tacit and explicit forms of knowledge is also a core factor in the facilitation of innovative ideas. Thus, in the utilization of knowledge, externalizing tacit knowledge into explicit knowledge, and internalizing tacit knowledge from explicit knowledge is imperative for the generation of innovation.

Chapter 3. Hypotheses

3.1 Framework

This study examines the impact of BDA capability on knowledge utilization. Specifically, we identify the detailed mechanism of BDA capability, focusing on the elements affecting mature knowledge utilization. To study our primary objective, we demonstrate how BDA capability works in the impact of mature knowledge utilization on creating innovation. We further extend our research on the interaction effect of BDA capability by distinguishing the knowledge maturity into tacit and explicit knowledge maturity. Figure 1 illustrates our overall research model and hypotheses.

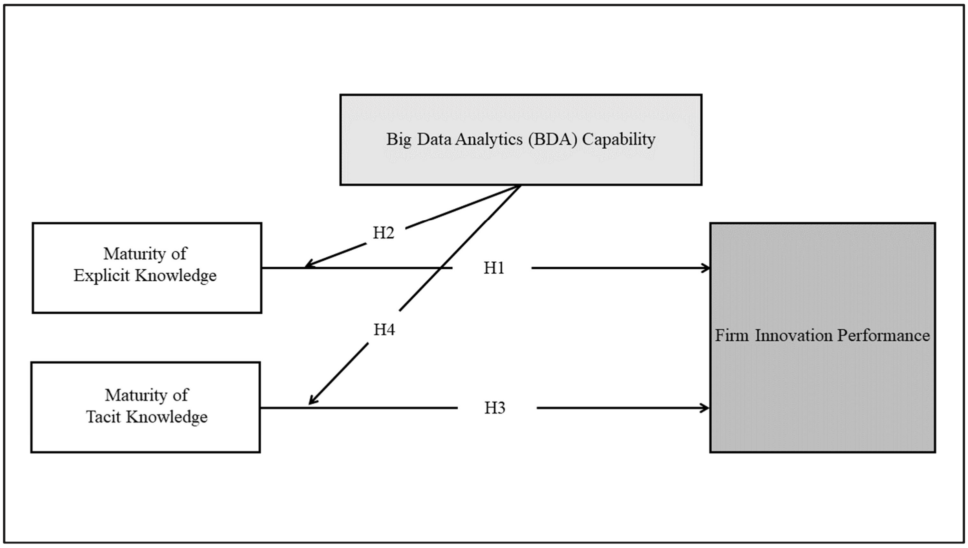


Figure 1. Research Model and Hypotheses.

3.2 Utilizing Mature Explicit Knowledge and BDA Capability

This study focuses on the impacts of knowledge contingent on maturity in the process of knowledge utilization. Even if utilizing recent knowledge enables a firm to increase the novelty of firm performance by quickly reacting to new trends, it can cause applicability and reliability issues due to its inexperience. By contrast, incorporating mature knowledge in innovation generation can complement the possible problems inherent with recent knowledge. Organizations with mature explicit knowledge tend to be more capable of encompassing the broader areas of knowledge and recombining extensive knowledge embedded in the existing knowledge base. Mature knowledge has acquired application experience in combining various knowledge over time. This increased experience can facilitate the precise prediction of whether the knowledge can fit into a changing environment in which innovation is formed. Thus, combining mature explicit knowledge in innovation generation can enhance the applicability of knowledge and promote more effective knowledge utilization.

Mature explicit knowledge is more likely to lead to reliable and valid innovations. As explicit knowledge is applied to innovation, it becomes knowledge with verified and tested experiences. Since mature explicit knowledge leaves behind information pertaining to its characteristics and uses as it matures, innovators can use this information to gain a deeper understanding of knowledge (Capaldo, Lavie, & Petruzzelli, 2017). The use of mature explicit knowledge can also dilute validity issues of inexperience, mitigating the errors that arise from lack of experience and reducing cases of its inappropriate application (Capaldo, Lavie, & Petruzzelli, 2017). Consequently, utilizing mature explicit knowledge in the generation of innovation can ensure the reliability of innovation and provide innovators an enriched understanding of knowledge.

As firms enlarge their application experience and broaden their scope of knowledge, they begin to build tacit knowledge. The internalized tacit knowledge enables them to accelerate the integration, transfer, and reconfiguration of existing knowledge elements to new ideas. The degree of mature knowledge that firms possess can present their competency to leverage tacit know-how and stimulate novel innovation by activating the conversion between explicit and tacit knowledge. Nonaka (1994) states that the interplay of tacit and explicit knowledge can lead to new ideas. Therefore, the extensive range of tacit knowledge accumulated throughout long-term experiences can act as a promotive element to generate brilliant ideas. In this respect, knowledge maturity can be an indicator of a firm’s innovation creation capability as an essential factor that leads to innovation.

Hypothesis 1 (H1): *An organization's overall explicit knowledge maturity has a positive impact on innovation performance.*

On the contrary, if organizations rely excessively on mature explicit knowledge, their ability to apply rising trends to innovation is prone to be diminished. It is highly likely that the area of knowledge covered by mature knowledge is not an area in which innovation is subject to active occurrence. If so, innovation using only mature knowledge might encounter a question of feasibility. In more severe cases, mature knowledge within an organization might become irrelevant to changing trends. There might be cases in which there is no room for further innovation in the knowledge area an organization's mature knowledge can address. Overall, utilizing mature explicit knowledge can have mixed effects on the creation of innovation.

The enhancement of BDA capabilities can mitigate the potential adverse effects of relying on mature explicit knowledge too heavily and maximize the advantages of knowledge maturity. First, BDA capabilities play a part in maximizing knowledge utilization beyond the limitations of the human abilities to use knowledge. Having an advanced BDA capability increases the utilization of vast amounts of data not only large in volume but also high in variety. It also helps to integrate external knowledge with existing data and stretch to new interpretations that are not limited to existing data that has already been applied. For instance, human behavioral patterns can be codified by collaborating with artificial intelligence (AI) or Internet of Things (IoT) technology.

These BDA technologies allow us to extract analyzable and interpretable data from human behaviors.

Second, high BDA capabilities can help firms respond more quickly to emerging trends, easing the obsolescence problem that mature knowledge can confront. For instance, with high-level BDA capability, firms can extract patterns from massive data and analyze market responses in real-time. It enables them to elicit useful and predictive information and promptly update existing information. Furthermore, new BDA-related technologies can facilitate the combination of emerging knowledge in new areas and existing knowledge that has long remained in an organization. Through this combination of knowledge, BDA capability can foster the new discovery in the unexplored areas where there seems to be no room for further innovation, which can tremendously deepen the depth of knowledge and secure areas that can lead to greater innovativeness.

Third, a high level of BDA capabilities can function as a mechanism to assist in the conversion between explicit and tacit knowledge. Leveraging explicit forms of knowledge, along with tacit knowledge, enhances the competency for extracting valuable business insights from newly acquired data. Since many decisions based on know-how or intuition are dependent on an individual's cognitive abilities, they are not subject to codification or modeling. However, utilizing BDA can help extract patterns from unstructured data and convert them into a codifiable form of knowledge. Thus, the conversion of knowledge can be accelerated by incorporating BDA. Overall, improving BDA capabilities can complement the possible issues of mature explicit knowledge and maximize its benefits. Thus, it is highly likely that high-level BDA capabilities will strengthen the positive effects of mature explicit knowledge on innovation performance.

Hypothesis 2 (H2): *BDA enhances the positive impact of an organization's overall maturity of explicit knowledge on innovation performance.*

3.3 Utilizing Mature Tacit Knowledge and BDA Capability

In consideration of the nature of tacit knowledge, employees with extensive job experience are likely to have developed a high degree of tacitness through their long-term careers. The long-term and relevant experience would have repeatedly exposed them to a learning environment in which they could continue to build tacit knowledge. Thus, firms with many career-experienced employees are likely to internalize the employees' experiential knowledge and organically acquire tacit knowledge from them. Same with explicit knowledge, tacit knowledge maturity might have varying effects. Generally, older organizations with more experienced employees tend to have higher maturity in their tacit knowledge. However, tacit knowledge might exist in an organization consisting of mostly inexperienced employees or a newly established organization, and tacit knowledge internalized in relatively new organizations tends to be less mature.

This study investigates the impact of mature tacit knowledge on innovation by comparing it with the less mature tacit knowledge. First, organizations that have internalized mature tacit knowledge are likely to be adept at implementing vision-sharing. The maturity of tacit knowledge implies that employees have more experience engaging in the creation of innovation. In the process, employees can share a consensus on the direction of knowledge utilization leading to innovation. By sharing solid goals within the organization, internal conflicts arising from a disagreement over the innovation generation process can be circumvented, and working with shared orientation enables the increase of overall work efficiency. Thus, the well-shared visions within organizations can facilitate the innovation creation process.

Second, the high maturity of tacit knowledge within an organization is likely to enable the organization to establish a stable organizational system and sustain a solid organizational structure. The extent to which an organization has accumulated mature tacit knowledge determines how many highly experienced employees the organization possesses, suggesting the entire organization is composed of members that are familiar with organizational life and have an adequate understanding of overall organizational structure. Such organizational stability can induce a more vigorous manifestation of tacit knowledge, leveraging various forms of tacit knowledge and facilitating its synergetic effects.

Third, as the organization's tacit knowledge matures, not only does the breadth of its tacit knowledge widen, but the depth also deepens, enabling it to capitalize on much broader and more profound tacit knowledge. Utilizing extensive and advanced knowledge allows organizations to implement more in-depth knowledge conversion. The corporate ability to execute wider-range conversions represents that the organization is more adept at exploiting comprehensive and in-depth knowledge. Thus, organizations with more mature tacit knowledge have a robust capability of accomplishing breakthrough innovations by utilizing extensive and in-depth knowledge.

Hypothesis 3 (H3): *An organization's overall tacit knowledge maturity has a positive impact on innovation performance*.

An overly mature tacit knowledge might cause detrimental effects that hamper the creation of new ideas. Previous studies on knowledge management have confirmed that human knowledge is subject to inertia (Hofsten, Vishton, Spelke, Fent & Rosarder, 1998; Kavcic, Krar & Doty, 1999). As tacit knowledge continually matures over time, reliance on prior knowledge and its existing trajectory can grow strong. In this respect, organizations relying on massively matured tacit knowledge can be biased toward the existing knowledge or path previously formed and insensitive to embracing changes or trends in utilizing new knowledge (Sharifirad, 2010). Although innovations result from recombining old ideas, relying only on prior knowledge without incorporating new ideas can become a hindering factor in the creation of breakthrough innovation.

A firm's BDA capabilities perform a substantial role in strengthening its advantages and compensating for the shortcomings that overly mature tacit knowledge causes to the organization. First, BDA competence contributes to organizing and utilizing the tacit quality of knowledge that is too sophisticated and equivocal to define or address at a human level. Specifically, for tacit knowledge heavily reliant on intuition or cognition, objective measurements are highly challenging. However, the issue can be mitigated by increasing BDA capability. The enhanced BDA capability strengthens the ability to find patterns in human behavior, extract analyzable datasets, and facilitate quantitative analysis. Furthermore, BDA-relevant technologies enable firms to increase accuracy in utilizing information that is high in volume, velocity, and variety. In this sense, increased BDA capability allows the utilization of the tacitness that exists in the previously uninterpretable knowledge domain leading to new discoveries.

Second, BDA capability facilitates the utilization of a broader and deeper range of knowledge, preventing it from being trapped in local maxima. Enhanced BDA capabilities enable firms to stimulate intra- and inter-firm knowledge sharing because it escalates the integration, transfer, and recombination of knowledge. It also helps to leverage a more comprehensive range of data, which supports broadening and deepening the scope of knowledge. A strong BDA capability helps to gain access to broader and more in-depth knowledge in the utilization of knowledge, thereby preventing knowledge from being limited or biased. Moreover, it can play a significant role in diminishing knowledge inertia or path dependency issues and reducing resistance against internalizing new knowledge.

Third, BDA capabilities can strengthen a firm's ability to convert tacit knowledge into explicit knowledge. Enhanced BDA-relevant technologies enable the transformation of non-codifiable knowledge into transmittable and codifiable forms of knowledge, serving to promote innovation. By enhancing such conversion capabilities, organizations can leverage a broader range of tacit knowledge, inducing new ideas essential to creating innovation. In sum, the strengthening of BDA capabilities allows an organization to maximize the beneficial effects of tacitness on innovation performance and improve disadvantages that are followed by excessive tacitness, ultimately leading to innovation.

Hypothesis 4 (H4): *BDA enhances the positive impact of an organization's overall tacit knowledge maturity on innovation performance.*

Chapter 4. Data and Methodology

4.1 Independent Variables

4.1.1 Big data analytics (BDA) capabilities

While a firm's BDA capability includes a variety of tangible assets, such as BDA-related resources and technologies, an employee's BDA-specific experience or skills are among the core elements of BDA capability. For this reason, an employee's inherent BDA capability can be used to measure a firm's overall BDA capability. We utilized the data from over 600,000 individual profiles for 159 pharmaceutical firms from their

LinkedIn webpages. The profile data encompassed an individual's basic information (*e.g.*, name, education background) to their job-related details (*e.g.*, current job title, past job experience). We constructed the dataset using the web-crawling technique, which has been widely used to scrape data from websites. Web crawling data are sourced from LinkedIn. We then counted the total number of employees working in jobs relevant to BDA using keywords. The keywords used include not only jobs directly related to BDA capabilities such as "data," or "analytics," but also people with programming or other related skills required for BDA capabilities such as "optimization," or "cloud computing." Details of the keywords are listed in Table 1.

This keyword list was built according to the classification of BDA-relevant skills presented by Wu *et al.* (2020) and the resources of BDA capabilities presented by Gupta & George (2016). Above all, we included employees with past experience working at firms likely to have developed high-level BDA capability based on the assumption that this past experience potentially induced the employees to be competent with BDA (Gupta & George, 2016). Many companies with a high level of BDA capabilities operate in IT-intensive industries, as previously discussed, and those companies have recently utilized BDA technologies throughout a variety of fields including marketing, retail, distribution, and research and development (R&D). Employees that worked for these companies are more likely to have the competency for analyzing big data since BDA-related tacit knowledge strengthens employees' BDA-related know-how and are inherent in the employees' cognition or intuition. Experiences exposing to the environments in which BDA was in active use were critical to increasing BDA-related capabilities. Therefore, we regarded the employee's past BDA-related experiences as a salient component of BDA capabilities.

We first counted the number of employees that were in data-related jobs or had relevant skills based on the list of keywords. Then, the companies were ranked according to the number of employees involved. Second, we measured our BDA capability in two major groups. We put the top 10 companies into a group with strong BDA capabilities. The other nine companies were classified as a group with less strong BDA capabilities. Secondly, for the group with strong BDA capabilities, we recounted the number of employees in the profession associated with BDA, including the employees with past work experience working at the other nine companies in the same group. Similarly, for the group with less strong BDA capabilities, we recounted the total number of employees capable of BDA, adding the number of employees with past working experience at companies in the strong BDA group.

Table 1. Taxonomy of Big Data Analytics Capability

Big Data Analytics Capability		
Data-related jobs	Technical skills	Experience
Data- (data specialist, data analyst, data scientist, data manager, data engineer, data	Data mining, Cloud computing, Distributed system,	Experience working at firms with strong BDA skills

entry manager, data technician, data consultant, data administrator, data officer)	Hadoop, Apache spark, Data visualization, Ensemble learning, Deep learning
Database- (database developer, database administrator, database specialist, database manager, database analyst, database architect, database, SQL server database administrator)	Genetic algorithm, R programming, Java, Machine learning, Natural language processing, Sentiment analysis, Neural network, Network analysis, Optimization, Python, C/C++ programming, AI.
Statistical- (statistical officer, administrator, assistant, consultant, researcher, research statistician, statistics manager)	

4.1.2. Explicit knowledge maturity

Utilizing patent data to study innovation and technical changes has a long history dating back to Schmookler (1966) (Hall *et al.* 2001; Wu *et al.*, 2020). Patent data has been compiled since the late 18th century so more than 100 years of longitudinal patent data exists, including backward and forward citations. Notably, this facilitates the introduction of a diverse measure that enriches the study of many fields. We utilized the United States Patent and Trademark Office (USTPO) patent data of 159 pharmaceutical firms to measure the maturity of explicit knowledge possessed by each firm. Knowledge can be specified in the form of explicit knowledge such as patents, licenses, or research contracts, which indicates the fact that patent data is an appropriate source for measuring explicit knowledge. To measure maturity, we identified how many old patents the firm accumulated. Thus, we determined the explicit knowledge maturity of each firm by identifying the extent to which each company held its old patents and leveraged them in the process of generating innovation (Howells, 1996).

4.1.3. Tacit knowledge maturity

To measure the tacit knowledge maturity variable, we scraped data from the LinkedIn webpage. LinkedIn provides information regarding an individual's profile data, including the individual's current job title, past work experience, educational background as well as basic demographic information. The individual profiles are designed to categorize options according to various attributes (*i.e.*, job title, graduation year, or experience), and the attributes consist of two types of options, descriptive and range style. As the range style, the experience option offers the number of employees included in the range from zero to 30 years.

As stated earlier, since tacit knowledge is the knowledge that is indwelled in the human body or cognition, the number of experienced employees within an organization can represent the extent to which the organization has internalized tacit knowledge from the innovation process wherein the employees can manifest their tacit knowledge. Thus, we set the rate of employees with long job experience as a proxy for tacit knowledge maturity. Specifically, we acquired the total number of employees with more than 10 years of work experience by setting the range. We then divided the number obtained into the total number of employees provided by the Compustat database to calculate the percentage of employees that had more than 10 years of work experience.

4.2 Dependent Variable

4.2.1. Innovation performance

The dependent variable, innovation performance, was measured as the number of patents filed by each firm in the US. To calculate the firm’s number of patents, we used the USTPO database. This measuring method is a verified method for exhibiting a firm’s innovation performance since patent counts have been widely used as an indicator of a firm’s technological capability. Moreover, the justification of the measurement has been backed up by many prior studies on innovation performance (Patel & Pavitt, 1987; Frame

& Narin, 1990; Acs, Anselin, & Varga, 2002, Chin *et al.*, 2009). We calculated the total number of patents filed in the USTPO for the observation year, 2017. The determination regarding the observation year was because patents applied for in 2017 represent a firm's patenting capabilities in the year of 2019, given that it typically takes two years to apply for and obtain a patent. Thus, we identified patents filed in 2017 to demonstrate the firm's innovation performance in 2019.

4.3 Control Variables

We constructed firm-level control variables that are expected to influence innovation performance and BDA capability. We included a firm's revenue and the total number of employees as control variables. The firm's revenue and total number of employees reflect the firm's size. We also assumed differences in size could result in differences in resources, including both tangible and intangible assets available for innovation. We used the Compustat annually updated database for the fiscal year 2017, which is the same year that the patents are granted. Then, logarithm transformation was applied to adjust the scale to the same as that of the explanatory and dependent variables.

4.4 Empirical Methods

We tested for the mediating effect of the BDA capability measure; the explanatory variables were predicted to exert a positive impact on the innovation performance measure in our study. We used the censored normal regression model (Tobit regression) as an empirical analysis method because Tobit regression is based on the fundamental assumption that a dependent variable contains many values that are centered at a specific value, which is often zero (McDonald and Moffit, 1980). The Tobit regression model assumes that the model contains error terms that show a truncated distribution (Li *et al.*, 2018). Our proxy for the dependent variable, total number of patents for each firm in the observation year, includes slightly over 30% of zero values, resulting in a left-censored data structure, and it can only be zero or a positive value. Given that our dependent variable is right-censored and has a lower-limit bound of zero, the Tobit regression model is an appropriate estimation method for these assumptions, considering the condition of the dependent variable.

Chapter 5. Results

Variables	1	2	3	4	5	6
1Innovation performance	1.000					
2 ln(*Revenue*)	0.391	1.000				
3 ln(*Employee*)	0.529	0.618	1.000			
4 *BDA Capability*	0.754	0.428	0.588	1.000		
5 *Explicit Knowledge Maturity*	0.638	0.398	0.552	0.498	1.000	

6 Tacit Knowledge Maturity	-0.096	-0.270	-0.267	-0.205	-0.152	1.000
Mean	20.12	5.491	6.416	0	1.994	0.578
S.D.	43.16	3.037	2.099	1	1.88	0.131
Min	0	0	2.398	-0.289	0	0.076
Max	349	14.876	11.631	7.026	6.675	1

Note. Number of observations = 158

Table 2. Descriptive Statistics and Correlations

Table 1 shows the basic descriptive statistics for the variables and the correlations between the variables. To verify the multicollinearity problem in our regression analysis, we implemented a variance inflation factor (VIF) test. The results show that the VIF value of each variable is below 2.26 with a mean of 1.67, suggesting that our regression analysis is not affected by a multicollinearity problem (Chatterjee, Hadi, & Price, 2000). The control variables—log-transformed revenue and the total number of employees—are positively correlated with innovation performance ($\rho = 0.391$ and $\rho = 0.529$, respectively). The correlation between the two control variables is significantly positive ($\rho = 0.618$). In terms of BDA capability measure, firms with stronger BDA capabilities have a high propensity to have higher innovation performance ($\rho = 0.754$), have higher revenue ($\rho = 0.428$), and a more significant number of employees ($\rho = 0.588$). Among the primary explanatory variable measures—explicit knowledge maturity and tacit knowledge maturity—explicit knowledge maturity measure has a significantly positive correlation with BDA capability ($\rho = 0.498$) and innovation performance ($\rho = 0.638$). By contrast, the employee maturity measure shows a significantly negative correlation with BDA capability (ρ = -0.205). Table 2 presents the results of the Tobit regression model estimated in our study.

Table 3. Results of Tobit Regression Models for the Effect of Explicit Knowledge- and Tacit Knowledge Maturity on Firm Innovation Performance.

	Model 1	Model 2	Model 3	Model 4
	Tobit	Tobit	Tobit	Tobit
Constant	−49.24***	−20.88**	−25.65**	−52.72***
	(9.330)	(9.031)	(12.84)	(11.60)

ln(*Revenue*)	1.489	0.526	-0.147	0.0678
	(1.215)	(0.790)	(0.825)	(0.673)
ln(*Employee*)	9.536***	1.211	0.250	-0.163
	(1.757)	(1.364)	(1.353)	(1.169)
BDAC		−40.82***	−96.73***	−157.4***
		(13.70)	(18.06)	(18.63)
Explicit Knowledge Maturity		10.05***		9.043***
		(1.298)		(1.093)
Tacit Knowledge Maturity			91.11***	89.38***
			(17.72)	(14.45)
Explicit Knowledge Maturity		11.08***		11.60***
x *BDA Capability*		(2.265)		(1.899)
Tacit Knowledge Maturity			289.8***	262.8***
x *BDA Capability*			(41.16)	(33.64)
Log likelihood	−791.9	−722.1	−726.9	−693.8
Chi2	53.27	193	183.2	249.6

Note. Number of observations =158; 158 uncensored observations;

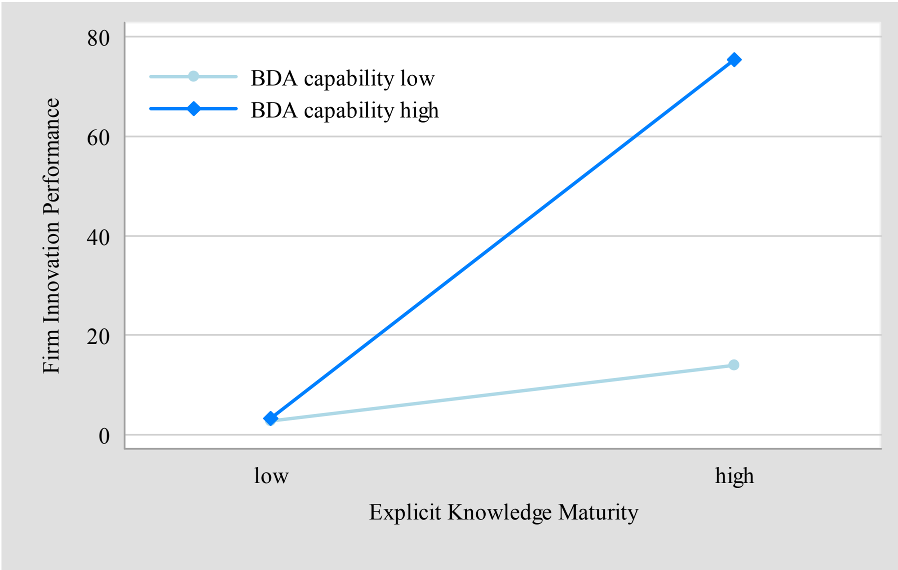
*p<0.10; ** p<0.05; *** p<0.01; Standard errors are in parentheses

Model 1 consists of control variables only. The results of Model 1 demonstrate that the relationship between the total number of employees and the level of innovation performance appears to be significantly positive, which means that firms with a higher number of employees show a tendency to have higher innovation performance (β = 9.536, one-tailed p = .000). On the other hand, the results found that there is no significant relationship between revenue and a firm's capability of generating innovation. Model 2 tests the main effect of explicit knowledge maturity and interactive effect between explicit knowledge maturity and BDA capability. We predict that the level of maturity in explicit knowledge embedded in innovation has a positive relationship with a firm's capability of generating innovation. The results from Model 2 show that the coefficient of explicit knowledge maturity shows a positive estimate (β = 10.05, one-tailed p = .000). That is, as predicted by Hypothesis 1, this result suggests that firms that retain more mature explicit knowledge show a more substantial capability in innovation generation. Hypothesis 2 predicts that a firm's capability to analyze big data strengthens the tie between explicit knowledge maturity and innovation performance in an even more positive direction. The result supports our prediction by demonstrating that the coefficient estimate of the interaction between explicit knowledge maturity and BDA capability is positive and statistically significant (β = 11.08, one-tailed p = .000). This result is in line with Hypothesis 2, suggesting that the positive effect of mature explicit knowledge in innovation generation can become more robust by reinforcing a firm's BDA capability.

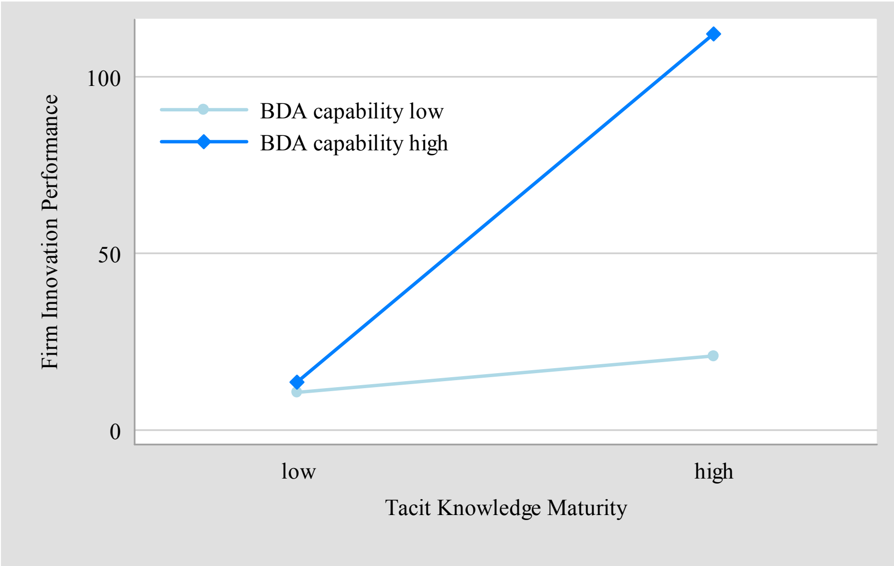
Model 3 examines the main effects of tacit knowledge maturity. Hypothesis 3 proposes that firms with a more significant number of mature employees with work experience have a positive outcome with innovation generation. Consistent with our prediction, the results show that the main effect of maturity in tacit knowledge has a positive association with a firm's capability in innovation generation (β = 91.11, one-tailed p = .000). In other words, this result supports the argument of Hypothesis 3, indicating that the retention of highly mature tacit knowledge within an organization can boost innovation performance. Model 3 also introduces the interaction effect of tacit knowledge maturity on innovation performance. Hypothesis 4 predicts that the effect of employee maturity on innovation performance can be reinforced by increasing BDA capability. In line with Hypothesis 4, the results show both positive and significant coefficients (β = 289.8, one-tailed p = .000), suggesting that a higher level of BDA capability makes the positive effect of tacit knowledge maturity in innovation performance even stronger.

Model 4 comprehensively analyzes the control variables, explanatory variables, and the interaction terms that show the interactive effect between the explanatory variables and the ability to analyze big data, introduced in Models 1, 2, and 3. The results of Model 4 are consistent with those shown earlier in Models 1, 2, and 3, reaffirming the positive effects of the explanatory variables—explicit knowledge maturity and tacit knowledge maturity—and the mediating effect of BDA capabilities on innovation performance that we identified in Models 1, 2, and 3. The effect of knowledge maturity and its interaction effect with BDA capabilities are significantly positive (β = 9.043 and β = 11.60, one-tailed p = .000, respectively). The effect of employee maturity and its interaction effect with BDA capabilities is also proven to be positive (β = 89.38 and β = 262.8, one-tailed p = .000, respectively).

Overall, these findings suggest that the maturity of explicit and tacit knowledge is connected to increased innovation performance and BDA capability strengthens the link, indicating that it works as a parameter shifter. Nonetheless, the Tobit regression model used for the estimation is a non-linear model, which makes it inappropriate to directly interpret the findings related to the interaction terms from the model coefficients (Carnahan *et al.*, 2010). Thus, we visualized the interaction effects using a graphical approach, also conducted by Hoetker (2007) (Carnahan*et al.* 2010). Figure 1 illustrates the marginal effects of BDA capability on the explicit knowledge maturity variable by splitting maturity and BDA capability into low and high into levels.



(a) Interaction between explicit knowledge maturity and BDA capability



(b) Interaction between tacit knowledge maturity and BDA capability

Figure 2. Interaction effects of BDA capability on Maturity

Figure 1a presents the interaction between different levels of explicit knowledge maturity and BDA capability. Here, high maturity is indicated to be one standard deviation above the average value, and low maturity is one standard deviation below the average value. The slope for low BDA capability is much flatter, implying that the overall positive effect of explicit knowledge maturity on innovation performance is relatively subtle when linked to BDA capability that is of a low level. A steeper slope to the high BDA capability line indicates that BDA capability interacts with the positive relationship between explicit knowledge maturity and innovation to a significant extent. Importantly, the difference in the mediating effect of BDA capability appears to be more robust at a high level of explicit knowledge maturity. At a low explicit knowledge maturity, the difference in the interactive effect of BDA capability between the low BDA capability curve and the high BDA capability curve is almost absent. These results suggest that the maturity of explicit knowledge may better lead to innovation when BDA capability is enhanced in organizations with higher explicit knowledge maturity. In other words, the benefits of strengthening BDA capabilities are more considerable.

Figure 1b illustrates consistent findings with Figure 1a, however, it introduces tacit knowledge maturity along with BDA capability. This figure shows a much steeper slope for high BDA capability, implying that BDA capability can have a shifting effect on the relationship between tacit knowledge maturity and innovation that moves the relationship to a more significant positive direction. Like explicit knowledge maturity, when the level of tacit knowledge maturity is high, the gap in the mediating effect of BDA capability is much higher, indicating BDA capability has a far-reaching impact. With tacit knowledge maturity, the difference in the interaction effects of BDA capability is insignificant. These results show that in organizations with high tacit knowledge maturity, the improvement of BDA capability reinforces the factors that lead to tacit knowledge maturity developing into technological innovation. Namely, the benefits of strengthening BDA capabilities are more substantial in organizations with a high level of tacit knowledge maturity.

In conclusion, these findings support both the maturity relevant hypotheses (H1 and H3) and hypotheses on the interaction effects of BDA capabilities (H2 and H4). Models 2 and 3 consist of a single term for each maturity level and an interaction term for BDA capability, demonstrating the effects of explicit and tacit knowledge maturity, respectively. Model 4 consolidates a single term for all maturity-related variables and an interaction term with BDA capability to demonstrate that the results of the Tobit regression model are consistent across all models.

Chapter 6. Discussion and Conclusion

Our research examines the interactive effect of BDA capability on mature knowledge utilization. By dividing knowledge into explicit and tacit, we specify the underlying mechanism of how BDA impacts mature knowledge utilization in more detail. The predictions raised in all of our hypotheses are supported. The results of our research indicated that a firm's BDA capability could reinforce the positive effect of utilizing mature knowledge on a firm's competency for generating novel innovation. The interactive effects of BDA capability differ depending on the form of knowledge. First, we discovered that as explicit knowledge matures, a firm becomes more capable of creating breakthrough innovation. We also found that in the interactive effect between explicit knowledge maturity and BDA capability, BDA capability further enhances the effect that the explicit knowledge maturity exerts on innovation creation. These results suggest that a firm possessing more mature explicit knowledge is better adept at leveraging accumulated knowledge by the high applicability and reliability that mature knowledge has and the growth of tacit knowledge within the organization. Overall, our findings indicate that the enhancement of BDA capability can significantly strengthen the relationship between maturity and innovation in a positive way by making the benefits of knowledge maturity even more advantageous and remedying the disadvantages of them. The results suggest not only that strong BDA capability can lead to a significantly strengthened link between maturity and innovation but also that organizations with higher maturity in explicit knowledge are more capable of maximizing the benefits of BDA capabilities.

Second, we found that mature tacit knowledge is positively connected to innovation performance. Our findings demonstrate that mature tacit knowledge can benefit from the interaction with BDA capability, indicating that organizations with a high level of BDA capability can develop the ability to organize internalized tacit knowledge and broaden the scope of their knowledge, capitalizing on their BDA capability. Moreover, strong BDA capability significantly helps to create new ideas by extending conversion capability to a level impossible to reach with existing technologies. By visualizing the interaction effects, we found that organizations high in tacit knowledge are better at making the most of their BDA related resources and technologies so that they can position themselves into a more advantageous area. In sum, the maturity in knowledge has a significant beneficial effect in the process of innovation generation, and such beneficial effects can be further enhanced by strengthening BDA capability, leading to innovations.

Our research contributes theoretically to the in-depth understanding of organizational maturity and the impact of innovation. In this study, organizational maturity is organized into explicit knowledge maturity and tacit knowledge maturity. This has contributed to expanding the theory by applying the concept of knowledge maturity, not just the classification by form of knowledge, in the existing knowledge-creation literature. Furthermore, we argue that the ability to use data is an important intermediary on the effect of knowledge maturity. Among the capacity to use knowledge, the role of BDA in contributing to maximizing the potential of long-grown knowledge has been clarified through this study. Since the existing literature on BDA has mainly focused on BDA's direct innovation performance, identifying the interaction effect of BDA contributed to broadening the scope of existing BDA studies.

We attempted to combine data from various sources and organize them into researchable datasets. By doing this, this study attempted to measure a firm's ability to use data externally and was able to demonstrate the relationship with knowledge outcomes. As a methodological contribution, this study improved the reliability of the regression model by visualizing the interactions between variables, which facilitated a more in-depth understanding of BDA's interaction effects. This study also contributes to a deeper understanding of new practices in which data utilization is emphasized as a company's core competency. Many companies that have not been directly related to data are trying to strengthen their ability to utilize data. The conclusion of the study shows that such a move has practical advantages in terms of the use of knowledge to generate innovation outcomes. In future follow-up studies, it might be promising to explore the knowledge-environmental characteristics in which BDA can function more effectively.

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초 록

빅데이터 시대가 도래했지만, 빅데이터가 기업의 지식 활용에 어떻게 기여하는지에 대한 이론적 연구는 여전히 제한적이다. 우리는 기업의 성숙한 지식의 효과적인 활용을 촉진하기 위해 기업의 빅 데이터 분석 역량의 효과를 검토한다. 특히, 빅 데이터 분석(BDA) 역량이 지식 성숙도와 혁신 성과 사이에서 작용하는 매개 효과와 기업의 전반적인 혁신 성과에 미치는 지식 성숙도의 직접적인 영향을 검토한다. 우리는 지식 성숙도가 기업의 새로운 혁신 창출 능력을

뒷받침할 수 있고, BDA 능력이 지식 성숙도와 혁신의 관계와 상호 작용함으로써 지식 성숙도의 긍정적 영향을 강화한다는 것을 확인한다. 분석 결과에 따르면, 성숙한 지식을 가진 조직들이 그들의 BDA 능력을 기반으로 성숙한 지식을 활용하는 능력이 더 뛰어나며, 그러한 높은 수준의 지식 활용은 혁신 성과에도 긍정적인 영향을 미친다는 것을 시사한다.

주요어 : 빅 데이터 분석 역량, 혁신, 지식 성숙도, 명시적 지식 성숙도, 암묵적 지식 성숙도

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