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Technological Complementarity and Product Innovation:

IIT Integration and Its Impact on Knowledge Flow

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Abstract

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IIT, often considered the next generation of general-purpose technology, supports a firm's innovation processes by creating new value through recombining and utilizing data. The present study analyzes how the integrated use of complementary intelligent information technologies (IITs) correlates with a firm's product innovation performance. In addition, the interaction term between those two is estimated to identify the moderation effect of IIT integration on knowledge flow activities. Using data from a Korean survey on manufacturing (2022 Korean Innovation Survey: Manufacturing), this paper provides evidence that the integrated use of multiple IITs can significantly affect a firm's likelihood of becoming a product innovator and achieving market success. For the estimation here, while controlling for various factors related to the propensity for innovation of a firm, Probit and Tobit model regressions were utilized with a control function approach to address endogeneity. Whereas the estimation results indicate that IIT integration usage is strongly associated with a firm's innovation performance, integrating IIT partially mitigates the effect of knowledge spillover activities on innovation. The findings suggest that integrating IITs while a firm pursues digital transformation can enhance the firm's innovation potential. However, these findings may vary depending on factors such as the firm's industry or resources.

Keywords: Digital Transformation, Intelligent IT, Knowledge Flow, Product Innovation, Technological Complementarity
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Chapter 1. Introduction

Since the 2010s, digital transformation has gained momentum, increasing the number of related research and administrative efforts. Each country worldwide develops and executes national digital transformation strategies to facilitate the industry's competitiveness (Chung et al., 2020). For example, in 2022, South Korea's Ministry of Trade, Industry, and Energy legislated to foster the digital transformation of industries by creating and utilizing industrial data and spreading intelligent information technology (IIT). In addition, some associations have established certificate systems to improve IIT's quality, suitability, and security. However, recent research, legislation, certificates, and administration focus more on introducing individual technologies than their interactions within the broader context of digital transformation.

Achieving a high degree of digital transformation can maximize business efficiency and drive business model innovation, enhancing a firm's competitiveness (Westerman et al., 2014). Despite its potential, a Korea Innovation Survey 2022 conducted by STEPI found that just 28% of manufacturing enterprises have adopted cutting-edge technologies. Moreover, firms reputed the influence of adopted IITs to be very low or low. This adverse perception of digital technology could delay its diffusion. Thus, this study investigates the underlying backgrounds for these negative perceptions. It mainly studies whether state-of-the-art technology is insufficient for improvement or if firms overlook the complexity associated with the technology adoption process.

The sheer volume and complexity of newly available data and the technological capabilities to process them can fundamentally alter how firms operate and innovate (Agrawal et al., 2019; Dumbil, 2013). As firms strive to revolutionize their business models in sync with the advancing technological landscape of nations and industries, the five core technologies (ICMB+AI: IoT, Cloud, Mobile, Big Data, and AI) have become vital assets. IIT allows data-driven decision-making and production management, impacting corporate innovation performance and navigating the transition to a data-driven ecosystem. It also provides managerial opportunities for new insights and value creation by utilizing constantly generated data from interconnected systems of products, machines, and devices. This enables companies to increase the efficiency and productivity of their operations. These technologies, often referred to as the next generation of general purpose technology, are highly versatile and adaptable to any industry and process, making them an "invention of methods of invention (IMI)" (Griliches, 1957, p.502), with the potential to transform the nature of innovation.

Significant research has been done to identify factors influencing a firm's sustainable competitiveness. It is widely agreed that the implementation of Intelligent Information Technology (IIT) has a positive influence on corporate innovation performance, improving productivity and innovation through data-driven decision-making and operational optimization (Reim et al., 2020; Lee et al., 2019; Garbuio & Lin, 2019; Wilkesmann & Wilkesmann, 2018). For example, analyzing user patterns enhances product suitability (Güther et al., 2017), and large data sets and learning algorithms can accurately predict phenomena and design interventions, transforming the innovation process (Cockburn et al., 2018). Thus, IIT is a versatile tool that supports various innovative activities that are not restricted to specific areas or purposes. Besides, each IIT functions as a catalyst, enhancing the efficiency of advanced technologies. Zhang and Quah (2023) point out that IIT enhances firms' ambidextrous innovation utilization. For example, enormous quantities of high-quality data are produced through highly efficient data supply and control. Likewise, AI functions as a new analytical tool, producing new knowledge and insights and creating a virtuous cycle.

The IIT ecosystem is centered around the data, characterized by the knowledge accumulated from previous activities, providing the basis for further innovation. In a data-driven economy, the desire for firms to keep their data private becomes a powerful incentive. However, it can reduce their ability to access more extensive data sets. Besides, newly available data is often collected in a heterogeneous, non-structured manner and external to the firm, in contrast to data collected intentionally (Anderson, 2008; Varian, 2010). Therefore, enhancing the ability to collect, analyze, and recombine knowledge to derive novel insights and value is a critical managerial task, along with interacting with other economic entities (Niebel et al., 2019). The harmony between each skill set and their interactions is critical to maximizing innovation capabilities. The lack of skills sustaining the balance might diminish the efficiency of innovation and decision-making operations.

The characteristics of IIT that contribute to new value creation are essential to understand as they are distinguishable from earlier innovation systems. Nevertheless, while the impact of individual IITs on a firm's innovation performance is widely discussed, empirical investigations on their complementary interactions are inadequate. This study aims to fill this gap by providing an empirical study of the impact of complementary IIT adoption on the firm's competitiveness. Furthermore, the study seeks to identify the interaction between knowledge flow and IIT adoption by focusing on the GPT characteristics of IITs, which distinguish them from traditional technology ecosystems. In particular, this paper investigates the interaction between tacit knowledge flows and firms' implementation of IITs, as they are considered the future GPT because of their versatility and utility.

This paper is structured as follows. The next section offers a literature review based on the theoretical perspective. Then, it demonstrates the data and empirical methodology. The discussion of the results and findings is followed by the conclusions and limitations of the study in the final section.

Chapter 2. Literature Review

2.1 Digital Transformation and Core Technologies

The conceptual framework and its boundaries of digital transformation are imprecise. Thus, Song et al. (2022) defined the current state of study and concepts related to digital transformation by conducting a comprehensive big-data analysis (bibliometrics) on the definition of digital transformation proposed by different institutions and researchers. The terms most often used interchangeably with digital transformation are digitization and digitalization. While these technology phases overlap in the technologies and applications, their objectives, goals, and timeframes lead to conceptual differences and similarities. Each phase has evolved through social and industrial changes, so while they share some common values, they have different technological backgrounds and objectives. Since this study aims to study technology adoption activities to create new value, it is reasonable to define and discuss digital transformation as the scope.

There are some differences in the concepts of digital transformation and core IITs defined by organizations and studies (Bounfour, 2015; Dalenogare et al., 2018; Morgan, 2018; Nwankpa & Roumani, 2016). Based on the literature, this study defines digital transformation as 'the creation of new intelligent information value through the organic interaction of digital new technologies.' Song et al. (2022) define five core technologies required to support digital transformation as enablers identified by analyzing the formal studies. In the context of this study, five technologies (ICBM+AI: IoT, Cloud, Big Data, Mobile, and AI) proposed by Song et al. (2022) were designated as core IIT. Accordingly, the scope of utilization and role of each technology were categorized into (1) data collection, (2) data management and analysis, and (3) intelligent information value creation (Jeon et al., 2017).

Since the early 2010s, advanced information and communication technology has reached the phase of digital transformation that transforms the entire span of industries., Compared to the previous phases of digitalization and digitization which mainly aimed to reorganize existing production data and procedures, digital transformation aims to create new value for firms. This study delves into the impact of complementary IIT integration on generating product innovation in the digital transformation phase. Therefore, firms that have adopted at least one IIT are considered to have already accomplished digitization and digitalization according to the cumulative nature of the technology.

2.2 IIT and Innovation

The relationship between emerging high-tech and firm competitiveness (innovation performance and intensity) has been widely studied as industries transition to the next revolution. In particular, the utilization of core data-driven technologies is considered to have the potential to cover both ends of a firm's activities, from supply chain and production management to business models (Bahoo et al., 2023; Gama & Magistretti, 2022; Güther et al., 2017; Liu et al., 2020; Nayernia et al., 2022).

Products, services, and business model: Data-driven decision-making gives rise to data-driven business model innovations that deliver new types of products and services by utilizing information in real-time about customers, product usage, and product-related conditions (Reim et al., 2020; Lee et al., 2019; Garbuio & Lin, 2019). For instance, IIT is highly relevant to effective product and service marketing by identifying user patterns and supporting user-specific product communications (Valter et al., 2018). Furthermore, it can transform the innovation environment by improving the fit between consumer preferences and product features (Güther et al., 2017).

Production and management process: IIT can support operation optimization and human activity automation, making precise diagnoses and decisions. Real-time network connectivity between devices can help businesses increase productivity by collecting and processing data over fast networks (Wilkesmann & Wilkesmann, 2018).

R&D and innovation process: The versatility of large data sets and improved learning algorithms can function as a new "innovation playbook" to predict phenomena with high accuracy and design effective interventions (Cockburn et al., 2018, p. 6). Furthermore, IIT can operate as an "invention of a method of invention" (IMI) that is highly applicable and transforms the nature of production and innovation processes in a broad range of sectors (Griliches, 1957, p.502).

Numerous literatures have shown that the utilization of IIT has the potential to improve firm performance across the spectrum of innovation activities. Furthermore, various empirical studies have shown that IITs positively affect product and process innovation across industries (Cockburn et al., 2018; Črešnar et al., 2023; Guo & Xu, 2021).

Data collection technology (IoT & 5G): This technology group enables interactions between entities by sharing data with minimal human intervention. As a result, the interconnected system allows businesses and production systems to auto-record, monitor, and adjust their activities. Li and Tian (2023) found that ICT can help improve total factor productivity (TFP) among Chinese firms that have executed digital transformation. However, they noticed that only real-time information collection and processing based on fast 5G communications had a significant correlation, while existing 4G-based ICTs were not significantly linked to TFP improvement.

Data management and analysis technology (Big Data & Cloud): Improving a firm's innovation capabilities through utilizing IIT can, directly and indirectly, affect its competitiveness. The synergy of capabilities such as data collection, analysis, and insights leads to improvements in the innovation process (Tian et al., 2022). Especially, companies with a large amount of available data and the technology capable of processing it can quickly utilize new information to create and implement innovations (Ghasemaghaei & Calic, 2020). Based on these benefits, enterprises can obtain sustainable competitive advantage by achieving revenue and profit improvements (Hao et al., 2019). This benefit is closely related to the three characteristics of data-driven technology: volume, velocity, and veracity (Ghasemaghaei & Calic, 2020; Rammer et al., 2022). Improved conformity between consumer preferences and product features positively impacts product innovation and market success (Niebel et al., 2019). Furthermore, adequate interaction with the information browsing technologies can increase the effectiveness of its adoption (Nayernia et al., 2022).

Intelligent Information Value Creation Technology (AI): AI adds value to innovation capabilities both inside and outside the firm by supporting the optimization of innovation and R&D process (Bahoo et al., 2023). AI can accelerate the creation of new knowledge by collecting, processing, and integrating data and knowledge (Liu et al., 2020). Along with creativity, AI capabilities positively impact performance (Makalef & Gupta, 2021). In particular, integrating existing knowledge with AI through predictive and deep learning helps firms generate radical innovations (Gama & Magistretti, 2022; Grashof & Kopka, 2023; Rammer et al., 2022). It also positively impacts firms' productivity and innovation through improved product design and automation (Bahoo et al., 2023).

AI can also create positive externalities that affect the innovation process. The application of AI supports the enhancement of tacit and explicit knowledge integration, which leads to productivity improvement, and the additional surplus created leads to greater R&D investment, creating a virtuous cycle (Bahoo et al., 2023; Liu et al., 2020; Rammer et al., 2022). Furthermore, the formation of intra- and inter-firm networks can be expected to mitigate physical constraints, resulting in a positive feedback loop that diffuses resources and knowledge (Liu et al., 2020). Inter-firm interaction is one of the critical factors that can maximize the potential of AI, as it allows firms to use AI to identify potential partners for open innovation through text mining (Yoon & Song, 2014). However, the value of AI may vary depending on the firm's size, specialization, industry, or usage of AI (Grashof & Kopka, 2023; Liu et al., 2020).

Niebel et al. (2019) investigated the relationship between big data analytics and innovation performance in German manufacturing and service firms using data from the ZEW ICT survey. They conducted the study using a fractional logit model that Papke and Wooldridge (1996) suggested to address potential issues of Tobit models, such as heteroscedasticity and inherent non-normality. Their estimation results demonstrated that big data analytics significantly enhances a company's innovation performance, notably in product innovation. This effect was observed in both industries, indicating that big data analytics has the potential to convert data into new knowledge, which drives fiscal growth. Similarly, Rammer et al. (2022) used CIS Germany data to examine the relationship between AI and innovation, focusing on two areas: increased sales from innovative products and cost savings from process innovations. They found that companies with more experience utilizing AI achieved higher innovation performance. However, both studies are limited by their reliance on data from specific countries, which may not fully capture the multinational landscape of technology adoption and innovation performance. Also, focusing on firms that actively use only specific technology may cause them to overlook the broader impacts on firms with lower technology intensity levels.

2.3 IIT Complementarity and Integration

IITs drive innovation based on their general-purpose technology (GPT) characteristics. In particular, IITs are utilized and converged across industries, providing innovative business models that positively impact the creation of new products and services that can change the competitive landscape (Gama & Magistretti, 2022; Ghasemaghaei & Calic, 2020; Güther et al., 2017; Liu et al., 2020; Tian et al., 2022). IIT is characterized by the convergence of artificial intelligence technology that creates new intelligent information value based on data and utilizes technology that collects, transmits, stores, and analyzes data to realize high-level information capabilities (KDI, 2018). Several opinions exist that the IIT characteristics, which can directly contribute to creating new value, should be understood differently from a previous perspective. However, this study aims to understand it based on Dosi's (1982) theory of technological paradigms.

Achieving a high level of digital transformation through IIT enables the interaction between technologies, generating more powerful synergies across business operations (Varian, 2018). The combined use of complementary technologies can generate more substantial synergies, as the theory of technological paradigms explains. Technological paradigms play a crucial role in shaping technology development, emphasizing the emergence of technological interdependencies and co-evolution. Technological paths are established through radical innovations, forming the foundation for technological development (Rosenberg, 1976, 1979). Each technological path claims superiority in solving technical problems, and the chosen technology forms a dominant technological trajectory. Importantly, these dominant technological trajectories are not mutually exclusive (Dosi, 1982). Instead, they exhibit strong complementarity through different forms of knowledge, experience, and skills (Rosenberg, 1976, 1979). The advancement or lack of progress in one technology can facilitate or hinder the development of another (Dosi, 1982). Thus, progress along technological trajectories is cumulative.

Each dominant technological trajectory of IIT forms strong complementarities within a technological paradigm. Individual IIT components result from continuous and discontinuous innovations in different technological sectors, forming independent technological paths (Rosenberg, 1976, 1979). As a result, each of the five core technologies (ICBM+AI) forms technological trajectories for each component stage of IIT, contributing to forming a technological paradigm due to their expansive applicability and potential.

ICMB+AI forms a hierarchical structure (see Figure 1), and this study classifies five core technologies into three groups according to the technological characteristics and functions, as Jeon et al. (2017) suggested. Despite their structural hierarchy, each technology actively interacts and supports the others, serving as complementary technology (McKinsey & Company, 2016). It indicates that integrating complementary technologies can lead to more powerful technological synergies. However, in the intricately intertwined digital technology ecosystem, an imbalance in technological utilization can hinder the development of complementary technologies (Dosi, 1982), highlighting the importance of maintaining a balance between each technological trajectory.

The underlying technologies operate as catalysts that enhance the efficiency of intertwined technologies. In particular, the rich and active interaction between each technology can create a virtuous data cycle, thereby generating synergies that further enhance the efficacy of technology adoption. As efficient and precise data collection becomes feasible, companies can utilize data management technologies to improve the accuracy of insights from captured real-time data. Correspondingly, accessing vast amounts of quality data supports AI in creating comprehensive and high-fitting knowledge sets. Zhang and Quah (2023) found that ambidextrous innovation positively influences the performance of Deep Neural Networks (DNNs). Handling large volumes of structured and unstructured data generated during various business operations is essential to obtain insights that drive decision-making and innovation using AI technologies. Thereby, each IIT is a foundational tool supporting the high efficiency of the system.

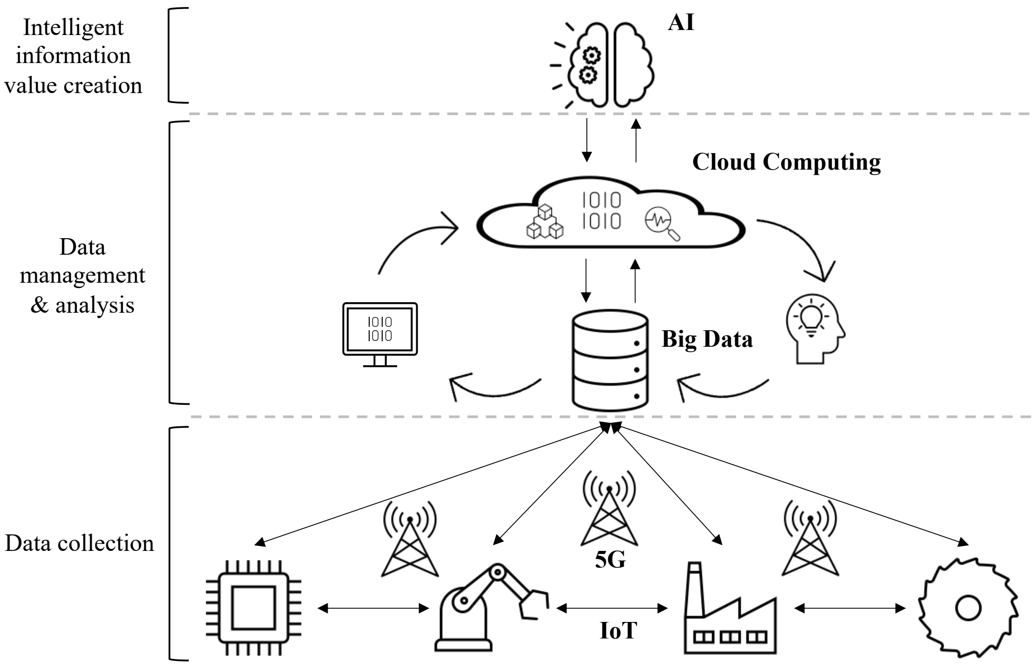

Figure 1. IIT structure and interactions

Alongside the promise of new technologies, the literature points out some challenges that may limit the impact of IIT (Cockburn, 2018; Nolan, 2020; Rammer et al., 2022; Reim et al., 2020). First, data availability and quality are significant challenges to successfully creating new intelligence value. If the breadth and granularity of data do not align with the end purpose or use, it can impede efficient decision-making (Güther et al., 2017). Leveraging IIT to generate high-quality innovation requires a continuous influx of quality data to be consistently filtered, combined, and reshaped (Rammer et al., 2022). In detail, the dynamics of technological complementarity to produce quality data, including digitizing, organizing, structuring, linking, and labeling processes, is required to achieve comprehensive digital business. Secondly, ensuring that the complementary data is sufficiently large and accessible while implementing a rich set of tools requires the formation of multidisciplinary and specialized teams, often associated with cost constraints. On the other hand, at the same time, excessive reliance and inertia on data resources can create barriers to obtaining new knowledge as it can lead to overlooking the importance of allocating other resources needed for growth and innovation success (Hao et al., 2019).

Each technological advancement drives complementary innovations needed to maximize the other's best potential (Brynjolfsson et al., 2017; Agrawal et al., 2019). Higher levels of tool technology adoption foster co-evolution through interactions between technologies and systems, creating a foundation for more substantial synergies across digital business operations (Varian, 2018). Many innovation-supporting technologies have formed specialized technological trajectories aimed at enhancing corporate productivity. In contrast, IITs, with their broad applicability, serve as an innovation playbook due to their technical characteristics and potential (Griliches, 1957; Trajtenberg, 2018; Wallach et al., 2015). Specifically, IITs support the development of fundamental methods for researchers to perform innovations, potentially transforming the essence of the innovation process (Wallach et al., 2015). Also, they can change innovation practices in R&D and business models, as they require new technology mixes and innovation processes (Seeber et al., 2020). While IITs have the potential to impact the performance of a firm positively, failure to adopt appropriate complementary technologies can hinder further growth. To address these liabilities, researching the relationship between the integrated use of complementary IITs and innovation capabilities is meaningful. This serves as the foundation for the first set of study hypotheses, which states that:

H1.1. The integrated use of IITs positively impacts innovation performance.

H1.2. The integrated use of IITs positively impacts the intensity of innovation.

2.4 Interaction between IIT and Knowledge Flow

IITs are considered innovative tools capable of altering the nature of innovation due to their high generalizability and potential to serve as foundational technologies across various industries and processes. As such, they are regarded as next-generation general purpose technologies (GPT), which lead to vertical and horizontal externalities (Bresnahan & Trajtenberg, 1995), closely associated with tacit knowledge and technological specialization (Granstrand et al., 1997; Nelson, 1989). In a data-driven economy, a firm's data is equivalent to the accumulated knowledge from past innovation activities. Firms are incentivized to keep their data private, but this exclusivity can limit access to larger datasets (Cockburn et al., 2018). Therefore, intentional knowledge flows through collaborative

R&D, and unintentional knowledge flows under geographical proximity are crucial for enhancing the understanding of innovation dynamics (Audretsch & Feldman, 2004).

In the context of advanced technologies and the uncertainties associated with high R&D costs, the new technology-economy system requires more complex combinations, necessitating accumulated expertise from areas beyond existing technological bases (Granstrand et al., 1997; Patel & Pavitt, 1997). Core foundational knowledge for innovation is often tacit and proprietary, demanding extensive organizational learning and interaction with precise geographical dimensions (Feldman & Kogler, 2010). GPTs exhibit cumulative, dynamic, and complementary characteristics in innovation. Supporting this idea, IITs necessitate new teamwork and technological combinations within R&D processes (Raghu & Schmidt, 2020). Moreover, technological advancement involves combining tacit and public knowledge (Cohen & Levinthal, 1990; Dosi, 1988), highlighting the importance of interactions among economic agents.

Collaborative activities such as joint R&D result in high knowledge inflow and outflow levels due to active participation in R&D tasks. Intentional collaboration allows parties to deepen their understanding of each other's work practices and specific skills, techniques, or competencies, facilitating mutual knowledge sharing. In such cases, the net result of knowledge inflow and outflow ultimately yields more significant benefits from the acquired knowledge than the losses from shared knowledge (Fey & Birkinshaw, 2005). Frequent interactions and the advantages of open technology sharing have widespread impacts. Joint R&D, in particular, fosters more opportunities for tacit knowledge spillover through accumulated experience and capability recombination, thanks to frequent exchanges with partner firms (Choi et al., 2012). Furthermore, combining in-house and joint R&D produces a synergistic effect on firm performance that exceeds the sum of their individual effects (Choi et al., 2012).

Extensive discussions have focused on the relationship between knowledge dynamics and firm performance (Feldman & Kogler, 2010). Tacit and proprietary knowledge and technology have precise geographical dimensions, and knowledge transfer tends to remain within these boundaries. Firms located near knowledge sources can achieve innovation more rapidly than those that are not (Audretsch & Feldman, 1996; Roper et al., 2017). However, some studies suggest that the spillover effects of technology and knowledge within clusters can be limited or may not yield significant advantages as firms are not only recipients of knowledge spillovers but also sources of knowledge production (Grilitsch & Nilsson, 2017; Huber, 2012). Direct interactions, such as face-to-face contact, can lead to unintended and intentional spillover of tacit and complex knowledge, potentially causing negative impacts (Sammarra & Biggiero, 2008).

Digital transformation efforts can play a vital role in advocating open innovation by providing a systematic and scalable innovation environment to share and co-create knowledge through cooperation. Whereas traditional knowledge transfer methods have several limitations, including difficulties in capturing and conveying tacit knowledge, IIT-based systems act as platforms that improve knowledge accessibility among interconnected entities (Kernan Freire, 2023). For instance, AI facilitates the acquisition of specialized knowledge using machine learning (Greene, 1987), and firms can expect greater efficiency in knowledge sharing by selectively incorporating relevant information. Additionally, IIT supports knowledge and creates high-performance work environments by capturing, analyzing, and sharing experiences without human intervention (North & Kumta, 2018).

The digital platform could enhance efficacy and efficiency, promoting inter-connectivity among stakeholders. For example, utilizing AI also helps select suitable knowledge-sharing partners, reduce unnecessary costs, strengthen inter-enterprise collaboration, and optimize knowledge dissemination (Mohammed et al., 2023). Samadhiya et al. (2023) suggest that AI enables real-time data transmission, enhancing collaboration and integration among supply chain stakeholders and improving cognitive processes. The use of IIT in predictive analytics, in particular, allows effective planning and reaction to emergencies within the supply chain. Additionally, AI-based methods can improve the accuracy of identifying potential partners by analyzing firm profiles and transaction data to predict customer-supplier relationships (Skulimowski & Köhler, 2023). Collaborating with knowledgeable and appropriate partners amplifies AI models' benefits and helps mitigate AI bias (Soleimani et al., 2022). Furthermore, the collaboration between digitally transformed firms and traditional industries fosters joint product development, encouraging non-IIT entities to adopt digital tools (Soe, 2020).

As technology matures and diffuses, reducing learning costs and improving technology accessibility are expected to impact the industry significantly. As such, using IITs can affect the impact of knowledge flows on innovation. Accordingly, the following study hypotheses were developed:

H2.1. IIT Integration strengthens the effect of agglomeration on product innovation.

H2.2. IIT Integration strengthens the effect of agglomeration on innovation intensity.

H3.1. IIT Integration strengthens the effect of joint R&D on product innovation.

H3.2. IIT Integration strengthens the effect of joint R&D on innovation intensity.

Conversely, there are several limitations in the interaction between IIT and knowledge spillover. In the early stages of technology diffusion within an industry, knowledge filters can become barriers to knowledge spillover, making it difficult for enterprises to adopt new knowledge and technologies (Proeger & Runst, 2020). Moreover, the initial adoption of technology can negatively affect a firm's productivity, so knowledge spillover may not ensure immediate benefits (Marsh et al., 2017). Specifically, if absorptive capacity is insufficient, it is challenging to gain advantages from the spread of new and innovative IIT knowledge (Huang et al., 2022). Technologies like AI and big data often require specialized knowledge and skills that are not easily transferable between companies or industries (Venturini, 2022). As a result, the technical complexity and novelty of IIT can create barriers that lead to resistance to knowledge spillover.

Since the mid to late 2010s, academic research on digital transformation has noticeably increased. However, many studies have focused on the effects of adopting several but separated specific technologies. Moreover, there is a lack of empirical research on the simultaneous adoption of complementary technologies necessary for enhancing corporate competitiveness through advanced digital business. This study aims to fill the gap by exploring the relationship between the combined use of IIT and corporate competitiveness based on the core technologies of digital transformation defined in numerous studies (H1.1 & H1.2). The research also aims to deepen traditional understandings of the unique IIT ecosystem by analyzing the interaction effects between IIT utilization and knowledge spillovers (H2.1 & 2.2, H3.1 & H3.2).

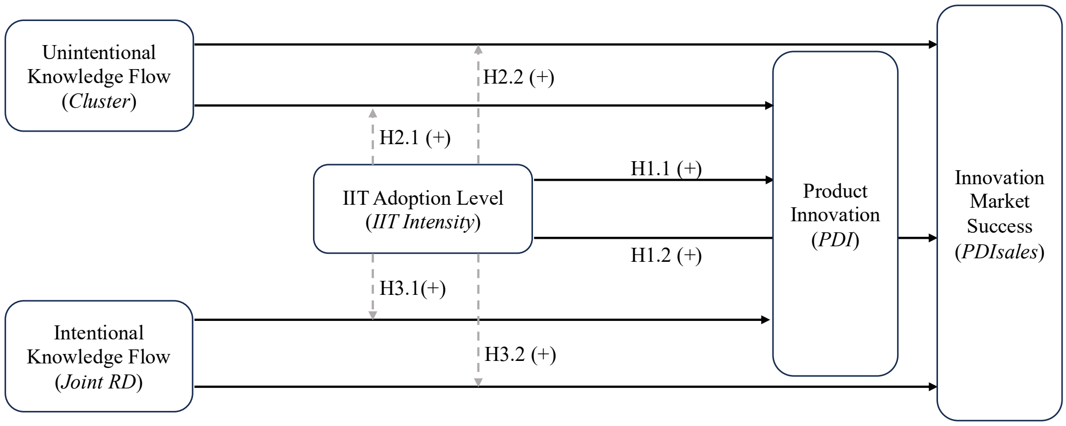

Figure 2. Research Hypotheses

Chapter 3. Research Methodology

3.1 Data

This study utilizes data from a Korean survey on manufacturing (2022 Korean Innovation Survey: Manufacturing), conducted by the Science and Technology Policy Institute (STEPI) in South Korea. The survey includes firm-level data on innovation activities from 2019 to 2021. The KIS incorporates financial information based on the Community Innovation Survey (CIS) methodology and follows the OECD's Oslo Manual guidelines. The KIS dataset comprises data from 4,000 manufacturing firms across 24 industries, each sample including firms with more than ten employees. The dataset covers the economic and geographical regions of each sample. The survey used includes a topic focusing on digital transformation and corporate innovation.

3.2 Definition and Measurements of the Variables

This study estimated two dependent variables. A dummy variable was used to measure product innovation (***PDI***). Respondents were asked to indicate whether they had introduced any product innovations between 2019 and 2021. A value of 1 was assigned if product innovation occurred and 0 otherwise. According to the descriptive statistics, over 28 percent of the observed firms engaged in at least one product innovation during 2019-2021 (see Table 1). There were 1,123 innovative firms and 2,877 non-innovative firms. Respondents were guided to differentiate between market-first and firm-first product innovations. This study considers product innovation to have occurred if new-to-market or new-to-firm products were launched, excluding mere improvements to existing products. Additionally, to measure the intensity of innovation, respondents were asked to indicate the percentage of 2021 sales revenue attributed to innovative products introduced between 2019 and 2021 (***PDIsales***). This captures the market success of product innovations (Mairesse & Mohnen, 2022; Laursen & Salter, 2006).

The study considered the adoption of five core technologies, also called digital transformation enablers, addressing the utilization level of IITs at the firm level. These technologies were grouped into three categories based on their roles and application scope, as presented by Jeon et al. (2017). Firms adopting IoT or 5G were classified as implementing data collection technologies. Firms that adopted Big Data or Cloud technologies were considered to have data management and analysis capabilities. The adoption of AI was used to determine whether firms were leveraging technologies to create intelligent information value.

An ordinal variable (***IIT Intensity***) was used to measure IIT adoption and complementary integration level, which were classified into three levels. A low level of integration (***Low***) specifies a firm utilizing a single IIT group without adopting a complementary technology group. Likewise, firms utilizing one or two complementary technology groups were considered to have mid-level (***Mid***) and high-level (***High***) integration, respectively. Among the observed firms, 1,443 had adopted at least one IIT, with data collection technologies being the most commonly used (1,226 firms).

Table 1. Model variables (definition and descriptive statistics)

Variable	Definition	Type	N	Mean	Std.d.	Min.	Max.
Innovation Output							
PDI	Firm has introduced product innovations during 2019-2021	D	1123	0.281	0.449	0	1
PDI sales	Share of sales in 2019-2021 with product innovations introduced during 2019-2021	S	1240	0.086	0.194	0	100
IIT Usage							
Data Collection	Firm has adopted data collection related technology (IoT or 5G)	D	1226	0.307	0.461	0	1
Data Mgmt. & Anal.	Firm has adopted data management and analysis related technology (Big Data or Cloud)	D	1113	0.278	0.448	0	1
AI	Firm has adopted value creation related technology (Artificial Intellegence)	D	130	0.033	0.177	0	1
IIT Intensity		O	1443	0.617	0.893	0	3
Low	Low-level IIT integration (complimentary IIT adoption: 0)	D	513	0.128	0.334	0	1
Mid	Mid-level IIT integration (complimentary IIT adoption: 1)	D	834	0.209	0.406	0	1
High	High-level IIT integration (complimentary IIT adoption: 2)	D	96	0.024	0.153	0	1
Knowledge Flow							
JointRD	Firm has conducted joint R&D during 2019-2021	D	470	0.118	0.322	0	1
Cluster	Firm is located in industrial cluster	D	1851	0.463	0.499	0	1
Control Variable							
RDsales	Innovation expenditure in 2021 per sales	M	2185	0.021	0.051	0.000	1.258
Size	Number of employees in the firm in 2021 (annual average at full-time equivalents, log)	L	4000	3.970	1.399	2.303	11.066
Age	Age of the firm in 2021 (years, log)	L	4000	2.871	0.659	1.099	4.489
Emp grad	Share of employed persons in the firm that hold master's degree or higher in 2021	S	299	3.799	6.865	0.000	95.000
IPR patent	Firm used patent to protect its intellectual property during 2019-2021	D	1425	0.356	0.479	0	1
Instrumental Variable							
Emp DX	Firm has a dedicated in-house digital transformation worker/team	D	344	0.086	0.280	0	1
Certificate	Firm has a certificate(s) of their business (Venture Enterprise, INNOBIZ, Green-Biz, ISO, etc.)	D	2315	0.579	0.494	0	1

D: dummy, L: logarithmic value, M: metric value, O: ordered value, S: share. Std.d.: standard deviation; Min.: minimum value; Max.: maximum value.

Data source: KIS Korean Innovation Survey 2022

Based on empirical literature on firm product innovation, various firm characteristics influencing innovation performance were controlled. R&D intensity, measured by R&D expenditure relative to total sales (***RDsales***), is identified as a crucial input factor for knowledge production and innovation success (Pakes & Griliches, 1980). Firm size, an essential factor for technology adoption, was controlled using the number of full-time employees (***Size***). Larger firms have more resources, which can positively influence technology adoption and innovation capabilities (Schumpeter, 1942). Additionally, the proportion of employees with a master's degree or higher (***Emp grad***) was controlled to identify the level of human capital, as employee knowledge, skills, and creativity significantly impact innovation capability (Vinding, 2006). The firm's maturity, measured by the years since establishment (***Age***), was also controlled, as it influences innovation capacity and advanced technology usage (Huergo & Jaumandreu, 2004). Younger firms might achieve higher sales proportions from new products due to a smaller existing product portfolio. Intellectual property protection activities, such as patenting (***IPR patent***), were controlled to account for the positive effects of intellectual property on R&D investment and innovation incentives (Behrens & Trunschke, 2020).

To identify the impact of knowledge flows on innovation through integrated IIT utilization, intentional and unintentional knowledge flows (***Knowledge***) were considered. Intentional knowledge flow from collaborative R&D enhances innovation by transferring tacit knowledge (Czarnitzki & Fier, 2003; Vanhaverbeke et al., 2007; Vrande et al., 2009). A variable indicating whether a firm conducted collaborative R&D (***JointRD***) between 2019 and 2021 was used to capture knowledge spillover from direct inter-firm interactions. Tacit knowledge often has localized characteristics, favoring firms with geographical proximity to knowledge sources (Audretsch & Dohse, 2007; Fritsch & Franke, 2004). Therefore, an industrial cluster (***Cluster***) was used to identify agglomeration externalities and unintentional knowledge flows due to geographic proximity. These two variables related to knowledge flow were used as interaction terms to measure their moderating effects on the high-level integration of IITs.

3.3 Model Specification and Estimation Strategies

Adopting new technologies can help firms enhance the efficiency of their products and operations, closely linking to their innovation strategies. Firms choose technologies they can best utilize to generate added value, considering factors such as internal resources, complementary assets, markets and customers, and competitors' strategies.

This study explores the potential correlation between the use of IIT and complementary technologies on innovation capabilities by controlling for key variables that drive innovation performance. The second objective is to investigate the moderating effects between knowledge flows and technologies characterized by tacit knowledge. Before analysis, it is essential to acknowledge that the level of technology utilization, other digitization efforts, and unobserved key innovation input variables might influence innovation outcomes. Some issues may also persist beyond the identified endogeneity, which future studies might address using panel data or other exogenous variables.

This study uses a control function approach to estimate endogenous explanatory variables. The first stage estimation is followed by second stage estimations (Probit model) to explore the differences in firms' product innovation capabilities (***PDI***) based on the level of technology adoption. Furthermore, Tobit model regression analyses estimate innovation intensity (***PDI sales***).

Within the knowledge production function framework proposed by Griliches (1979), this study analyzes how the level of IIT adoption contributes to firms' innovation performance and intensity. Additionally, the knowledge production function and estimation methods used in this empirical analysis are based on Niebel et al. (2019), which have been modified and further developed for this study. The framework assumes a transformation process where various inputs related to knowledge accumulation can lead to innovation performance in firms. A brief explanation of the empirical model for the knowledge production function is as follows. $\boldsymbol{y}_{1i}^{*}$ represents the latent propensity of firm $\boldsymbol{i}$ to achieve product innovation. The level of complementary technology adoption and other firm/market characteristics are denoted as $\boldsymbol{IIT}_{ni}$ and the vector $\boldsymbol{c}_{1i}$, respectively, where n is the number of IITs adopted by firm $\boldsymbol{i}$. Variables related to the utilization of IIT by firms are collected, and the control variables are expressed as the vector $\boldsymbol{x}_{1i} \equiv (\boldsymbol{IIT}, \boldsymbol{c}_1)$, simplifying the analytical framework. The first stage of the empirical model for the knowledge production function assumes a linear additive relationship (Niebel et al., 2019) as follows:

$$\begin{aligned} \boldsymbol{y}_{1i}^{*} &= \beta_1 \widehat{\boldsymbol{IIT}}(Low)_i + \beta_2 \widehat{\boldsymbol{IIT}}(Mid)_i + \beta_3 \widehat{\boldsymbol{IIT}}(High)_i + \gamma'_1 \boldsymbol{c}_{1i} + \boldsymbol{e}_{1i} \\ &= \sum_{n=1}^{3} \beta_n \widehat{\boldsymbol{IIT}}_{ni} + \gamma'_1 \boldsymbol{c}_{1i} + \boldsymbol{e}_{1i} = \delta' \boldsymbol{x}_{1i} + e_{1i} \end{aligned} \quad \text{Eq. (1)}$$

In this model, β represents the variable of interest in this study, capturing the effect of the level of complementary IIT adoption on the propensity for innovation. The term $\boldsymbol{e}_{1i}$ denotes the error term that affects $\boldsymbol{y}_{1i}^{*}$ but remains unobserved, assumed to be identically and independently normally distributed. The observed dependent variable, $\boldsymbol{y}_{1i}^{*}$, is the event of launching an innovative product in the market and is defined as follows:

$$\boldsymbol{y}_{1i} = 1[\boldsymbol{y}_{1i}^{*} > 0] \qquad \text{Eq. (2)}$$

$\boldsymbol{y}_{1i}$ denotes an indicator function that takes the value of 1 if the condition is met and 0 otherwise. Equations (1) and (2) constitute the first part of the analysis, estimating the relationship between the adoption of complementary IIT and the occurrence of product innovation in firms through a Probit model.

This study aims to estimate the relationship not only between the use of complementary technologies and the occurrence of innovation but also between such use and the intensity of a firm's innovation, as expressed in the following way:

$$\begin{aligned}\boldsymbol{y}_{2i}^{*} &= \beta_1 \widehat{\boldsymbol{IIT}}(Low)_i + \beta_2 \widehat{\boldsymbol{IIT}}(Mid)_i + \beta_3 \widehat{\boldsymbol{IIT}}(High)_i + \gamma'_2 \boldsymbol{c}_{2i} + \boldsymbol{e}_{2i} \\ &= \sum_{n=1}^{3} \beta_n \widehat{\boldsymbol{IIT}}_{ni} + \gamma'_2 \boldsymbol{c}_{2i} + \boldsymbol{e}_{2i} = \delta' \boldsymbol{x}_{2i} + \boldsymbol{e}_{1i}\end{aligned} \qquad \text{Eq. (3)}$$

Similar to many empirical studies that measure innovation intensity, this research assumes that the observable innovation intensity, measured by the sales proportion of innovative products, is defined by the following rule:

$$\boldsymbol{y}_{2i} = 1[\boldsymbol{y}_{2i}^{*} > 0]\boldsymbol{y}_{2i}^{*} \qquad \text{Eq. (4)}$$

When using equations (3) and (4) together, the standard Tobit model is derived (Tobin, 1958). This considers the nonlinear nature of the conditional expectation function $E(\boldsymbol{y}_{2i}^{*}|\boldsymbol{x}_{2i})$ because the proportion of firms that do not generate sales from new innovative products is negligible. The conditional expectation for the model composed of equations (3) and (4) is as follows:

$$E(\boldsymbol{y}_{2i}|\boldsymbol{x}_{2i}) = \boldsymbol{\Phi}\left(\frac{\delta'_{2}\boldsymbol{x}_{2i}}{\sigma}\right)\delta'_{2}x_{2i} + \sigma\boldsymbol{\phi}\left(\frac{\delta'_{2}\boldsymbol{x}_{2i}}{\sigma}\right) \qquad \text{Eq. (5)}$$

In this context, $\boldsymbol{\Phi}_i$ denotes the standard normal cumulative distribution function, while $\boldsymbol{\phi}_i$ denotes the density function. Potential issues can arise when estimating the Tobit model due to its solid and restrictive distributional assumptions. It assumes that the observed innovation intensity results from a single process influenced by the same set of determinants (Niebel et al., 2019). Additionally, if heteroskedasticity or non-normality exists, Tobit estimates can be inconsistent, unlike ordinary least squares estimates.

It is important to note that this study addresses endogeneity issues common in the empirical literature on digital transformation technologies. The Durbin-Wu-Hausman test was conducted to determine the presence of endogeneity in the data. The test's result indicates the presence of endogeneity at a very high confidence level. Furthermore, the study confirmed the presence of endogeneity by a highly significant correlation between the error terms of the endogenous variable (***IIT intensity***) and the dependent variable (-0.634, $p < 0.0001$). The significant correlation between the error terms suggests that a traditional model without controlling for endogeneity may produce biased estimates. By including the Control Function Approach, this study effectively addresses the endogeneity issue, yielding more reliable estimates of the impact of IIT intensity. Considering the endogeneity of firms' technology adoption, the presence of a dedicated digital transformation workforce (***Emp DX***) and the attainment of corporate certificates (***Cert***) are employed to estimate technology adoption ($\widehat{\boldsymbol{IIT}_n}$) in the first stage. Subsequently, the estimated endogenous variables are included in the second stage estimations (Probit and Tobit models).

The control function approach estimates residuals through a first-stage auxiliary regression and includes these estimated residuals in the second-stage regression to control for endogenous variables (Wooldridge, 2015). This method is particularly advantageous because it involves fewer assumptions and is more straightforward to estimate than the maximum likelihood method. It also effectively addresses endogeneity in nonlinear models (i.e., Probit, Tobit), featuring flexibility. The control function approach adheres to conditional independence and parametric assumptions. Moreover, using generalized residuals as control functions in parametric nonlinear models (Terza, 2009) can resolve problems associated with estimating complex and non-standard control functions caused by dummy endogenous variables (Wooldridge, 2014).

Firms with certificates (Cert) can expect external advantages, including improved social perception and financial and administrative support such as preferential loans with prime rates and public procurement opportunities (Bouvard & Levy, 2018). Firms seeking potential growth opportunities through certificates will likely be more proactive in adopting new technologies to enhance their innovation capabilities (Correa et al., 2010).

Besides the two covariates (***Cert*** and ***Emp DX***) this study uses firm size to address endogeneity. Larger-size firms with more resources are more likely to have an advantage in innovation capabilities and adoption of new technology. The mathematical expression for the first stage estimation is presented in equation (6) as follows:

$$\sum_{n=1}^{3} \widehat{\boldsymbol{IIT}}_{ni} = \beta_0 + \beta_1 EmpDX_i + \beta_2 Cert_i + \beta_3 Size_i + \boldsymbol{e}_i \qquad \text{Eq. (6)}$$

The second objective of this study is to explore the moderating effects between knowledge flow and technologies characterized by tacit knowledge. Interaction variables between knowledge flow and the level of technology adoption were included to estimate these moderating effects. It is important to note that when estimating the moderating effects between endogenous variables (***IIT intensity***) and exogenous variables (***Knowledge***), the exogenous variable used in the second-stage estimation, firm size (***Size***), is correlated with the endogenous variable. Since technology adoption and firm size are correlated, the interaction terms between these variables and knowledge flow will inherently have correlations. Therefore, failing to consider the exogenous variables correlated with the endogenous variables during estimation can lead to bias (deHaan et al., 2023). Consequently, an additional interaction variable (***Size×Knowledge***) is included to estimate the moderating effects of knowledge flow accurately.

Chapter 4. Empirical Results and Discussion

This section presents the estimation results. Tables 2 and 3 show the treatment effects of IIT adoption on product innovation and intensity. Comparing firms that have adopted IIT to those have not yet, the result revealed that IIT adoption significantly and positively impacts product innovation and market success. This finding indicates the potential of IIT utilization to enhance a firm's innovation performance (Bahoo et al., 2023; Gama & Magistretti, 2022; Güther et al., 2017; Liu et al., 2020; Nayernia et al., 2022).

Tables 4 and 5 include five models each to measure the impact of complementary IIT adoption on firm innovation performance and intensity, using a two-stage estimation with instrumental dummies. Models 1 and 6 include only firm characteristics to refine the variability of the dependent variable at the firm level. Models 3 and 8 illustrate the moderating effects of unintentional knowledge flow due to geographical dimensions (clusters), while Models 5 and 10 show the moderating effects of intentional knowledge flow due to collaborative R&D.

Table 2. Treatment effect (IIT adoption on product innovation)

PDI	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
IIT Adoption (1 vs 0)	0.571	0.034	16.890	0.000	0.505	0.638
Population mean	0.112	0.005	21.670	0.000	0.101	0.122

Table 3. Treatment effect (IIT adoption on the share of innovation product sales)

PDI sales	Coefficient	Robust std. err.	z	P>|z|	[95% conf. interval]	
IIT Adoption (1 vs 0)	0.641	0.046	14.060	0.000	0.552	0.730
Population mean	0.154	0.006	27.270	0.000	0.142	0.165

4.1. Impact of Complementary IIT on Firm Competitiveness

Model 1 (Table 4) and Model 6 (Table 5) present the regression results analyzing the impact of IIT and complementary technology adoption levels on the occurrence of product innovation and the intensity of innovation. Both models show that the estimated coefficients for complementary IIT adoption levels exhibit the expected signs across all three levels. Furthermore, comparing the sizes of the estimated coefficients for IIT adoption levels indicates that more active adoption of complementary IITs has a greater substantial impact.

Table 4. Coefficient estimates on PDI (Probit regression)

DV: PDI	Model 1	Model 2	Model 3	Model 4	Model 5
IIT Intensity					
Low	**1.071*****	**1.059*****	**1.106*****	**1.026*****	**1.151*****
	(0.0736)	(0.0742)	(0.0986)	(0.0772)	(0.0806)
Mid	**1.700*****	**1.681*****	**1.609*****	**1.657*****	**1.733*****
	(0.0789)	(0.0802)	(0.103)	(0.0835)	(0.0863)
High	**2.209*****	**2.205*****	**2.234*****	**2.100*****	**2.249*****
	(0.174)	(0.174)	(0.203)	(0.183)	(0.194)
Control Variable					
RDsales	**5.664*****	**5.659*****	**5.629*****	**5.298*****	**5.212*****
	(0.497)	(0.497)	(0.497)	(0.507)	(0.502)
Size	**0.0924*****	**0.0915*****	**0.125*****	**0.0761*****	**0.0757****
	(0.0220)	(0.0220)	(0.0276)	(0.0224)	(0.0239)
Age	**0.0278**	**0.0281**	**0.0229**	**0.0290**	**0.0251**
	(0.0348)	(0.0349)	(0.0349)	(0.0357)	(0.0353)
Emp grad	**1.355*****	**1.365*****	**1.355*****	**1.340*****	**1.309*****
	(0.293)	(0.294)	(0.295)	(0.303)	(0.300)
IPR patent	**0.427*****	**0.425*****	**0.426*****	**0.407*****	**0.394*****
	(0.0475)	(0.0476)	(0.0477)	(0.0485)	(0.0481)
Cluster		**0.0744**	**0.325***		
		(0.0425)	(0.139)		
JointRD				**0.493*****	**0.854*****
				(0.0654)	(0.215)
Interaction					
Low*Cluster			**-0.0784**		
			(0.119)		
Mid*Cluster			**0.122**		
			(0.102)		
High*Cluster			**-0.0814**		
			(0.247)		
Low*JointRD					**-0.597*****
					(0.163)
Mid*JointRD					**-0.251**
					(0.141)
High*JointRD					**-0.316**
					(0.282)
Size*Cluster			**-0.0633***		
			(0.0313)		
Size*JointRD					**-0.0367**
					(0.0424)
Constant	**-1.943*****	**-1.971*****	**-2.085*****	**-1.915*****	**-1.926*****
	(0.119)	(0.121)	(0.135)	(0.121)	(0.123)
N			4000		

Standard errors in parentheses *** p<0.05, ** p<0.01, *** p<0.001**

Data source: KIS Korean Innovation Survey 2022

Table 5. Coefficient estimates on PDIsales (Tobit regression)

DV: PDI sales	Model 6	Model 7	Model 8	Model 9	Model 10
IIT Intensity					
Low	**0.1299*****	**0.1361*****	**0.1453*****	**0.1239*****	**0.1505*****
	(0.025)	(0.0249)	(0.0357)	(0.0251)	(0.0275)
Mid	**0.224*****	**0.2344*****	**0.2393*****	**0.2211*****	**0.2425*****
	(0.0204)	(0.0206)	(0.0308)	(0.0205)	(0.0224)
High	**0.2592*****	**0.2543*****	**0.3369*****	**0.2522*****	**0.3722*****
	(0.0467)	(0.0464)	(0.0596)	(0.0468)	(0.0558)
Control Variable					
RDsales	**1.5242*****	**1.5208*****	**1.498*****	**1.4025*****	**1.4745*****
	(0.1378)	(0.1368)	(0.1359)	(0.1402)	(0.1387)
Size	**0.0701*****	**0.0709*****	**0.0898*****	**0.0639*****	**0.0863*****
	(0.0071)	(0.0071)	(0.0094)	(0.0072)	(0.0081)
Age	**0.0219**	**0.0218**	**0.0187**	**0.0216**	**0.0139**
	(0.0138)	(0.0137)	(0.0137)	(0.0139)	(0.0137)
Emp grad	**0.4847*****	**0.4678*****	**0.4422*****	**0.4705*****	**0.4438*****
	(0.1131)	(0.1124)	(0.1122)	(0.1134)	(0.1119)
IPR patent	**0.2183*****	**0.2213*****	**0.2226*****	**0.2117*****	**0.1967*****
	(0.0188)	(0.0187)	(0.0186)	(0.0189)	(0.0186)
Cluster		**-0.0577*****	**0.1184***		
		(0.017)	(0.053)		
JointRD				**0.1035*****	**0.651*****
				(0.0234)	(0.0753)
Interaction					
Low*Cluster			**-0.0241**		
			(0.0493)		
Mid*Cluster			**-0.0159**		
			(0.0404)		
High*Cluster			**-0.2221***		
			(0.0935)		
Low*JointRD					**-0.1607****
					(0.0627)
Mid*JointRD					**-0.1892*****
					(0.0499)
High*JointRD					**-0.3809*****
					(0.0979)
Size*Cluster			-0.0367**		
			(0.0119)		
Size*JointRD					**-0.0867*****
					(0.0145)
Constant	**-0.8000*****	**-0.7761*****	**-0.8487*****	**-0.7809*****	**-0.8526*****
	(0.0449)	(0.0449)	(0.0561)	(0.045)	(0.0464)
N			4000		

Standard errors in parentheses *** p<0.05, ** p<0.01, *** p<0.001**

Data source: KIS Korean Innovation Survey 2022

Table 6. Average marginal effects of IIT intensity on PDI

		Marginal Effects	std. err.	z	P>|z|	[95% conf. interval]	
IIT Intensity							
	Low	**0.319**	**0.026**	**12.170**	**0.000**	**0.268**	**0.371**
	Mid	**0.546**	**0.028**	**19.640**	**0.000**	**0.492**	**0.601**
	High	**0.693**	**0.044**	**15.620**	**0.000**	**0.606**	**0.780**

Table 6 shows the marginal effect of each level of IIT adoption on a firm's propensity to product innovation. The marginal effects of the activities that constitute data-driven technology are all statistically significant, and a firm's innovation probability increases as the intensity level increases. For firms that have not adopted IIT, the expected probability of innovation increases by at least 31.93 percent when they transform into a digital business. Supposing a firm has already achieved a low level of information-oriented business, it can expect to become an innovator with a higher probability depending on the number of complementary technologies it adds.

The results show that adopting multiple technologies can create more significant synergies with IIT adoption and its effects (Varian, 2018). Beyond the occurrence of innovation, the diversification of IIT adoption also positively influences innovation intensity. This suggests that IIT complementarity is closely related to the market success of innovative products, contributing to improved alignment between customer needs and product offerings. Therefore, the results of this study support hypotheses H1.1 and H1.2 at a significant level.

The results based on the technology adoption level reveal that active interactions between technologies are crucial for creating new value, and the hierarchical structure of technologies supports higher-hierarchy technologies. For instance, advanced IITs like AI require a continuous influx of high-quality data to maintain their efficacy (Rammer et al., 2022). Without the technology to store and manage a sufficient volume of high-quality data, continuously creating new intelligent information value can be challenging. Similarly, securing the technological capability to bring in new data can act as a catalyst, increasing the utility of higher-tier technologies like data analysis. The complexity of the digital ecosystem suggests that firms should consider the balance between technological capabilities before adopting new technologies.

4.2. Marginal Effects of IIT Integration

Table 7 shows the average marginal effects of each IIT on innovation propensities. Cloud technology, which shows the highest average marginal effect, is expected to improve innovation propensities by approximately 56 percent compared to those where no digital technologies are adopted. IoT follows with a high adoption effect (approximately 52.8 percent). These results are likely due to the differences in the roles of each technology.

5G and Big Data, respectively, support IoT and Cloud computing. 5G forms a pathway for real-time information communication as a wireless network to support information communication between objects performing tasks, thereby enhancing the efficiency of interactions between objects. Li & Tian (2023) pointed out that for the utilization of networks between entities such as machines to lead to an increase in a company's TFP, real-time information collection and processing through 5G technology is required, and data transmission speeds below 4G do not lead to significant improvements. In other words, 5G is a supporting technology for IoT that enhances the efficiency of interactions between network objects. Big Data supports the information processing of cloud computing by collecting, storing, and managing previously unusable large-scale data sets. Through cloud computing, companies can distribute and compute large amounts of data stored in Big Data, thereby increasing the utility of information.

Table 7. Average marginal effects of each IIT on PDI

DV: PDI	(1)	(2)	(3)	(4)	(5)
IIT adoption					
IoT	**0.528***** (0.027)				
5G		**0.462***** (0.038)			
Big Data			**0.446***** (0.045)		
Cloud				**0.559***** (0.027)	
AI					**0.334***** 0.079
Control Variables					
RDsales	**1.620***** (0.126)	**1.852***** (0.130)	**1.932***** (0.130)	**1.643***** (0.125)	**2.004***** (0.131)
Size	**0.047***** (0.005)	**0.054***** (0.005)	**0.048***** (0.006)	**0.031***** (0.006)	**0.065***** (0.005)
Age	**0.010** (0.010)	**0.013** (0.010)	**0.013** (0.010)	**0.009** (0.010)	**0.018*** (0.010)
Emp grad	**0.396***** (0.083)	**0.402***** (0.085)	**0.377***** (0.085)	**0.383***** (0.082)	**0.410***** (0.086)
IPR patent	**0.134***** (0.015)	**0.154***** (0.016)	**0.156***** (0.016)	**0.137***** (0.015)	**0.160***** (0.016)

Standard errors in parentheses *** p<0.05, ** p<0.01, *** p<0.001**

Table 8 shows the average marginal effects of the IIT groups classified according to the scope and purpose. The results reveal that firms that have not undertaken digital transformation can expect the most remarkable improvement in innovation propensity by adopting data management and analysis technologies among the three groups. As reviewed in section 2.2, companies can accelerate new insights and effective decision-making by adopting technologies that efficiently analyze the data (Ghasemaghaei & Calic, 2020; Tian et al., 2022). Furthermore, analyzing unstructured data enhances the compatibility between consumer preferences and products, thereby gaining an advantage in launching new products with higher market success potential (Niebel et al., 2019). The high average marginal effect of data collection-related technologies is likely due to the possibility of reactive and efficient automation with minimal human intervention.

Table 8. Average marginal effects of IIT group adoption on PDI

DV: PDI	(1)	(2)	(3)
IIT adoption (Group)			
Coll	**0.527*** **		
	(0.027)		
Mgmt		**0.546*** **	
		(0.028)	
AI			**0.334*** **
			(0.079)
Control Variables			
RDsales	**1.613*** **	**1.646*** **	**2.004*** **
	(0.126)	(0.125)	(0.131)
Size	**0.039*** **	**0.027*** **	**0.065*** **
	(0.006)	(0.006)	(0.005)
Age	0.006	**0.007**	0.018*
	(0.010)	(0.010)	(0.010)
Emp grad	**0.383*** **	**0.365*** **	**0.410*** **
	(0.082)	(0.082)	(0.086)
IPR patent	**0.135*** **	**0.134*** **	**0.160*** **
	(0.015)	(0.015)	(0.016)

Standard errors in parentheses **$*$ p<0.05, ** p<0.01, *** p<0.001**

For a firm to increase its propensity to innovate by leveraging emerging technologies, it incurs additional costs related to acquiring and operating the technology, including specialized labor. Efforts to minimize the additional input costs can contribute to financial improvement, and the new surplus can stimulate R&D inputs, leading to a virtuous cycle. In addition to the effect of the level of IIT adoption, the research estimates the effect each combination of technologies has on a firm's propensity to innovate (see Table 9). Three combinations of technologies are proposed by pairing three different technology groups (data collection, data management and analysis, and AI). Among these, a combination of data collection, data management, and analysis was found to have the most significant impact on innovation. Compared to firms with no digital transformation efforts, those who adopted those two simultaneously can expect a 53.65 percent higher innovation propensity. This result confirms that, as Nayernia et al. (2022) found, the appropriate level of interaction between data management and analysis technologies and information browsing technologies can further enhance the effectiveness of technology adoption. The impact of combining the two technologies at each end of the vertical hierarchy is approximately 31.65 percent. The marginal effect of adopting the upper two technologies is similar (34.11 percent).

Despite industry expectations for AI, the lower impact of combinations with AI than do not is likely due to technological limitations in firms' innovation decisions. The potential to contribute directly to creating new knowledge through recombination distinguishes AI from ICBM (Makalef & Gupta, 2021). In particular, it can help generate radical innovation (Gama & Magistretti, 2022) and enable efficient automation, positively impacting firm productivity (Bahoo et al., 2023). More importantly, however, many firms consider AI technology with uncertainty concerning its technical feasibility (Rammer, 2022). In particular, the lack of explanation and transparency about how AI results are derived raises credibility concerns for decision-makers (the black box problem).

Table 9. Average marginal effects of combined IIT groups usage on PDI

DV: PDI	(1)	(2)	(3)
IIT combination			
Coll. & AI	**0.3165****		
	(0.0920)		
Coll. & Mgmt.		**0.5365*****	
		(0.2969)	
Mgmt. & AI			**0.3411*****
			(0.7791)
RDsales	**2.016*****	**1.6964*****	**2.0058*****
	(0.1317)	(0.1260)	(0.1311)
Size	**0.0666*****	**0.0346*****	**0.6457*****
	(0.0051)	(0 .0056)	(0.0051)
Age	**0.0174***	**0.0065**	**0.0179***
	(0.0102)	(0.0100)	(0.0102)
Emp grad	**0.414*****	**0.3678*****	**0.4143*****
	(0.0862)	(0.0827)	(0.0861)
IPR patent	**0.1611*****	**0.1403*****	**0.1614*****
	(0.01589)	(0.0153)	(0.0159)

Standard errors in parentheses *** p<0.05, ** p<0.01, *** p<0.001**

4.3. Effects of Control Variables

R&D intensity and firm size positively influence innovation performance, demonstrating that firms with higher absorptive capacity have more robust innovation capabilities (Cohen & Levinthal, 1990; Pakes & Griliches, 1980). The significant impact of employee capabilities on innovation is also reaffirmed (Vinding, 2006). Although various questions have been raised about the effectiveness of intellectual property protection activities like patents in incentivizing innovation (Arora, 1997; Cohen et al., 2020; Mansfield, 1986; Teece, 1986), the data used in this study show that approximately 63 percent of innovative firms use patents to protect their intellectual property. The results of the analysis indicate that patent use positively affects product innovation. Notably, small innovative firms that find it challenging to use non-statutory protection methods tend to rely on patents to protect their profitability (Lee et al., 2018), which can serve as an innovation incentive for firms. Supporting this observation, about 82 percent of the total observed sample used in this study consists of SMEs.

4.4. Effects of IIT on Knowledge Flow

Model 3 (Table 4) and 8 (Table 5), as well as Model 5 (Table 4) and 10 (Table 5), analyze the moderating effects of knowledge flow from agglomeration (clusters) and collaborative R&D, respectively. As the research confirms, proximity to knowledge sources can significantly enhance innovation by facilitating knowledge flow, including unintentional interactions (Audretsch & Feldman, 1996; Roper et al., 2017). Similarly, collaborative R&D benefits innovation as it promotes knowledge exchange among partners. The regression results further validate these findings, demonstrating that knowledge flow can enhance both the occurrence and intensity of innovation by lowering barriers to appropriability and improving access to new information.

While the results show that the individual effects of IIT adoption and knowledge flow positively impact product innovation and innovation intensity, their interaction tends to mitigate these positive effects. Specifically, regarding innovation intensity, direct knowledge exchange activities show a statistically significant negative moderating effect when interacting with IIT adoption, regardless of the level of complementary technology adoption. However, the regression coefficients may not always be statistically significant.

Several factors might explain the negative moderating effects observed. Firstly, an excessive inflow of unsuitable data or the lack of technological capabilities to process such data could decrease the efficiency of the innovation process. This is particularly challenging for firms that adopt only data collection technologies (IoT or 5G). They might struggle to process and utilize external data effectively, limiting their ability to create new value. Consequently, these firms may face difficulties leveraging data beyond the specialized (non)structured data used for their products (Li & Tian, 2023).

Similarly, firms that operate only data management and analysis technologies (Cloud or Big Data) might find it challenging to handle and manage excessive data inflows from external sources, reducing efficiency (Ghasemaghaei & Calic, 2020). Low-quality knowledge production due to recombining data with low expertise and connectivity can lead to a vicious cycle of low-value data. Firms with sufficient scale and innovation capabilities might find uncontrolled and unnecessary noise detrimental to their efficiency if they fail to manage the data inflow. On the other hand, over-reliance on digital technologies can also risk overlooking the importance of other resources essential for sales and innovation (Hao et al., 2019).

Previous studies highlight several constraints in the interaction between IIT and knowledge flows. Proeger and Runst (2020) observed that the polarization of technology adoption—achieving either high levels of digitalization or none—is particularly evident in SMEs. The data for this study comprises about 82 percent of SMEs (3,281 companies), and nearly half of these (1,492 companies) were found not to have adopted IIT at all. This suggests that SMEs are susceptible to knowledge filters that hinder the conversion of new knowledge into economically beneficial knowledge (Proeger & Runst, 2020). Additionally, if an enterprise's absorptive capacity is insufficient, the positive interaction between IIT adoption and knowledge flows can be nullified (Huang et al., 2022). IIT implementation requires specialized knowledge and skills, and the additional costs associated with technology adoption may make firms reluctant to hire additional professional staff. Moreover, the development and dissemination of IIT are still incomplete, so there may be several limitations to achieving visible effects from IIT-based knowledge spillovers.

Secondly, the characteristics of the manufacturing industries studied might act as barriers to knowledge spillover. The high appropriability of digital assets, such as data, could significantly influence the adverse moderating effects. Firms in industries with lower technological complexity, such as pharmaceuticals, machinery, and manufacturing sectors, tend to use formal protection more frequently to safeguard their intellectual property (Arundel & Kabla, 1998; Cohen et al., 2000). Specifically, when core manufacturing capabilities involve primarily explicit knowledge or when the turnover cycle of crucial personnel is rapid (Gallie & Legros, 2012), patent protection becomes more effective (Woo et al., 2015). High appropriability can hinder knowledge flow, preventing externally acquired knowledge from converting to new intelligent information value. However, it is essential to note that appropriability also positively influences innovation and its intensity by providing innovation incentives, adding complexity.

The interaction between firm size and knowledge flow, included in the estimations to address endogeneity, also indicates a negative moderating effect on the combined effects of the two factors. Securing complementary assets, which correlated with the firm's size, is positively associated with knowledge production (Teece, 1986). However, large firms with powerful internal innovation capabilities may be central to knowledge production, causing them to be more reluctant to engage in external relations due to potential knowledge leakage.

Chapter 5. Conclusion

This study examined the impact of adopting and integrating complementary IITs on product innovation and its market success in South Korean manufacturing firms using Probit and Tobit models with a control function approach and various control variables. Additionally, it explored the moderating effects of interactions between IIT adoption and knowledge spillovers. The findings are consistent with existing literature, showing that adopting new technologies positively influences firm competitiveness (Cockburn et al., 2018; Črešnar et al., 2023; Guo & Xu, 2021) and that diversifying technology adoption enhances synergies among technologies (Dosi, 1982; Varian, 2018). The impacts of IIT adoption varied significantly with the level of complementary technology adoption. Although some measures were not statistically significant, the interaction between the two innovation factors exhibited a mitigating effect.

In the context of technological change and innovation diffusion, introducing new methods for solving technical problems and fostering innovation occurred within a theory of technological paradigm suggested by Dosi (1982). The technological paradigm encompasses standard methodologies and norms for handling technical issues. The technological trajectories formed by five main IITs act as digital transformation enablers, providing a sandbox for innovations under the technological paradigm. These trajectories are not mutually exclusive and support each other through iterative interactions (Rosenberg, 1976, 1979). The empirical estimations from Models 1 and 6 confirmed the importance of securing capabilities to support advanced technologies for firms to generate innovations, secure competitive advantages, and transform market structures. Decision-makers should recognize that imbalances in technological capabilities can undermine the efficiency of the innovation process and restrain the relationship between IIT and innovation. However, as adopting and operating multiple new technologies involves significant cost constraints during implementation and maintenance, it is necessary to consider the firm's and industry's circumstances.

The empirical analysis confirmed that not only the level of IIT integration but also firm-level absorptive capacity (such as size and education level) and inputs (R&D) were significant, emphasizing the importance of incentives like patents. The manufacturing industry's characteristics, often explicit in their core knowledge, drive firms to strengthen intellectual property protection through patents. High appropriability can act as an obstacle to knowledge spillovers. The study confirmed through Models 3 and 5, as well as Models 8 and 10, that high appropriability negatively impacts smooth data-driven knowledge flow. Access to high-quality data is crucial for creating innovation value using IIT. Thus, it is essential to consider dynamically adjusting appropriability to promote the flow of high-quality data, fostering a virtuous cycle of innovation through knowledge recombination. However, it is necessary to note that the effectiveness of these strategies may differ depending on the specific technologies adopted by the firms.

This study reveals that adopting and integrating IITs significantly enhances a firm's product innovation propensity and market success. Each technology plays a supportive role that strengthens the utility of others, leading to a virtuous cycle: 5G boosts IoT by enabling real-time communication, and Big Data enhances cloud computing by efficiently managing large data sets. Data management and analysis technologies are particularly effective in driving innovation, especially for firms new to digital transformation, by facilitating quicker insights and decision-making. Combining data collection technologies with management and analysis technologies enhances the highest innovation propensity at 53.65 percent. However, AI-included combinations have a lower impact due to current technological limitations and uncertainties, such as the black box problem affecting trust in AI. Overall, the strategic adoption of IITs and the synergistic use of these supporting technologies are essential for maximizing innovation.

The results of this study suggest several implications for companies and industries adopting new digital technologies to facilitate digital transformation. First, if a company is in the early stages of digital transformation or has already adopted one or more IITs, it may consider introducing complementary IITs. Integration of multiple IITs can enhance the synergy between technologies. Second, technology diffusion across the industry is required to maximize the effects of IIT usage. Achieving digital transformation at the industry level can improve knowledge accessibility and the efficiency of open innovation among entities. Third, while IIT has the potential to improve interactions between companies, its effects may be adverse until the technology matures and diffuses at a certain level. Therefore, firms should also focus on enhancing their in-house innovation capabilities. As over-reliance on technology can negatively affect its innovation capacity, it is crucial to manage the various factors that influence innovation capabilities continuously.

Despite offering a comprehensive understanding of firms' technology adoption decisions, this study has notable limitations. First, the data spans from 2019 to 2021, which does not capture the dynamic nature of knowledge spillovers that occur as innovation emerges and diffuses. Additionally, the cross-sectional data limits the ability to capture long-term innovation dynamics. Second, The KIS data does not identify interactions between firms adopting different technologies or spontaneously agglomerated clusters, which could raise bias. Last but not least, this research is restricted to understanding how adopting and integrating new technologies impacts the factors correlated to a firm's competitiveness. However, each firm has distinctive innovation capabilities, including various existing technologies and experience. In other words, new technologies interact uniquely with the firm's existing innovation activities. This interaction can differ based on the type and level of the current technologies. Under technological cumulativeness, following studies regarding the interactions between cutting-edge technologies and the existing technologies, or the previous generation technology, will allow us to explore innovation efficiently.

Generalizing the results should be done with caution. Although the study targeted nearly all manufacturing industries, the analysis was based solely on South Korean data. Also, the discovered effects may vary depending on specific industry and firm characteristics. From a resource-based view, each company is considered a unique entity with specific resources and capabilities, resulting in heterogeneous IIT utilization levels that help it attain competitive advantages (Gal et al., 2019; Radicic & Petković). Furthermore, the study followed Song et al. (2022) and Jeon et al. (2017), categorizing the range and usage of IIT. However, appropriate technology may differ by conditions and circumstances since the specifications of each may vary even if they are allocated in the same technology group. Identifying knowledge flows might generate different results depending on the partners involved in collaborative activities. Future research could explore the varied effects of various IIT combinations, utilize longitudinal data, and further segment knowledge flows.

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Appendices

Appendix 1. Correlation matrix of model variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) IIT intensity	1.0000									
(2) JointRD	0.1851	1.0000								
(3) Cluster	0.1687	0.0864	1.0000							
(4) RDsales	0.1316	0.2277	0.0511	1.0000						
(5) Size	0.3338	0.3136	0.1333	0.0675	1.0000					
(6) Age	0.1776	0.1272	0.0582	0.0162	0.3816	1.0000				
(7) Emp grad	0.1460	0.1229	0.0241	0.0865	0.2540	0.1193	1.0000			
(8) IPR patent	0.2090	0.2587	0.1221	0.1376	0.4569	0.2055	0.1469	1.0000		
(9) Emp DX	0.3991	0.2481	0.0873	0.0961	0.4030	0.1742	0.1146	0.2503	1.0000	
(10) Certificate	0.2172	0.2390	0.2059	0.2501	0.3795	0.2209	0.1470	0.4095	0.1949	1.0000

Data source: KIS Korean Innovation Survey 2022

Appendix 2. CFA Probit with endogenous variable result

DV: PDI		**Coefficient**	**Std. err.**	**z**	**P>|z|**	**[95% conf. interval]**	
IIT Intensity							
	Low	1.071	0.074	14.550	0.000	0.927	1.216
	Mid	1.700	0.079	21.540	0.000	1.545	1.855
	High	2.209	0.174	12.730	0.000	1.869	2.549
RDsales		5.664	0.497	11.410	0.000	4.691	6.637
Size		0.092	0.022	4.200	0.000	0.049	0.136
Age		0.028	0.035	0.800	0.425	-0.040	0.096
Emp grad		1.355	0.293	4.620	0.000	0.780	1.929
IPR patent		0.427	0.048	8.990	0.000	0.334	0.520
DV: IIT Intensity		**Coefficient**	**Std. err.**	**z**	**P>|z|**	**[95% conf. interval]**	
Size		0.140	0.016	8.990	0.000	0.109	0.171
Emp DX		1.081	0.066	16.250	0.000	0.950	1.211
Cert		0.394	0.041	9.560	0.000	0.313	0.475
corr(e.DX_intensity, e.PDI_D)		-0.634	0.040	-15.760	0.000	-0.706	-0.548

Abstract (Korean)

차세대 범용 기술로 고려되는 지능정보기술(IIT)은 데이터의 활용과 재조합을 기반으로 새로운 지능정보 가치의 창출을 이끌며 이는 기업의 혁신을 지원한다. 본 연구는 상호 보완적 지능정보기술의 통합과 기업의 제품 혁신 성과 사이의 관계를 분석한다. 나아가, 지능정보기술의 통합이 지식 흐름에 미치는 조절 효과를 식별하기 위해 두 공변량 사이의 상호작용 효과를 추정한다. 대한민국의 설문 자료(2022 한국기업혁신조사: 제조업)를 활용한 본 연구는 기업이 혁신가로 거듭날 뿐만 아니라 혁신 제품의 시장 성공을 달성함에 있어 지능정보기술의 다중 사용에 따른 기술 통합이 긍정적 효과를 지니는 증거를 제시한다. 추정을 위해서 기업의 혁신 경향과 관련이 있는 여러 변수가 통제되었으며, 내생성을 고려해 통제 함수 (control function) 접근법에 기반한 Probit 및 Tobit 모델 회귀 분석이 실시되었다. 추정 결과는 기술 통합과 기업의 혁신 제품 발생 사이에 강한 상관관계가 있음을 보여준다. 반면, 기술 통합은 지식 파급 활동에 완화 효과를 지니는 것으로 나타났다. 본 연구 결과를 통해 기업은 디지털 전환 달성에 지능정보기술의 다중 도입과 통합 추구함으로써 혁신 잠재력을 더욱 높일 수 있을 것으로 기대한다. 다만, 이러한 발견은 기업이 속한 산업 및 보유 자원 등 여러 요인에 따라 다르게 나타날 수 있다.

주요어 : Digital Transformation, Intelligent IT, Knowledge Flow, Product Innovation, Technological Complementarity

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