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Digital Transformation and Innovation Performance in Manufacturing Firms: The Mediating Role of Absorptive Capacity and the Moderating Role of R&D Human Capital

Jang, Seung-hwan¹

¹ College of Humanity and General Education, Seokyeong University

* Corresponding author: Jang, Seung-hwan, Email: jangsh@skuniv.ac.kr

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Abstract: This study empirically investigated the effect of digital transformation on innovation performance in manufacturing firms and examined the mediating role of absorptive capacity and the moderating role of R&D human capital. As manufacturing industries increasingly experience rapid technological changes driven by artificial intelligence (AI), big data, the Internet of Things (IoT), and smart manufacturing systems, digital transformation has emerged as a critical strategic factor for enhancing organizational competitiveness and innovation capability. However, prior studies have suggested that the adoption of digital technologies alone does not necessarily guarantee sustainable innovation performance. Therefore, this study attempted to explain the relationship between digital transformation and innovation performance from the perspectives of organizational learning and human capital. Data were collected from 402 employees working in Korean manufacturing firms through online and offline surveys. The collected data were analyzed using Structural Equation Modeling (SEM) with SPSS 29.0 and SmartPLS 4.0. The results indicated that digital transformation had a significant positive effect on innovation performance and absorptive capacity. In addition, absorptive capacity positively influenced innovation performance and partially mediated the relationship between digital transformation and innovation performance. Furthermore, R&D human capital significantly moderated the relationship between digital transformation and innovation performance, indicating that the positive effect of digital transformation on innovation performance was stronger in firms with higher levels of R&D human capital. The findings suggest that digital transformation contributes to innovation performance not only through technological efficiency but also through enhanced organizational learning and knowledge utilization capabilities. This study provides academic implications by integrating digital transformation, absorptive capacity, and R&D human capital into a comprehensive research framework. In addition, it offers practical implications for manufacturing firms by emphasizing the importance of organizational learning systems and the development of R&D personnel capabilities alongside digital technology investment.

Keywords: Digital Transformation; Innovation Performance; Absorptive Capacity; R&D Human Capital; Manufacturing Firms; Smart Manufacturing; Organizational Learning; Industry 4.0; Digital Innovation; Structural Equation Modeling (SEM)

1. Introduction

The manufacturing industry is a core sector that drives national economic growth and industrial competitiveness, requiring continuous technological innovation and productivity improvement. However, the global manufacturing environment has recently undergone fundamental structural changes due to the rapid advancement of cutting-edge digital technologies such as Artificial Intelligence (AI), Big Data, the

Internet of Things (IoT), Cloud Computing, Digital Twins, and Smart Factories. In particular, the spread of Industry 4.0 has demanded digital-based innovation across manufacturing firms' production systems, supply chain structures, customer value creation methods, and organizational operating systems (Frank et al., 2019).

In the past, the competitive advantage of manufacturing firms was largely determined by large-scale facility investments and production efficiency. Recently, however, the extent to which firms effectively utilize digital technologies to strengthen organizational innovation capabilities and knowledge utilization capacity has become a key determinant of corporate competitiveness (Nambisan et al., 2019). Accordingly, manufacturing firms are actively promoting digital transformation through the adoption of AI-based production management systems, smart factory implementation, data-driven quality management systems, automated facilities, and digital collaboration platforms.

Digital transformation extends beyond simple IT adoption or process computerization. Rather, it represents a comprehensive strategic change that fundamentally restructures organizational strategies, operational processes, and value creation systems around digital technologies (Vial, 2019). Verhoef et al. (2021) defined digital transformation as a strategic change process in which firms fundamentally transform their business models and organizational operations through the utilization of digital technologies. Furthermore, Warner and Wäger (2019) argued that digital transformation enhances an organization's dynamic capabilities, thereby creating sustainable competitive advantage.

Particularly in manufacturing firms, digital transformation has been reported to significantly influence production process automation, production efficiency improvement, supply chain optimization, quality management enhancement, and innovation performance improvement (Bresciani et al., 2021). Recently, Korean manufacturing firms have also actively pursued digital-based manufacturing innovation in line with smart manufacturing innovation policies and the expansion of government-supported smart factory programs. According to the Ministry of SMEs and Startups (2024), the adoption rate of smart factories among domestic manufacturing firms has continuously increased, alongside the expansion of digital-based production management systems.

Nevertheless, recent studies have consistently suggested that the adoption of digital technologies does not necessarily lead to innovation performance. In practice, even when firms adopt similar levels of digital technologies, substantial differences in innovation performance are observed across firms, and some companies fail to achieve expected innovation outcomes despite large-scale digital investments (Warner & Wäger, 2019). This implies that internal organizational capabilities and human resources, rather than digital technologies themselves, may serve as critical determinants of the effectiveness of digital transformation.

In particular, within manufacturing firms, the expertise of research and development (R&D) personnel and the organization's knowledge utilization capabilities are regarded as crucial factors determining the success of digital transformation. Since manufacturing industries require high levels of technical expertise and organizational learning capabilities in areas such as production processes, technological innovation, quality management, and product development, the role of R&D personnel capable of effectively understanding and utilizing digital technologies is extremely important (Subramaniam & Youndt, 2005).

R&D human capital refers to the specialized knowledge, technical competencies, creativity, and problem-solving capabilities possessed by R&D personnel and is considered a key intangible asset that determines organizational innovation performance (Becker, 1993). Cohen and Levinthal (1990) argued that organizational innovation performance is determined by the prior knowledge and learning capabilities of organizational members and explained that absorptive capacity serves as a core mechanism of innovation activities.

Absorptive capacity refers to an organization's ability to identify, absorb, transform, and utilize external new knowledge (Cohen & Levinthal, 1990), and its importance has become increasingly emphasized in the context of digital transformation. Digital transformation can positively influence the development of organizational absorptive capacity by strengthening data accessibility and information flow within organizations and by expanding opportunities to utilize external knowledge and technological information (Zahra & George, 2002). Enhanced absorptive capacity ultimately functions as a key factor in improving product innovation, process innovation, and technological innovation performance.

However, prior studies have several limitations. First, existing digital transformation research has mainly focused on the direct relationship between the level of digital technology adoption and organizational performance, while relatively insufficient attention has been paid to explaining the organizational mechanisms through which digital transformation leads to innovation performance. Second, empirical studies examining the role of absorptive capacity in the relationship between digital transformation and innovation performance in manufacturing firms remain limited. Third, there is also a lack of studies analyzing the moderating effect of R&D human capital in explaining why the effects of digital transformation differ across firms. Fourth, in the Korean context, most studies have focused primarily on smart factory adoption or the level of digital technology utilization, whereas studies that integratively consider organizational learning and human capital perspectives remain limited (Kim & Lee, 2022; Park & Kim, 2021).

Accordingly, this study aims to empirically examine the effect of digital transformation on innovation performance in manufacturing firms and to analyze the mediating effect of absorptive capacity and the moderating effect of R&D human capital in this relationship. Specifically, this study proposes the following research questions. First, how does digital transformation affect the innovation performance of manufacturing firms? Second, does digital transformation strengthen organizational absorptive capacity? Third, does absorptive capacity mediate the relationship between digital transformation and innovation performance? Fourth, does R&D human capital function as a moderating factor that strengthens the relationship between digital transformation and innovation performance?

This study has academic significance in that it explains the relationship between digital transformation and innovation performance not merely from the perspective of technology adoption, but from an integrated perspective of organizational learning capability and human capital. Furthermore, the findings are expected to provide practical implications by suggesting that, in the process of establishing digital innovation strategies for manufacturing firms, not only technological investment but also the establishment of organizational learning systems and the enhancement of R&D personnel capabilities are critically important.

2. Theoretical Background

2.1. Digital Transformation

Digital transformation has recently emerged as one of the most important research topics in the fields of business administration, technology management, information systems, and innovation studies. Digital transformation is defined not merely as the adoption of IT systems or the automation of business processes, but as a process that fundamentally changes an organization's overall strategy, structure, operational methods, and value creation processes through digital technologies (Vial, 2019).

Vial (2019) defined digital transformation as “an organizational innovation process that fundamentally transforms an organization's value creation mechanisms and operational systems through the utilization of digital technologies.” Verhoef et al. (2021) explained that digital transformation is a multidimensional concept encompassing business model innovation, customer experience enhancement, and operational efficiency improvement.

In manufacturing firms, digital transformation is closely associated with Industry 4.0. Industry 4.0 refers to the concept of intelligent and automated production processes through the utilization of AI, IoT, big data, robotics, and cyber-physical systems (CPS) (Frank et al., 2019). Through these technologies, manufacturing firms can achieve improved production efficiency, cost reduction, advanced quality management, and enhanced production flexibility.

Recent studies have reported that digital transformation strengthens organizational innovation capabilities and competitive advantage. Bresciani et al. (2021) argued that digital technologies promote innovation performance by improving organizational collaboration efficiency and information processing capabilities. Nambisan et al. (2019) explained that digital technologies facilitate organizational innovation by enabling new forms of knowledge recombination and value creation.

Domestic studies have also continuously emphasized the importance of digital transformation. Kim Young-hoon and Lee Jung-min (2022) reported that the level of smart factory implementation significantly affects the operational performance and organizational innovation of manufacturing firms. Park Jung-soo and Kim Sung-hoon (2021) analyzed that digital-based production systems improve process innovation and organizational performance. In addition, Lee Soo-hyun and Park Ji-hoon (2021) explained that the level of digital technology utilization strengthens the innovation capabilities of manufacturing firms.

However, some studies have pointed out that investment in digital technologies alone cannot guarantee sustainable innovation performance (Warner & Wäger, 2019). This suggests that the effects of digital transformation may vary depending on internal organizational capabilities and the level of human resources.

2.2. Innovation Performance

Innovation performance refers to the level of innovation outcomes created through a firm's development and application of new products, services, production processes, technologies, and organizational operating methods (OECD, 2018). Joseph Schumpeter (1942) explained innovation as a core driver of economic growth and corporate competitive advantage, and since then, innovation performance has been widely utilized as a key performance variable in business administration and technological innovation research.

Early innovation studies tended to measure innovation performance primarily

in terms of technological development outcomes or the introduction of new products. However, recent studies conceptualize innovation performance as a multidimensional construct that includes product innovation, process innovation, organizational innovation, and marketing innovation (OECD, 2018). In particular, for manufacturing firms, the importance of process innovation and technological innovation is further emphasized because production technology and process operations directly influence corporate competitiveness.

Innovation performance is closely associated with a firm's sustainable competitive advantage. Michael Porter (1990) identified innovation capability as a key determinant of competitive advantage, while David Teece (2007) explained that continuous innovation is a critical factor determining corporate survival in rapidly changing industrial environments. Particularly in the digital economy, the speed of technological change is extremely rapid; therefore, firms that fail to continuously generate innovation performance are likely to lose market competitiveness.

In the context of digital transformation, the concept of innovation performance has become even broader. Digital technologies improve organizational information-processing capabilities and collaboration efficiency while enabling new forms of knowledge recombination and value creation (Nambisan et al., 2019). For example, AI-based production management systems enhance the efficiency of production processes, while big data analytics enable firms to identify consumer needs more precisely, thereby expanding opportunities for product innovation.

Frank et al. (2019) explained that smart manufacturing systems improve production efficiency, operational agility, and technological innovation levels. In addition, Bresciani et al. (2021) reported that firms with higher levels of digital technology utilization demonstrate greater innovation speed and superior new product development performance.

Domestic studies have also actively discussed the relationship between digital-based manufacturing innovation and innovation performance. Lee Soo-hyun and Park Ji-hoon (2021) analyzed that the level of digital technology utilization significantly influences product innovation and technological innovation. Furthermore, Moon and Choi (2021) explained that smart manufacturing capability simultaneously improves productivity and innovation performance.

However, recent studies have pointed out that investment in digital technologies alone does not automatically improve innovation performance (Warner & Wäger, 2019). In other words, even when firms adopt the same digital technologies, differences in innovation performance emerge across firms, and such differences may be explained by variations in organizational learning capability and human resource levels.

Particularly in manufacturing firms, digital technologies are more likely to lead to substantial innovation performance when combined with the organization's knowledge utilization capabilities rather than being limited to simple production automation. Therefore, in explaining innovation performance, it is necessary to consider not only digital technologies themselves but also the organization's internal learning capabilities and human resource competencies.

2.3. Absorptive Capacity

Absorptive capacity refers to an organization's ability to identify, acquire, transform, and utilize new knowledge from the external environment (Cohen & Levinthal, 1990). Wesley Cohen and Daniel Levinthal (1990) argued that organizational innovation performance is determined not simply by the adoption

of technologies, but by how effectively organizations understand and utilize new knowledge.

Absorptive capacity has been widely employed as a core concept in the fields of organizational learning and innovation research, and its importance has become increasingly emphasized in the context of digital transformation. Shaker Zahra and Gerard George (2002) classified absorptive capacity into potential absorptive capacity and realized absorptive capacity.

Potential absorptive capacity refers to the ability to identify and acquire external knowledge, whereas realized absorptive capacity refers to the ability to integrate acquired knowledge within the organization and utilize it in actual innovation activities. In other words, merely collecting external technologies and information is insufficient; organizations must also establish internal learning systems capable of linking such knowledge to innovation activities.

In the digital transformation environment, the importance of absorptive capacity has increased further because the volume of information and the complexity of technologies that organizations must process have grown dramatically. In AI-, big data-, and IoT-based manufacturing environments, organizations must be capable of analyzing and utilizing diverse external technological and market information in real time, which requires organizational learning capabilities and knowledge-sharing systems (Warner & Wäger, 2019).

Lane et al. (2006) explained that absorptive capacity is a key mechanism determining an organization's long-term innovation performance. In addition, David Teece (2007) identified absorptive capacity as a core component of dynamic capability and argued that it is a critical factor determining organizational adaptability in rapidly changing technological environments.

Recent digital innovation studies have also highlighted absorptive capacity as a key variable. Nambisan et al. (2019) explained that an organization's ability to recombine knowledge determines innovation performance in digital innovation environments and argued that such capability is ultimately dependent on the organization's level of absorptive capacity.

Domestic studies have also actively discussed the relationship between absorptive capacity and innovation performance. Kim Tae-hoon and Jung Min-soo (2022) analyzed that absorptive capacity is a key factor enhancing technological innovation performance and organizational performance in manufacturing firms. Park Ji-hoon and Lee Sung-min (2021) explained that organizational learning capability and knowledge-sharing levels strengthen innovation performance in smart manufacturing environments.

Particularly in manufacturing firms, where production technologies and market environments change rapidly, the ability to effectively learn and utilize new external technological knowledge is critically important. Therefore, absorptive capacity is highly likely to function as an important mediating mechanism in the process through which digital transformation leads to innovation performance.

2.4. R&D Human Capital

R&D human capital refers to the specialized knowledge, technical competencies, creativity, problem-solving abilities, and learning capabilities possessed by research and development personnel within an organization (Subramaniam & Youndt, 2005). According to Human Capital Theory, the knowledge and competencies of organizational members constitute key intangible assets that determine a firm's

productivity and competitive advantage (Becker, 1993).

Particularly in manufacturing firms, where technological innovation and product development are critically important, the competency level of R&D personnel directly affects corporate competitiveness. In the recent digital transformation environment, the importance of R&D human capital has become even greater as organizations increasingly require understanding and utilization capabilities related to AI, data analytics, automation systems, and smart manufacturing technologies.

Subramaniam and Youndt (2005) explained that human capital plays a crucial role in the formation of organizational knowledge creation capabilities and innovation competencies. In addition, Wesley Cohen and Daniel Levinthal (1990) argued that organizational absorptive capacity is determined by the prior knowledge level of organizational members. In other words, organizations with a greater number of employees possessing high levels of expertise are more likely to effectively understand and utilize new technologies.

Recent digital innovation studies have also emphasized the importance of human resources equipped with digital capabilities. Warner and Wäger (2019) explained that the success of digital transformation depends on the level of digital understanding and learning capability among organizational members. Nambisan et al. (2019) likewise argued that digital technology-based innovation ultimately leads to substantial performance outcomes through the creativity and problem-solving abilities of organizational members.

Domestic studies have continuously discussed the relationship between R&D human capital and innovation performance. Kim Young-hoon and Hwang Sung-min (2023) reported that the level of digital capability in manufacturing firms significantly affects technological innovation performance. Lee Soo-hyun and Jung Min-ho (2022) analyzed that the expertise of R&D personnel strengthens smart manufacturing innovation performance.

Particularly in manufacturing firms, the role of R&D human capital is even more critical because digital technologies must not only be adopted but also applied to actual production sites and innovation activities. Firms possessing high levels of R&D human capital are more likely to effectively understand digital technologies and disseminate them throughout the organization, thereby maximizing innovation performance.

Therefore, R&D human capital is likely to function as an important moderating factor that strengthens the relationship between digital transformation and innovation performance.

2.5. Prior Studies on the Relationships Among Variables and Hypothesis Development

2.5.1 Relationship Between Digital Transformation and Innovation Performance

Recent studies have identified digital transformation as a key factor that enhances organizational innovation performance. Digital technologies improve organizational information-processing capabilities and collaboration efficiency while enabling new forms of knowledge recombination and value creation (Nambisan et al., 2019).

Verhoef et al. (2021) explained that digital transformation strengthens firms' operational agility and innovation capabilities. Frank et al. (2019) reported that smart manufacturing technologies improve production efficiency and the level of product innovation.

Domestic studies have also confirmed a positive relationship between digital transformation and innovation performance. Park Jung-soo and Kim Sung-hoon (2021) analyzed that digital-based production systems improve the level of process innovation in manufacturing firms. Kim Young-hoon and Lee Jung-min (2022) explained that the level of smart factory implementation significantly affects organizational innovation and production performance. Accordingly, the following hypothesis was established.

Hypothesis 1: Digital transformation will have a positive (+) effect on innovation performance.

2.5.2 Relationship Between Digital Transformation and Absorptive Capacity

Digital transformation enhances organizational data accessibility and information-sharing levels while strengthening organizational learning capabilities and knowledge utilization capacity (Warner & Wäger, 2019).

Shaker Zahra and Gerard George (2002) explained that information accessibility and learning systems are important for organizations to effectively absorb external knowledge. Digital transformation is likely to positively influence the development of absorptive capacity by promoting collaboration and knowledge sharing among organizational members.

Domestic studies have also reported that the level of digital technology utilization improves organizational knowledge sharing and learning capabilities. Kim Tae-hoon and Jung Min-soo (2022) found that digital technology utilization positively affects organizational knowledge-sharing and learning capabilities. Therefore, the following hypothesis was established.

Hypothesis 2: Digital transformation will have a positive (+) effect on absorptive capacity.

2.5.3 Relationship Between Absorptive Capacity and Innovation Performance

Absorptive capacity is regarded as a core organizational capability that enables firms to effectively integrate and utilize knowledge acquired from the external environment (Cohen & Levinthal, 1990). Particularly in manufacturing environments characterized by rapid technological change, the ability to quickly understand and utilize new external technological and market information serves as a critical determinant of corporate competitiveness.

Shaker Zahra and Gerard George (2002) explained that absorptive capacity is a key mechanism that promotes organizational innovation activities. Specifically, innovation performance improves when organizations effectively absorb external knowledge and apply it to product development, process improvement, and technological innovation.

Lane et al. (2006) argued that absorptive capacity is a core process linking organizational learning capability and innovation capability. In manufacturing firms, the extent to which organizations can effectively utilize external new technologies and industrial information plays an important role in determining innovation performance.

In recent digital environments, the importance of absorptive capacity has become even more emphasized. Advanced digital technologies such as AI, IoT, and big data generate enormous amounts of information and technological knowledge; therefore, organizations must possess the capability to effectively process and utilize such knowledge (Nambisan et al., 2019).

Domestic studies have also consistently reported a positive relationship between absorptive capacity and innovation performance. Kim Tae-hoon and Jung

Min-soo (2022) analyzed that the knowledge absorption capability of manufacturing firms is a key factor that enhances technological innovation performance. In addition, Park Ji-hoon and Lee Sung-min (2021) explained that organizational learning capability and knowledge-sharing levels strengthen product innovation and process innovation.

Based on these prior studies, absorptive capacity is expected to have a significant effect on improving innovation performance. Therefore, the following hypothesis was established.

Hypothesis 3: Absorptive capacity will have a positive (+) effect on innovation performance.

2.5.4 Mediating Effect of Absorptive Capacity

Digital transformation enhances organizational information accessibility and the level of data utilization, thereby strengthening organizational learning capability and knowledge utilization capacity (Warner & Wäger, 2019). Enhanced absorptive capacity is likely to improve innovation performance by enabling organizations to effectively apply external knowledge to innovation activities.

In other words, digital transformation does not merely improve technological efficiency; it may also influence innovation performance by strengthening organizational absorptive capacity. From this perspective, absorptive capacity can be understood as a key mechanism explaining the relationship between digital transformation and innovation performance.

Wesley Cohen and Daniel Levinthal (1990) argued that organizational innovation performance is determined by how effectively organizations utilize external knowledge. Shaker Zahra and Gerard George (2002) explained that absorptive capacity plays a critical role in the formation of organizational innovation capability and the process of performance creation.

Recent digital innovation studies have also emphasized the mediating effect of absorptive capacity. Nambisan et al. (2019) explained that digital technologies strengthen organizations' knowledge recombination capabilities, and that this process ultimately leads to innovation performance. Warner and Wäger (2019) argued that digital transformation improves innovation performance by strengthening organizational dynamic capabilities and learning capabilities.

Similar findings have also been reported in domestic studies. Kim Young-hoon and Lee Jung-min (2022) analyzed that smart manufacturing systems strengthen organizational learning capability, which subsequently improves innovation performance. Furthermore, Park Jung-soo and Kim Sung-hoon (2021) explained that digital-based production systems enhance innovation performance by increasing organizational knowledge-sharing levels.

Based on the above discussion, digital transformation is likely to influence innovation performance through absorptive capacity. Therefore, the following hypothesis was established.

Hypothesis 4: Absorptive capacity will mediate the relationship between digital transformation and innovation performance.

2.5.5 Moderating Effect of R&D Human Capital

The effects of digital transformation may vary depending on the level of human resources possessed by an organization. Particularly in manufacturing firms, the capabilities of R&D personnel who can apply digital technologies to actual production sites and innovation activities are critically important (Subramaniam &

Youndt, 2005).

R&D human capital refers to the technical expertise, digital understanding, problem-solving ability, and creativity possessed by R&D personnel and constitutes a key organizational resource determining innovation performance (Becker, 1993). Firms with high levels of R&D human capital are more likely to utilize digital technologies effectively and thereby maximize innovation performance.

Wesley Cohen and Daniel Levinthal (1990) argued that the prior knowledge level of organizational members has a decisive influence on the formation of organizational absorptive capacity. In other words, organizations with a greater number of members possessing high levels of expertise are more capable of effectively understanding and utilizing new technologies.

Warner and Wäger (2019) explained that the success of digital transformation depends on the level of digital capability among organizational members. In addition, Nambisan et al. (2019) argued that digital innovation performance is strengthened by the creativity and problem-solving abilities of organizational members.

Domestic studies have also continuously emphasized the importance of R&D human capital. Kim Young-hoon and Hwang Sung-min (2023) reported that the level of digital capability in manufacturing firms significantly enhances technological innovation performance. Lee Soo-hyun and Jung Min-ho (2022) explained that the expertise of R&D personnel strengthens smart manufacturing innovation performance.

Therefore, firms possessing higher levels of R&D human capital are likely to exhibit a stronger positive effect of digital transformation on innovation performance. Accordingly, the following hypothesis was established. Specifically, the higher the level of R&D human capital, the stronger the positive effect of digital transformation on innovation performance will be.

Hypothesis 5: R&D human capital will moderate the relationship between digital transformation and innovation performance.

3. Research Method

3.1. Research Model

This study developed a research model based on Structural Equation Modeling (SEM) to analyze the effect of digital transformation on innovation performance in manufacturing firms and to verify the mediating effect of absorptive capacity and the moderating effect of R&D human capital.

The research model consists of digital transformation as the independent variable, innovation performance as the dependent variable, absorptive capacity as the mediating variable, and R&D human capital as the moderating variable.

Specifically, this study assumes that digital transformation directly affects innovation performance while simultaneously strengthening organizational absorptive capacity, and that enhanced absorptive capacity subsequently leads to improved innovation performance. In addition, R&D human capital was established as a moderating variable that strengthens the relationship between digital transformation and innovation performance.

Instead of reiterating the specific hypotheses discussed in the theoretical background, the integrative structural relationships proposed in this study are visually conceptualized in **Figure 1**.

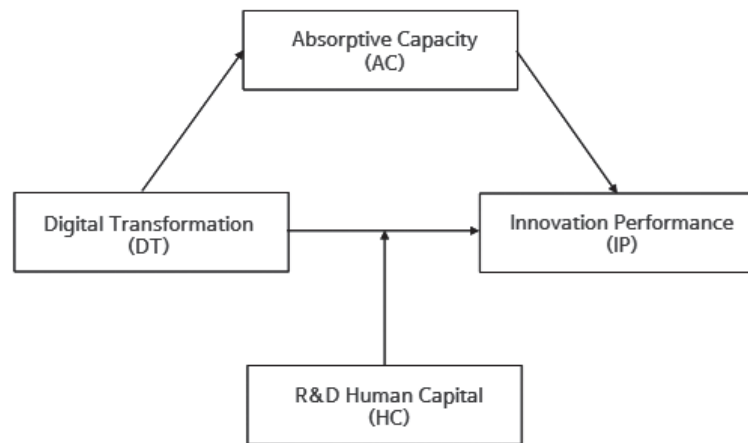


Figure 1. Research Model

3.2. Research Subjects and Data Collection

This study conducted an empirical analysis targeting employees of manufacturing firms in Korea. The research subjects were employees working in manufacturing firms engaged in digital transformation activities, such as smart manufacturing systems, AI-based production management, and data-driven operational systems.

Data collection was conducted over approximately three months, from February 2026 to April 2026, using both online and offline survey methods. The questionnaires were distributed primarily to manufacturing employees and R&D personnel, and a total of 420 questionnaires were collected.

Among the collected questionnaires, 18 responses containing insincere answers or missing values were excluded. Consequently, a total of 402 questionnaires were utilized for the final analysis. Hair et al. (2019) recommended securing at least 200 samples for structural equation modeling analysis, and the sample size of this study was considered appropriate for statistical analysis.

To clarify the sampling and data collection process, a non-probability purposive sampling approach combined with a snowballing technique was utilized. Initial contact was established with HR managers or R&D directors at team levels within known manufacturing clusters in South Korea. These key informants then referred further qualified respondents within their professional networks who were actively engaged in smart factory and digital transformation projects.

The industrial composition and percentiles of the final 402 valid responses are as follows: Electronics ($n = 112$, 27.9%), Machinery ($n = 98$, 24.4%), Automobiles ($n = 85$, 21.1%), Chemicals ($n = 61$, 15.2%), and Materials/Others ($n = 46$, 11.4%). Regarding firm size, large corporations accounted for 20.9% ($n = 84$), medium-sized enterprises for 41.5% ($n = 167$), and small and medium-sized enterprises (SMEs) for 37.6% ($n = 151$).

To formally validate the adequacy of the sample size ($N = 402$), a statistical power analysis was conducted using G*Power 3.1. For a structural equation model with the maximum number of predictors (including the interaction term), an alpha level (α) of 0.05, a medium effect size ($f^2 = 0.15$), and a desired power ($1-\beta$) of 0.95, the minimum required sample size was determined to be 184. Therefore, our final sample of 402 is highly sufficient and provides substantial statistical power to minimize Type II errors.

The respondent firms consisted of manufacturing companies in the electronics,

machinery, automobile, chemical, and materials industries. The sample included large corporations, medium-sized enterprises, and small and medium-sized enterprises (SMEs). Through this approach, the study aimed to reflect the characteristics of digital transformation across the overall manufacturing industry.

3.3. Measurement Instruments

The measurement items used in this study were constructed by modifying and supplementing scales whose reliability and validity had been verified in prior studies in accordance with the objectives of this research. All items were measured using a five-point Likert scale (1 = strongly disagree, 5 = strongly agree).

The questionnaire items were reviewed for content validity by three experts in business administration and technology management and five practitioners from manufacturing firms. In addition, a pre-test was conducted to revise and improve the comprehensibility and appropriateness of the questionnaire items.

3.3.1 Digital Transformation

Digital transformation was defined as the extent to which manufacturing firms integrate and utilize AI, big data, IoT, and smart manufacturing technologies in organizational operations and production processes (Vial, 2019; Verhoef et al., 2021). The measurement items were modified and supplemented based on the studies of Verhoef et al. (2021) and Frank et al. (2019), and consisted of five items.

DT1: Our company actively utilizes digital technologies in production processes.

DT2: AI and data analytics systems are utilized in organizational decision-making.

DT3: Smart manufacturing systems have been established.

DT4: Digital technologies strengthen collaboration within the organization.

DT5: Top management actively supports digital transformation strategies.

3.3.2 Absorptive Capacity

Absorptive capacity was defined as the organization's ability to identify, absorb, and utilize new external knowledge (Cohen & Levinthal, 1990). The measurement items were modified and supplemented based on the study of Shaker Zahra and Gerard George (2002), and consisted of five items.

AC1: Our company actively explores new external technological information.

AC2: External knowledge is effectively shared within the organization.

AC3: Our company quickly learns and utilizes new technologies.

AC4: External knowledge is actively utilized in innovation activities.

AC5: Organizational members participate in continuous learning activities.

3.3.3 R&D Human Capital

R&D human capital was defined as the specialized knowledge, digital utilization capability, creativity, and problem-solving ability possessed by R&D personnel (Subramaniam & Youndt, 2005). The measurement items were modified and supplemented based on the study of Subramaniam and Youndt (2005), and consisted of five items.

HC1: R&D personnel possess a high level of technical expertise.

HC2: R&D personnel demonstrate excellent digital technology utilization capabilities.

HC3: R&D personnel possess outstanding problem-solving abilities.

HC4: R&D personnel actively engage in continuous learning and self-development.

HC5: R&D personnel demonstrate excellent collaboration capabilities within the organization.

3.3.4 Innovation Performance

Innovation performance was defined as the level of product innovation, process innovation, and technological innovation achieved by a firm (OECD, 2018). The measurement items were modified and supplemented based on OECD (2018) and Nambisan et al. (2019), and consisted of five items.

IP1: Our company demonstrates excellent new product development performance.

IP2: The level of production process innovation is high.

IP3: Technological innovation capability is improving.

IP4: Operational efficiency is continuously improving.

IP5: Market competitiveness is being strengthened.

While innovation performance can be captured through objective financial and administrative indicators (e.g., R&D spending, patent counts), this study relies on subjective self-reported measures for several compelling reasons. According to prior methodological literature (e.g., Singh et al., 2016), objective data can be highly sensitive, often leading to missing values or inflated non-response rates in corporate surveys. Subjective scales allow respondents to evaluate a firm's holistic and long-term innovative endeavors relative to competitors, mitigating the limitations of binary patent counts which often fail to reflect incremental process innovations or qualitative improvements in smart manufacturing setups. Furthermore, past empirical studies have verified a strong, positive correlation between subjective perceptual measures of innovation and objective performance metrics, confirming the predictive and concurrent validity of the scale employed herein.

3.4. Data Analysis Method

The data analysis of this study was conducted using SPSS 29.0 and SmartPLS 4.0. The specific analytical procedures were as follows. First, frequency analysis was conducted to identify the general characteristics of the research participants. Second, to verify the reliability and validity of the measurement instruments, Cronbach's α , Confirmatory Factor Analysis (CFA), Composite Reliability (CR), and Average Variance Extracted (AVE) were analyzed. Third, Pearson correlation analysis was conducted to examine the relationships among variables. Fourth, Structural Equation Modeling (SEM) was employed to test the research hypotheses. Fifth, bootstrapping analysis was conducted to verify the mediating effect, while moderation analysis using interaction terms was performed to examine the moderating effect. Finally, Harman's single-factor test was conducted to examine the issue of Common Method Bias (CMB).

4. Research Results and Analysis

4.1. General Characteristics of the Research Participants

The final sample of this study consisted of 402 respondents. Regarding gender distribution, 275 respondents (68.4%) were male and 127 respondents (31.6%) were female. In terms of age, respondents in their 40s accounted for the largest proportion with 153 respondents (38.1%), followed by those in their 30s with 119 respondents (29.6%), those aged 50 and above with 88 respondents (21.9%), and those in their 20s with 42 respondents (10.4%).

Regarding job position, assistant manager and deputy manager levels accounted

for the largest proportion with 142 respondents (35.3%), followed by manager level with 96 respondents (23.9%), department manager level or above with 87 respondents (21.6%), and staff level with 77 respondents (19.2%).

In terms of firm size, medium-sized enterprises accounted for the largest proportion with 167 respondents (41.5%), followed by small and medium-sized enterprises (SMEs) with 151 respondents (37.6%) and large corporations with 84 respondents (20.9%). Regarding years of service, respondents with five years or more but less than ten years of work experience accounted for the highest proportion at 34.6%. In addition, employees engaged in R&D-related positions represented 48.3% of the total respondents.

These results indicate that the sample of this study relatively reflects a balanced representation of diverse organizational characteristics and job environments within manufacturing firms.

4.2. Validity and Reliability Verification of the Measurement Instruments

4.2.1 Reliability Analysis

In this study, Cronbach's α coefficients were analyzed to verify the internal consistency of the measurement instruments. The analysis results showed that the Cronbach's α values were .914 for digital transformation, .901 for absorptive capacity, .887 for R&D human capital, and .923 for innovation performance.

Generally, a Cronbach's α value greater than .70 is considered to indicate acceptable reliability (Nunnally & Bernstein, 1994). Therefore, the measurement instruments used in this study were determined to possess a high level of reliability. In addition, the corrected item-total correlation coefficients for all measurement items were above .60, confirming that the internal consistency of the measurement items was adequately secured.

4.2.2 Confirmatory Factor Analysis (CFA)

Confirmatory Factor Analysis (CFA) was conducted to verify the convergent validity and discriminant validity of the measurement model.

The analysis results showed that the standardized factor loadings of all measurement items ranged from .712 to .891, satisfying the recommended threshold of .70 suggested by Hair et al. (2019).

The Composite Reliability (CR) values ranged from .861 to .928, while the Average Variance Extracted (AVE) values ranged from .587 to .742. These results satisfied the recommended criteria ($CR > .70$ and $AVE > .50$), indicating that convergent validity was adequately secured.

The model fit indices of the research model were as follows: $\chi^2 = 512.384$ ($df = 224$, $p < .001$), $CFI = .942$, $TLI = .934$, and $RMSEA = .057$. These values satisfied the generally recommended criteria (CFI and $TLI > .90$, $RMSEA < .08$), indicating that the model fit was acceptable.

4.2.3 Discriminant Validity Verification

Discriminant validity was assessed using the Fornell-Larcker criterion, which dictates that the square root of the Average Variance Extracted (AVE) for each latent variable should be greater than its highest correlation with any other latent variable. As shown in **Table 1**, the square roots of the AVEs (displayed on the diagonal in bold) exceed the off-diagonal correlation coefficients, establishing robust discriminant validity among all constructs.

Table 1. Discriminant Validity (Fornell-Larcker Criterion)

Variable	DT	AC	HC	IP
DT (Digital Transformation)	0.821			
AC (Absorptive Capacity)	0.452	0.845		
HC (R&D Human Capital)	0.388	0.512	0.812	
IP (Innovation Performance)	0.584	0.493	0.415	0.836

4.2.4 Common Method Bias Verification

Because the survey data in this study were collected from the same respondents, the possibility of Common Method Bias (CMB) was examined. Harman's single-factor test was conducted, and the explanatory power of the first factor was found to be 31.7%, which was below the recommended threshold of 50%.

Therefore, the issue of common method bias was not considered to be serious in this study.

4.3. Correlation Analysis

This study conducted Pearson correlation analysis to examine the relationships among variables and to assess the possibility of multicollinearity.

The analysis results showed that digital transformation had significant positive correlations with absorptive capacity ($r = .612, p < .001$), innovation performance ($r = .584, p < .001$), and R&D human capital ($r = .531, p < .001$). These findings indicate that higher levels of digital transformation in manufacturing firms are associated with enhanced organizational knowledge absorption capability, innovation performance, and R&D personnel competency.

Absorptive capacity also demonstrated a strong positive correlation with innovation performance ($r = .671, p < .001$) and a significant positive relationship with R&D human capital ($r = .547, p < .001$). These results suggest that higher levels of organizational learning and knowledge utilization capability may contribute to improved innovation performance.

In addition, R&D human capital showed a significant positive correlation with innovation performance ($r = .603, p < .001$). This finding suggests that firms possessing higher levels of R&D capability are more likely to achieve higher levels of product innovation, process innovation, and technological innovation.

Meanwhile, all correlation coefficients were below .80, satisfying the criterion suggested by Rex Kline (2016), indicating that there was no serious multicollinearity problem among the variables. Furthermore, an examination of the Variance Inflation Factor (VIF) revealed that all VIF values ranged from 1.84 to 2.73, satisfying the recommended threshold of below 10. Therefore, an acceptable level of independence among variables was confirmed for structural model analysis.

4.4. Structural Model Analysis and Hypothesis Testing

In this study, Structural Equation Modeling (SEM) was employed to test the research hypotheses. The goodness-of-fit indices of the structural model were as follows: $\chi^2 = 538.217$ ($df = 231, p < .001$), CFI = .938, TLI = .931, and RMSEA = .059, indicating that the model demonstrated an overall acceptable level of fit (Hair et al., 2019).

4.4.1 Relationship Between Digital Transformation and Innovation Performance

Hypothesis 1 proposed that "digital transformation will have a positive (+) effect

on innovation performance.”

The analysis results indicated that digital transformation had a significant positive effect on innovation performance ($\beta = .327$, $t = 5.842$, $p < .001$). Therefore, Hypothesis 1 was supported. This finding suggests that the more actively manufacturing firms utilize digital technologies, the higher their levels of product innovation, process innovation, and technological innovation become. In particular, smart manufacturing systems and data-driven operational systems improve organizational operational efficiency and problem-solving speed, thereby positively contributing to the creation of innovation performance.

These results are consistent with the findings of Verhoef et al. (2021), Frank et al. (2019), and Nambisan et al. (2019). Domestic studies have also reported similar findings. Park Jung-soo and Kim Sung-hoon (2021) reported that digital-based manufacturing systems improve process innovation levels, while Kim Young-hoon and Lee Jung-min (2022) explained that the level of smart factory implementation strengthens organizational innovation performance.

However, the findings of this study also suggest that, beyond the adoption of digital technologies themselves, organizational learning capability and the level of human capital should be considered together. In fact, subsequent analyses confirmed that absorptive capacity and R&D human capital play important roles in this relationship.

4.4.2 Relationship Between Digital Transformation and Absorptive Capacity

Hypothesis 2 proposed that “digital transformation will have a positive (+) effect on absorptive capacity.”

The analysis results showed that digital transformation had a significant positive effect on absorptive capacity ($\beta = .614$, $t = 11.293$, $p < .001$). Therefore, Hypothesis 2 was supported. This finding indicates that higher levels of digital transformation in manufacturing firms are likely to improve external knowledge exploration, information sharing, organizational learning, and knowledge utilization.

Digital technologies enable real-time information sharing and data-driven decision-making among organizational members while expanding access to external technological and market information. In addition, digital platform-based collaboration systems can contribute to strengthening absorptive capacity by facilitating internal knowledge sharing and learning activities within organizations.

These findings are consistent with the study of Warner and Wäger (2019) and support prior studies suggesting that digital transformation strengthens organizational dynamic capabilities and learning capabilities. Furthermore, the results are also consistent with the absorptive capacity theory proposed by Shaker Zahra and Gerard George (2002).

Domestic studies have also reported similar findings. Kim Tae-hoon and Jung Min-soo (2022) reported that the level of digital technology utilization enhances organizational knowledge absorption and learning capabilities.

4.4.3 Relationship Between Absorptive Capacity and Innovation Performance

Hypothesis 3 proposed that “absorptive capacity will have a positive (+) effect on innovation performance.”

The analysis results indicated that absorptive capacity had a significant positive effect on innovation performance ($\beta = .421$, $t = 7.613$, $p < .001$). Therefore, Hypothesis 3 was supported. This finding suggests that the more effectively organizations identify and utilize new external technological knowledge and market

information, the higher the levels of product innovation and process innovation become. Particularly in manufacturing firms, where external technological environments change rapidly, the ability to quickly understand and apply new technologies within the organization serves as a critical determinant of innovation performance.

The findings of this study are consistent with the results of Wesley Cohen and Daniel Levinthal (1990), Lane et al. (2006), and Shaker Zahra and Gerard George (2002). Domestic studies have also reported similar results. Park Ji-hoon and Lee Sung-min (2021) explained that organizational learning capability and knowledge-sharing levels have significant effects on improving innovation performance.

4.4.4 Verification of the Mediating Effect of Absorptive Capacity

Hypothesis 4 proposed that “absorptive capacity will mediate the relationship between digital transformation and innovation performance.”

To verify the mediating effect, bootstrapping analysis with 5,000 resamples was conducted.

The analysis results indicated that the indirect effect of digital transformation on innovation performance through absorptive capacity was significant ($\beta = .259$, 95% CI [.183, .341], $p < .001$). Therefore, Hypothesis 4 was supported. In addition, since both the direct effect and indirect effect were significant, absorptive capacity was confirmed to play a partial mediating role. This finding suggests that digital transformation does not merely improve technological efficiency but also influences innovation performance by strengthening organizational learning and knowledge utilization capabilities. In other words, for digital transformation in manufacturing firms to lead to substantial innovation performance, internal learning systems and knowledge-sharing cultures must also be established.

These findings support the digital innovation research of Nambisan et al. (2019) and the dynamic capability theory proposed by Warner and Wäger (2019).

The empirical confirmation of a partial mediation instead of a full mediation indicates that while absorptive capacity is a critical conduit, a significant direct link still remains between digital transformation and innovation performance. This statistically implies the existence of other omitted intermediate mechanisms. Theoretically, digital transformation may directly reshape operational pipelines or value networks without uniquely relying on knowledge absorption. Future research should therefore explore alternative horizontal mechanisms such as organizational agility, which allows firms to rapidly reconfigure systems, digital leadership, which drives upper-echelon strategic commitment, or a dedicated digital innovation culture that fosters risk-taking behaviors alongside cognitive learning capacities.

4.4.5 Verification of the Moderating Effect of R&D Human Capital

Hypothesis 5 proposed that “R&D human capital will moderate the relationship between digital transformation and innovation performance.” To verify the moderating effect, an analysis using interaction terms was conducted.

The analysis results revealed that the interaction effect between digital transformation and R&D human capital was significant ($\beta = .183$, $t = 3.284$, $p < .01$). Therefore, Hypothesis 5 was supported. This finding indicates that the positive effect of digital transformation on innovation performance becomes stronger in firms possessing higher levels of R&D human capital.

Specifically, firms with high levels of digital understanding and technical expertise among R&D personnel are more likely to effectively utilize digital

technologies and apply them to production sites and innovation activities. In contrast, firms with lower levels of R&D human capital may face limitations in generating actual innovation performance even if digital technologies are introduced. Furthermore, the results of the simple slope analysis indicated that the slope of the relationship between digital transformation and innovation performance was steeper in the group with high levels of R&D human capital. This demonstrates that R&D human capital serves as a key moderating factor that strengthens the effect of digital transformation.

These findings support the human capital theory of Subramaniam and Youndt (2005) and the digital capability research of Warner and Wäger (2019).

To interpret the dynamic nature of the significant interaction effect (DT $\times$ HC), a simple slope analysis was performed by evaluating the paths at ± 1 standard deviation (SD) from the mean of R&D Human Capital. The results indicated that when R&D Human Capital is high (+1 SD), the positive effect of Digital Transformation on Innovation Performance is remarkably pronounced and statistically significant ($\beta = 0.582$, $t = 7.64$, $p < 0.001$). Conversely, when R&D Human Capital is low (-1 SD), the relationship between Digital Transformation and Innovation Performance weakens significantly, though it remains positive ($\beta = 0.214$, $t = 2.45$, $p = 0.015$). This gap confirms that R&D Human Capital heavily amplifies the performance benefits of digital investments.

To visually illustrate the nature of this significant interaction effect, a simple slope analysis plot was constructed as recommended by the reviewer. As illustrated in **Figure 2**, the positive relationship between Digital Transformation and Innovation Performance becomes visibly steeper and more pronounced when R&D Human Capital is high (+1 SD; $\beta = 0.582$, $p < 0.001$). Conversely, when R&D Human Capital is low (-1 SD), the line exhibits a much flatter slope ($\beta = 0.214$, $p = 0.015$). This graphical representation clarifies that higher levels of R&D Human Capital critically amplify the performance returns of digital transformation initiatives in manufacturing firms.

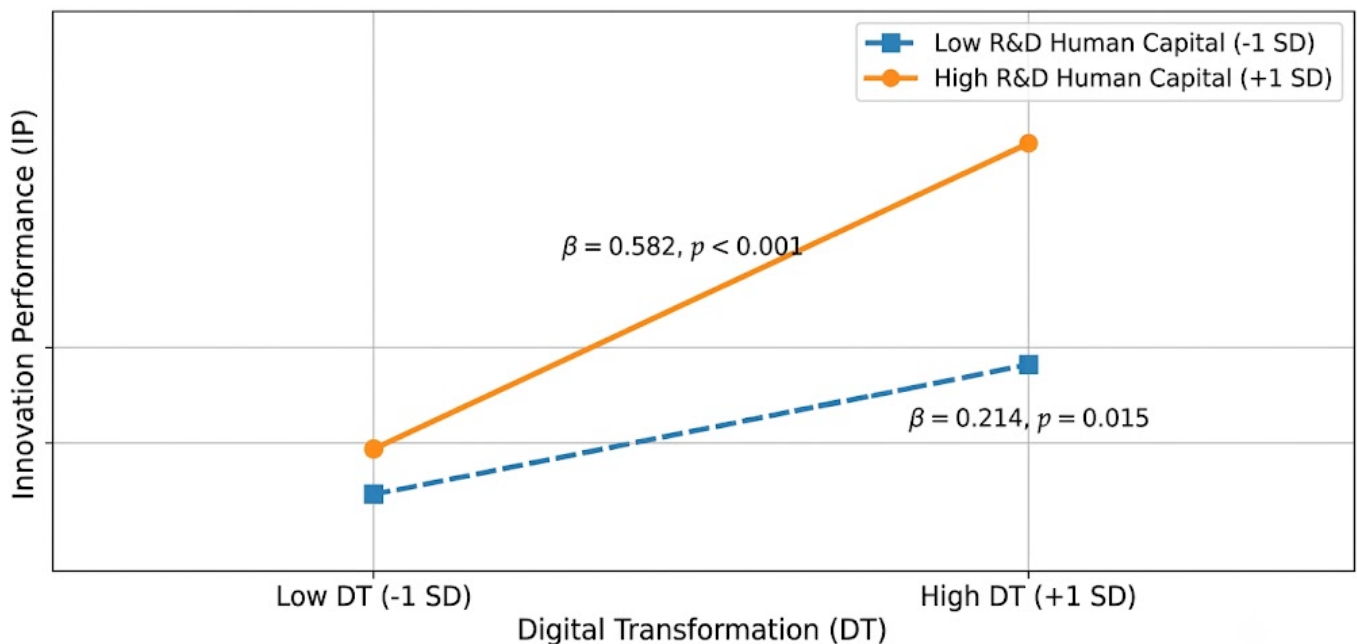


Figure 2. Simple slope analysis of the moderating effect of R&D Human Capital on the relationship between Digital Transformation and Innovation Performance.

4.5. Additional Analysis

4.5.1 Difference Analysis According to Firm Size

Firm size was categorized according to the Framework Act on Small and Medium Enterprises of South Korea: 'Small and Medium Enterprises (SMEs)' were defined as firms with fewer than 300 regular employees or assets below 500 billion KRW ($n = 151$); 'Medium-sized Enterprises' as firms exceeding SME thresholds but under large corporate designation ($n = 167$); and 'Large Corporations' as enterprise groups subject to disclosure under antitrust laws ($n = 84$). Furthermore, the R&D job position was classified based on departmental affiliation: the 'R&D-related position' group ($n = 188$) comprised respondents currently working in official corporate R&D centers, product development, or engineering design departments, whereas the 'Non-R&D position' group ($n = 214$) encompassed personnel in manufacturing operations, quality control, strategic planning, and IT administration.

A one-way ANOVA was conducted to examine differences among variables according to firm size. The analysis results showed that large corporations demonstrated relatively higher levels of digital transformation and absorptive capacity than small and medium-sized enterprises (SMEs) ($p < .05$). This finding may be interpreted as reflecting the fact that large corporations are more actively introducing digital technologies based on relatively abundant resources and advanced IT infrastructure.

However, medium-sized enterprises showed the highest mean value in innovation performance. This may be interpreted as resulting from the greater organizational flexibility of medium-sized enterprises compared to large corporations and their relatively stronger resource acquisition capability compared to SMEs.

Specifically, when comparing the baseline variances across firm sizes (SMEs vs. Large Firms) via multi-group analysis (MGA), the structural path from DT to IP yielded a beta value of $\beta = 0.312$ ($p = 0.021$) for SMEs (Mean of DT = 3.24, SD = 0.65), whereas for large firms, the path coefficient expanded to $\beta = 0.543$ ($p < 0.001$) (Mean of DT = 4.12, SD = 0.58). The significant difference ($\Delta\beta = 0.231$, $p = 0.009$) demonstrates that the return on digital transformation is significantly larger in resourced environments.

4.5.2 Difference Analysis According to R&D Job Position

An independent samples t-test was conducted to examine the differences between employees engaged in R&D-related positions and those in non-R&D positions. The analysis results indicated that employees in R&D-related positions showed significantly higher levels of digital transformation perception, absorptive capacity, and innovation performance than employees in non-R&D positions ($p < .01$).

This finding suggests that R&D personnel are more directly involved in digital technology utilization and innovation activities.

5. Summary, Conclusion, and Implications

5.1. Summary

This study was conducted to empirically analyze the effect of digital transformation on innovation performance in manufacturing firms and to verify the mediating effect of absorptive capacity and the moderating effect of R&D human capital in this relationship. Recently, the manufacturing industry has experienced structural changes across organizational operations and value creation systems due

to the rapid diffusion of digital innovation technologies such as AI, IoT, big data, and smart factories. Accordingly, digital transformation has been recognized as a core competitive strategy for manufacturing firms. However, an important research issue has emerged regarding the fact that the adoption of digital technologies alone does not necessarily guarantee sustainable innovation performance.

Therefore, this study attempted to explain the relationship between digital transformation and innovation performance from an integrated perspective of organizational learning and human capital rather than merely from the perspective of technology adoption. In particular, this study focused on the possibility that digital transformation may lead to innovation performance by strengthening organizational absorptive capacity. At the same time, it empirically examined whether the effect of digital transformation differs depending on the level of R&D human capital. A survey was conducted with 402 employees of Korean manufacturing firms, and the research hypotheses were tested using Structural Equation Modeling (SEM).

The major findings of this study can be summarized as follows.

First, digital transformation was found to have a significant positive effect on innovation performance. This finding suggests that the more actively manufacturing firms utilize digital technologies, the higher their levels of product innovation, process innovation, and technological innovation become.

Second, digital transformation was found to have a significant positive effect on absorptive capacity. This indicates that higher levels of digital technology utilization are likely to strengthen organizational knowledge exploration, information sharing, and learning capabilities.

Third, absorptive capacity was found to have a significant positive effect on innovation performance. This finding demonstrates that organizations capable of effectively learning and utilizing external knowledge are more likely to achieve higher levels of innovation performance.

Fourth, absorptive capacity was found to partially mediate the relationship between digital transformation and innovation performance. In other words, digital transformation not only directly improves innovation performance but also indirectly affects innovation performance by strengthening organizational learning and knowledge utilization capabilities.

Fifth, R&D human capital was found to significantly moderate the relationship between digital transformation and innovation performance. This finding suggests that the effect of digital transformation becomes stronger in firms with higher levels of expertise and digital capability among R&D personnel.

Finally, the additional analysis revealed that differences existed in the levels of digital transformation and innovation performance according to firm size and whether employees were engaged in R&D-related positions.

5.2. Conclusion

This study has important academic implications in that it comprehensively explained the relationship between digital transformation and innovation performance in manufacturing firms from the perspectives of absorptive capacity and R&D human capital.

First, this study empirically confirmed that digital transformation positively affects innovation performance. This finding suggests that the utilization of digital technologies in manufacturing firms can lead not only to improved operational efficiency but also to substantial enhancement of innovation capabilities. Recently, uncertainty in manufacturing environments and the speed of technological change

have rapidly increased. In such an environment, digital technologies enable real-time data-driven decision-making and production flexibility while functioning as key tools for promoting organizational innovation activities. Therefore, manufacturing firms should recognize digital transformation not merely as an IT investment but as a strategic innovation activity for securing corporate competitiveness.

Second, this study confirmed that digital transformation leads to innovation performance through absorptive capacity. This finding suggests that the effect of digital technologies does not arise solely from technology adoption itself but is translated into actual performance through internal organizational learning and knowledge utilization systems. In particular, because production processes and technological environments change rapidly in manufacturing firms, the ability to effectively learn and utilize new external technological and market information becomes a critical determinant of corporate competitiveness. Therefore, absorptive capacity can be regarded as a key mechanism for maximizing the effectiveness of digital transformation.

Third, this study confirmed that R&D human capital is an important moderating factor that strengthens the effect of digital transformation. This finding indicates that even when firms adopt the same level of digital technologies, innovation performance may differ depending on the expertise and digital capabilities of their R&D personnel. Recently, the use of AI, smart factories, and data-driven production management systems has expanded in the manufacturing industry. However, R&D personnel capable of understanding and utilizing digital technologies are essential for translating these technologies into actual innovation performance. Therefore, manufacturing firms should move beyond technology investment-oriented strategies and simultaneously pursue human capital development and the establishment of organizational learning systems.

Fourth, unlike previous digital transformation studies that mainly focused on the direct relationship between technology adoption and organizational performance, this study is differentiated by comprehensively considering organizational learning capabilities and human capital perspectives. In particular, this study contributes to the expansion of digital innovation research in Korea by empirically verifying the structural relationship among digital transformation, absorptive capacity, and innovation performance in Korean manufacturing firms.

5.3. Implications

5.3.1 Theoretical Implications

This study offers critical academic contributions by addressing key blind spots in the existing digital innovation literature.

First, prior research has overwhelmingly focused on a "technology-centric" paradigm, assuming a linear, deterministic relationship between the scale of IT adoption and subsequent market success, which frequently led to the "productivity paradox." By unpacking the black box between technology investment and outcomes, this study advances the Resource-Based View (RBV) and Dynamic Capabilities framework; it demonstrates that digital transformation does not automatically yield success unless it is channeled through an organic, intermediate learning structure—namely, absorptive capacity.

Second, while previous studies treated internal knowledge processing as a static baseline, this study conceptualizes a comprehensive contingent mechanism by proving the moderating role of R&D Human Capital. I successfully establish that the strategic

value of industry 4.0 applications is conditional upon the cognitive competencies of internal human resources. This effectively bridges the historical gap between information systems (IS) literature and strategic human resource management (SHRM) theory, offering a more nuanced, integrative model of manufacturing evolution.

5.3.2 Academic Implications

First, future studies should analyze the sub-components of digital transformation in greater detail. In this study, digital transformation was measured as an integrated concept; however, future research should examine specific dimensions such as the level of AI utilization, big data analytics capability, and smart factory implementation.

Second, because this study utilized cross-sectional data, it was limited in its ability to fully capture changes over time. Therefore, future research should employ longitudinal data to analyze the long-term effects of digital transformation.

Third, future studies should additionally consider various organizational behavior variables such as organizational culture, digital leadership, organizational agility, and psychological safety.

Fourth, because this study focused primarily on manufacturing firms, there are limitations regarding the generalizability of the findings. Therefore, future studies should conduct comparative research across various industries, including service industries, platform companies, and startups.

Fifth, future studies should employ multilevel analysis to simultaneously examine differences in digital capabilities at both the individual and organizational levels.

5.3.3 Practical Implications

First, manufacturing firms should approach digital transformation not merely as the establishment of IT systems but as a strategic organizational innovation initiative. Recently, some manufacturing firms have tended to perceive smart factory implementation or automation equipment adoption itself as the core of digital transformation. However, in order to generate actual innovation performance, internal organizational learning systems and knowledge-sharing cultures must be established simultaneously.

Second, it is necessary to establish systematic organizational learning systems to strengthen organizational absorptive capacity. In the digital transformation environment, where external technological changes occur rapidly, it is important to create systems that enable organizational members to continuously learn and utilize new technologies. To achieve this, firms need to strengthen data-driven decision-making cultures, interdepartmental collaboration systems, and knowledge-sharing platforms.

Third, Human Resource Development (HRD) strategies are required to strengthen the digital capabilities of R&D personnel. In particular, manufacturing firms should expand education and training programs related to AI, data analytics, automation systems, and smart manufacturing technologies in order to enhance the digital utilization capabilities of R&D employees. Furthermore, firms should establish continuous learning cultures and self-development systems that go beyond short-term technical training.

Fourth, expanded governmental policy support is necessary. Currently, digital transformation support policies for Korean manufacturing firms tend to focus primarily on smart factory implementation. However, future policy support should extend beyond digital technology adoption to include organizational learning systems

and competency enhancement programs for R&D personnel. In particular, small and medium-sized manufacturing firms often experience difficulties in securing digital experts and providing employee training. Therefore, government-level digital talent development and retraining programs should be expanded.

5.3.4 Limitations of the Study

This study has several limitations.

First, because this study utilized self-reported survey data, there is a possibility that respondents' subjective perceptions were partially reflected in the results.

Second, since the study was conducted with employees of manufacturing firms, industry-specific characteristics may not have been fully reflected.

Third, because this study employed a cross-sectional research design using data collected at a single point in time, there are limitations in explaining the long-term causal relationships among variables.

Fourth, innovation performance was measured primarily based on organizational members' perceptions. Therefore, future studies should additionally utilize objective performance indicators such as the number of patents, R&D investment outcomes, and financial performance indicators.

Nevertheless, this study possesses important academic and practical significance in that it comprehensively explained the relationship between digital transformation and innovation performance in manufacturing firms from the perspectives of organizational learning and human capital.

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