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# What Drives Smart Tech Choices? Comparing Manufacturing and Service Firms' Journey into Intelligent IT

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This study explores the roles of digital literacy and privacy concerns in shaping the intention to use intelligent information technology (IIT) across the manufacturing and service sectors, a key consideration for digital transformation in contemporary businesses. By surveying 316 mid- to senior-level managers from technology-based companies, split evenly between these two sectors, and employing structural equation modeling and multi-group analysis, this research integrates digital literacy and privacy concerns within the established Technology Acceptance Model (TAM) framework. The findings reveal that digital literacy (DL) universally and positively influences the intention to use IIT (ITU) in both sectors, though the underlying mechanisms differ significantly. In the manufacturing sector, DL directly influenced ITU. Conversely, digital information sharing lacked a direct effect on ITU but demonstrated a fully mediated effect through perceived usefulness (PU), thereby indirectly influencing ITU. In the service sector, higher DL amplified privacy concerns (PC); this privacy concern negatively moderated the effect of DL on PU, and consequently, PC also negatively moderated the overall impact of DL on ITU through PU. Notably, the effect of perceived ease of use (PEOU) on ITU varies significantly between the sectors. The study concludes that while digital literacy is crucial in both contexts, significant structural differences exist in the relationships among perceived ease of use, perceived usefulness, privacy concerns, and the ultimate intention to use IIT. These insights underscore the need for sector-specific strategies to ensure the effective adoption of IIT during digital transformation.

Keyword: Intelligent Information Technology, Technology Acceptance Model, Digital Literacy, Privacy Concern

## Ⅰ. Introduction

Intelligent information technology (IIT) refers to advanced computing technologies capable of performing cognitive functions typically associated with human intelligence, such as learning, inference, decision-making, and problem-solving, through leveraging sophisticated algorithms and data-driven method-

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ologies (Aleksander, 2004). Specifically, IIT encompasses technologies like artificial intelligence (AI), of which significantly enhance operational efficiency, strategic decision-making, and innovation across industries (Guo et al., 2019). Its attributes—innovativeness, potential for change, abstractness, and uncertainty—are expected to significantly influence societal dynamics both positively and negatively. IIT's application, which spans multiple sectors, predominantly in advanced countries, enhances the core competencies in new business models (Guo et al., 2019). Aleksander (2004) argues that advances in IIT, particularly AI, represent genuine progress in computational capability rather than mere rebranding, as they continue to address previously unforeseen challenges, significantly influencing mainstream information technology. Thus, IIT's application is not just a laboratory-based experiment disconnected from pragmatic computing but a fundamental enabler of organizational competitiveness and innovation capacity. However, studies on the intention to use IIT (ITU) are limited, particularly in technology-based companies (Alsetoohy et al., 2019), underscoring the need for in-depth research to understand usage intentions and develop effective services (Ul-Hameed et al., 2019; McKnight et al., 2020).

Extensive research has confirmed that the technology acceptance model (TAM) is a robust framework for understanding the acceptance and usage of IIT (Gefen and Straub, 2000). In line with the focus of this study, the TAM's effectiveness in predicting usage intentions and behaviors makes it ideal for exploring the adoption of IIT in technology-based companies (Koufaris and Hampton-Sosa, 2004). This research extends the TAM by incorporating factors such as digital literacy (DL), digital information sharing (DIS), and privacy concerns (PC), which are crucial for technology adoption.

This study acknowledges sector-specific variations in technology adoption and builds on Pavitt's (Pavitt, 1984) assertion that innovation patterns differ between the manufacturing and service sectors. It critiques the traditional assimilation approach, which views these sectors as homogeneous, following Gadrey, Gallouj, and Weinstein (Gadrey et al., 1995), which posits distinct innovation forms in services compared with in manufacturing. Previous literature highlights that digital transformation significantly reshapes manufacturing processes by leveraging advanced digital tools, such as smart manufacturing and Industry 4.0 technologies, thus dramatically improving productivity, efficiency, and flexibility (Savastano et al., 2019). Conversely, digital transformation in the service sector frequently involves enhancing organizational processes, customer interactions, and innovative business practices through ICT applications (Arnaud et al., 2025). Prior studies have also highlighted significant differences in the adoption of information and communication technology (ICT) in service and manufacturing sectors (Dholakia et al., 1991; Chatterjee et al., 2021). Despite these distinctions, existing research rarely examines why and how certain critical factors, such as digital literacy, digital information sharing, and privacy concerns, differently influence the adoption of IIT across manufacturing and service sectors. The study's objective is to delineate these sector-specific differences and suggest practical and policy recommendations based on the varying ITU in manufacturing and service sectors. By examining business professionals' perceptions of and attitudes toward their operational use, this study aims to understand their intentions for practical applications and strives to identify the factors influencing their operational acceptance.

# Ⅱ. Theoretical background

## 2.1 Technology Acceptance Model (TAM) and Its Extensions

The Technology Acceptance Model (TAM), developed by Davis (1989), provides a robust theoretical framework to explain and predict user acceptance of information technology based on two fundamental constructs: perceived usefulness (PU) and perceived ease of use (PEOU) (Sprenger and Schwaninger, 2021; Venkatesh and Bala, 2008). Recognizing the limitations of the original TAM in addressing diverse technological contexts and adoption factors, subsequent extensions of TAM, such as TAM2 (Venkatesh and Davis, 2000), TAM3 (Venkatesh and Bala, 2008), and UTAUT (Venkatesh et al., 2003), introduced antecedent variables to enhance explanatory and predictive power.

In this study, three critical variables—digital literacy, digital information sharing, and privacy concern—are integrated into the original TAM framework (Venkatesh and Bala, 2008) mapping onto individual differences, social influence, and system characteristics, respectively, to more effectively capture the unique dynamics of IIT adoption. Digital literacy, defined as the ability to find, evaluate, and utilize digital content, is fundamental for engaging effectively with IIT. In terms of TAM antecedents, digital literacy aligns with individual differences, representing the personal capabilities necessary to effectively utilize new technologies (Venkatesh and Bala, 2008). Hamutoğlu et al. emphasize that digital literacy equips individuals to participate in the digital society (Hamutoglu et al., 2020), enhancing their perceptions of usefulness and ease of use (Venkatesh and Bala, 2008).

DIS reflects the collaborative and data-sharing behaviors essential in IIT environments.

Research on Knowledge Management Systems highlights how technologies supporting information sharing facilitate knowledge creation and organizational performance (Thomas et al., 2008). These insights underscore the role of DIS in influencing PU and overall acceptance of IIT, as individuals who actively share information are more likely to find IIT beneficial and integrate it into their workflows.

Privacy concern, a growing issue in the digital landscape, reflects individuals' apprehension about risks to their personal data. Zostant and Chataut discuss the ethical implications of privacy in the context of digital technologies, linking heightened concerns to hesitancy in adopting data-intensive systems (Zostant and Chataut, 2023).

By addressing these factors, the extended TAM framework provides a comprehensive and theoretically coherent model that aligns individual capabilities, social behaviors, and ethical considerations with the traditional constructs. This structured mapping of antecedents onto clearly defined theoretical categories such as individual differences, social influence, and system characteristics offers valuable insights for understanding and promoting IIT acceptance.

### 2.2 Digital literacy, Digital information sharing and Privacy Concern

This study aims to analyze the relationship between DL, DIS, PC, which are the four major antecedent factor groups proposed in the TAM basic framework (Venkatesh and Bala, 2008), individual differences, system characteristics, social influence, and facilitating conditions as proposed in the TAM framework (Venkatesh and Bala, 2008).

First, DL is mapped to individual differences in TAM. DL refers to the knowledge, skills, and abilities necessary to interact effectively with digital technology (Khan and Vuopala, 2019) and possesses characteristics that reflect users' self-efficacy and personal capabilities (Venkatesh and Bala, 2008). Since Gilster's (1997) initial research, the concept of DL has expanded to include the ability to discover, evaluate, create, and communicate information using digital mean, encompassing cognitive and technical competencies (Pool, 1997). Especially in the context of the Fourth Industrial Revolution, where information and knowledge management are central, DL is regarded as a core element that activates the creation and sharing of digital content. Pool (1997) defined DL as the ability to understand, combine, and use information obtained through computers. This study synthesizes these definitions to define DL as "the ability to collect, analyze, and use information for problem-solving through the use of digital devices." Second, DIS is mapped to the social influence factor. DIS refers to activities such as sharing self-generated or others' content online, characterized by social behavior where multiple participants interact to form a common information pool (Chen and Hung, 2010; Jadin et al., 2013). Such information sharing activities promote collaboration among organizational members, prevent redundant resource allocation, and enhance organizational efficiency (Han and Kang, 2007). In other words, DIS contributes to the formation of social norms through information sharing and interaction within a group, thereby closely aligning with the social influence factors of TAM. Accordingly, this study expects that DIS will positively influence individual technology adoption intentions by fostering user interaction and information sharing culture within the social influence category of TAM. Third, PC can be classified as system characteristics. The rapid development of Generative AI technology has significantly increased concerns about privacy infringement and personal data protection (Gupta et al., 2023). Such privacy concerns are directly linked to system characteristics such as data management policies and information protection levels when adopting AI-based technologies (Vardalachakis et al., 2024). These concerns are evident in practice; for example, evidence from data-intensive financial services shows that perceived risk—covering security/privacy, performance, and financial risk—depresses performance and effort expectancies, implying that privacy-related concerns can indirectly dampen PU and PEOU unless mitigated (Kim and Kim, 2019). Golda et al. (2024) also emphasize that a multidimensional strategy involving users, developers, organizations, and policymakers is essential to address the privacy threats posed by Generative AI. In other words, PC is directly related to system characteristics such as system security, reliability, and privacy protection levels, and can therefore be classified as a system characteristic factor in TAM. This study proposes PC as a core element of system characteristics within the TAM framework to evaluate its influence on users' system acceptance intentions.

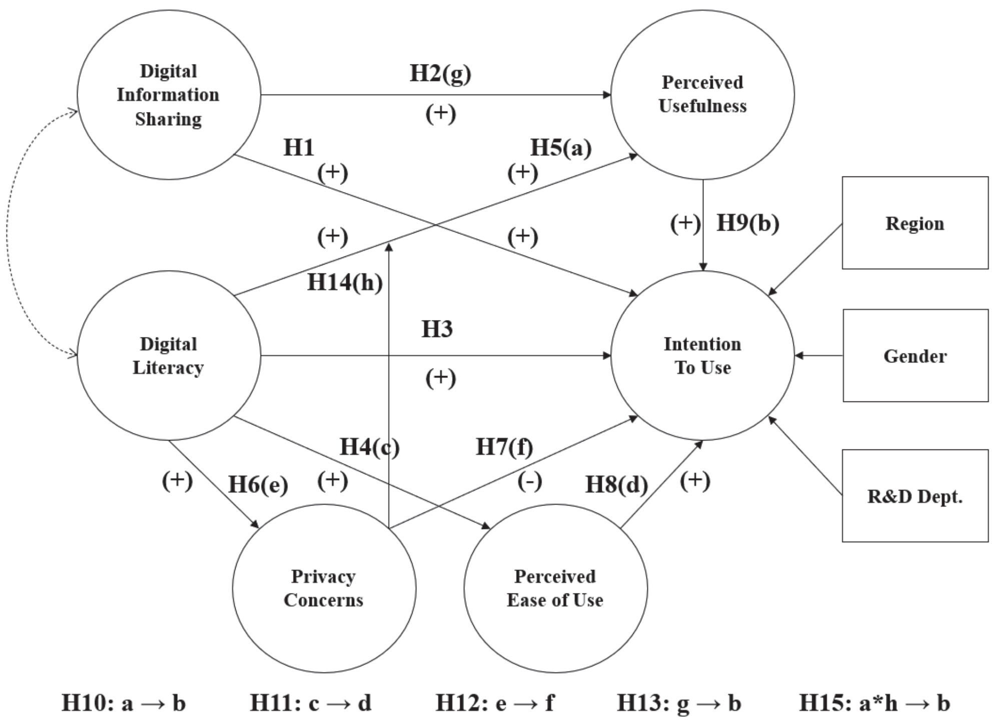
### 2.3 Technology-based manufacturing and service sectors

Technology-based companies that leverage their proprietary technology for profit through product manufacturing or service development feature high value added and growth potential (Cho et al., 2017). South Korea, known globally for its advanced manufacturing capabilities and strong ICT infrastructure, actively supports technology-based companies to drive economic growth and job creation. Similarly, Europe also distinguishes knowledge-based manufacturing from service sectors, recognizing their distinct innovation dynamics in policy and statistical analyses. For example, previous research indicates notable differences in innovation activities between services and manufacturing in countries like Europe (Djellal and and Gallouj, 1999; Hollenstein, 2003; Cainelli et al., 2006; Pires et al., 2008), suggesting the need to compare these sectors to better understand cooperation patterns in innovation and technology adoption. In particular, this study explores the sector-specific implications of digital literacy, digital information sharing, and privacy concerns—factors deemed crucial yet underexamined across these two sectors. Digital literacy significantly influences employees' adaptability and their capacity for innovation, enabling successful integration of digital tools (Arnaud et al., 2025). Additionally, digital information sharing is vital for enhancing collaborative practices and organizational performance, especially where processes heavily depend on real-time data exchange, a common characteristic of digital transformation in manufacturing (Savastano et al., 2019). Furthermore, privacy concerns emerge prominently due to intensified data-driven environments in both sectors, potentially hindering the acceptance of IIT by affecting user trust and perceived risks (Arnaud et al., 2025). Therefore, understanding these factors' sector-specific implications provides novel insights and addresses existing gaps in the literature, highlighting the unique value and originality of the present study.

# Ⅲ. Research design

## 3.1 Model and hypotheses

Grounded in an extended Technology Acceptance Model (TAM), this study investigates the ITU of intelligent information technology. The proposed model (Figure 1) features DIS and DL as independent variables, with PU, PEOU, and PC acting as mediators. Addressing a gap in integrated research, the study's primary contribution lies in examining sector type (manufacturing vs. service) as a key moderator, which offers practical insights for advanced economies. The model, which includes R&D center presence, headquarters location, and gender as controls, is tested in the context of South Korea, an ideal setting given its advanced ICT and balanced industrial structure. This comparative analysis offers practical insights for advanced countries facing challenges such as aging populations, labor shortages, and declining competitiveness. We empirically validate the framework first by using covariance-based structural equation modeling (CB-SEM) to test the path hypotheses, and subsequently by employing partial least squares SEM (PLS-SEM) for the importance-performance map (IPMA) and multi-group analyses (MGA) (Hair, 2022).




〈Figure 1〉 Research model

### 3.2 Research on DIS, PU, and ITU

With ICT advancements, consumers have found it increasingly easier to share digital information. Individuals tend to share information that they find valuable and useful, particularly in environments perceived as having high entertainment and informational value (Shang et al., 2020). In today's collaborative work environments, the ease of DIS is a crucial determinant of a technology's perceived value. The positive relationship between DIS and PU can be understood through the lens of task requirements and organizational effectiveness.

Jarvenpaa and Staples (2000) found that in environments with high task interdependence—where an individual's work is dependent on the efforts of others, the need to communicate and share information becomes critical for performance. Collaborative technologies that facilitate easy information exchange are thus essential for meeting these interdependent task needs.

Building on this, a technology with superior DIS capabilities directly enables users to perform these vital collaborative tasks more efficiently. According to the foundational definition of the Technology Acceptance Model (TAM), PU is "the degree to which a person believes that using a particular system would enhance his or her job performance" (Davis, 1989). Therefore, by empowering users to fulfill the critical need for information sharing in interdependent settings, a technology high in DIS directly enhances their perceived job performance, leading to a higher PU. This logic suggests a direct, positive influence of information sharing capabilities on the perceived utility of a technology.

*Hypothesis 1: DIS positively influences users' ITU of IIT.*

*Hypothesis 2: DIS positively influences users' PU of IIT.*

### 3.3 Research on DL, PU, PEOU, and ITU

In the era of digital transformation, the role of employees and their capabilities is paramount. DL defined as a competence consisting of the abilities of employees to utilize digital technologies in work-related practices, is a critical antecedent to technology acceptance. Recent research applying the Theory of Planned Behavior (TPB) provides a robust framework for understanding how DL influences user perceptions and intentions.

Specifically, Cetindamar et al. (2021) conceptualize DL as a form of Perceived Behavioral Control (PBC). This is conceptually analogous to PEOU in the TAM framework. Therefore, as an employee's DL increases, so does their perceived ability to control and manage the technology, which in turn enhances PEOU. The same study also demonstrates that DL positively influences the optimistic dimensions of Technology Readiness (TR), such as the belief that technology offers increased control, flexibility, and efficiency in one's work. This positive outlook on performance-enhancing outcomes is functionally equivalent to an increase in PU. Thus, higher DL leads to a stronger belief in technology's utility.

While the primary impact of DL on technology use is often mediated through these perceptions of ease of use and usefulness, it can also foster a general confidence that directly encourages an ITU. Based on these mechanisms, we propose the following hypotheses.

*Hypothesis 3: DL positively influences users' ITU of IIT.*

*Hypothesis 4: DL positively influences users' PEOU of IIT.*

*Hypothesis 5: DL positively influences users' PU of IIT.*

### 3.4 Research on DL and PC

With the advancement of ICT, substantial amounts of data are being collected and stored as big data, facilitating various value-creation activities. As users increasingly engage with digital technologies, they become more aware of the potential misuse of their personal information, particularly in the context of AI-driven intelligent systems. This awareness, enhanced through digital literacy, often results in elevated PC (Lim, 2012; Moon, 2014; Park, 2014).

This dynamic is well-explained by Privacy Calculus Theory, which posits that users weigh the perceived benefits of technology against the perceived risks of privacy invasion (Carlsson and Nilsson, 2023). DL enables individuals to better understand how data is collected, analyzed, and utilized—enhancing perceived benefits, but also sensitizing them to potential risks. Especially in data-intensive environments, users with higher DL are more likely to exhibit heightened privacy concerns as they can more accurately assess potential privacy threats.

According to this theory, such concerns act as significant psychological barriers to technology adoption. As users perceive greater risk of privacy invasion, their intention to use IIT may diminish. This relationship may vary across sectors: in service industries, where customer-facing technologies require handling more personal data, the impact of PC may be more pronounced than in manufacturing sectors.

*Hypothesis 6: DL positively influences PC about IIT.*

*Hypothesis 7: PC negatively influences users' ITU of IIT.*

### 3.5 Research on PU, PEOU, and ITU

The relationships between PU, PEOU, and ITU form the core of the Technology Acceptance Model (TAM) and have been validated as the most robust predictors of technology adoption across countless studies. The primary driver of this model is the link between PU and ITU. As Davis (1989) originally posited, individuals form an intention to use a system because they believe it will enhance their job performance; this belief in the technology's utility is the most fundamental determinant of acceptance.

PEOU also plays a critical dual role. It directly influences ITU, as technologies that require less cognitive effort are intrinsically more appealing to users. Furthermore, PEOU is a significant antecedent to PU; a system that is easier to operate allows users to more readily discover and leverage its useful functionalities, thereby enhancing its perceived usefulness (Davis, 1989). Evidence from an AI adoption study also corroborates the core TAM pathways from PEOU to intention through PU within AI service contexts, while highlighting that ease of use may not directly translate into intention absent perceived usefulness (Lee and Kim, 2022). This mechanism is consistent with recent serviceinterface results where usability-enhancing tools such as social presence and selfreference strengthen acceptance pathways, particularly when humanlike interaction is salient (Shin and Sohn, 2024). The consistent validation of these foundational relationships in diverse contexts, such as mobile applications and specialized platforms (Joo, 2018; Pae, 2018), provides a solid basis for the following hypotheses.

*Hypothesis 8: Users' PEOU of IIT influences positively their ITU.*

*Hypothesis 9: Users' PU of IIT positively influences their ITU.*

### 3.6 Mediating effects of PC, PU, and PEOU on ITU

Building upon the direct relationships mentioned above, this study hypothesizes that PU, PEOU, and PC act as crucial mediating mechanisms. These variables explain how the effects of DL and DIS are translated into ITU.

Specifically, higher DL is expected to enhance users' competence, which in turn increases both PEOU by reducing cognitive effort and PU by enabling users to unlock more features. These positive perceptions, as core TAM tenets, then foster greater ITU. Conversely, DL can also heighten awareness of data risks, increasing PC, which then acts as a psychological barrier that suppresses ITU. Finally, the enhanced functionality of DIS contributes to better performance on interdependent tasks, which elevates PU and subsequently drives ITU. These mediating pathways are critical for a nuanced understanding of technology acceptance.

*Hypothesis 10: Users' PU of IIT positively mediates the relationship between DL and ITU.*

*Hypothesis 11: Users' PEOU of IIT positively mediates the relationship between DL and ITU.*

*Hypothesis 12: Users' PC of IIT negatively mediates the relationship between DL and ITU.*

*Hypothesis 13: Users' PU of IIT positively mediates the relationship between DIS and ITU.*

### 3.7 Moderating effect of sector type and PC

A study examining the impact of non-technical innovation on technological innovation performance found significant differences between the manufacturing and service sectors (Lee, 2016). This sectoral distinction is particularly salient when considering the adoption of intelligent information technologies, as the nature of data and user interaction differs fundamentally.

The service sector, for instance, is characterized by innovation that is highly interactive and relational, emphasizing "soft" aspects like close cooperation with customers and organizational changes (Tether, 2005). Such deep-seated customer interaction inherently involves the handling of personal and often sensitive data, making PC a primary barrier to user acceptance.

Conversely, while the manufacturing sector has traditionally focused on operational data, the rise of smart factories in Industry 4.0 introduces new privacy considerations related to employee monitoring, complex supply chains, and B2B data exchange (Tang et al., 2025).

Therefore, PC are not a uniform construct across industries but rather a context-dependent factor whose moderating influence is shaped by the sectoral environment. The increasing importance of privacy in the era of Generative AI further amplifies these differences (Gupta et al., 2023; Golda et al., 2024). Given these dynamics, we argue that PC play a critical moderating role in the relationships between PEOU, DL, PU, and subsequent ITU. Specifically, we propose hypotheses H14 and H15 to test how privacy concerns moderate the pathways to technology acceptance, anticipating that this moderation effect may manifest differently across sectors.

*Hypothesis 14: PCs moderate the relationship between PEOU and ITU of the IIT, such that higher PC weaken the positive relationship between PEOU and ITU.*

*Hypothesis 15: PCs moderate the indirect relationship between DL and ITU of the IIT via PU, such that higher privacy concerns weaken the positive indirect relationship between DL and ITU through PU.*

# Ⅳ. Empirical analysis

## 4.1 General characteristics of the sample

The survey targeted 316 employees from advanced technology-based companies, evenly split between the manufacturing and service sectors, excluding the self-employed and freelancers. It focused on mid- to senior-level employees in firms with over 10 employees, balancing technology-based manufacturing and service companies across metropolitan and non-metropolitan areas. The sample comprised 157 manufacturing (49.7%) and 159 service firms (50.3%). Demographically, it included 261 men (82.6%) and 55 women (17.4%), primarily in their 40s (47.5%), followed by 50s (25.3%) and 30s (21.2%). Over half of the companies had fewer than 300 employees (55.4%). Most of the respondents, 59.2% (187 individuals) reported using information technology. The respondents mostly worked in companies aged 10–30 years (50.0%), followed by firms over 30 years (25.3%) and firms under 10 years (24.7%).

## 4.2 Results

### 4.2.1 Validity of the measurement model

(1) Convergent validity analysis

To establish the validity of the measurement model, a confirmatory factor analysis (CFA) was conducted on the entire dataset. The results, as detailed in Table 1, confirm the convergent validity of the constructs. All measurement items loaded significantly and substantially onto their respective latent constructs, as evidenced by their high t-values (all t-values 〉 9.105, p 〈 .001). This indicates that the indicators are strong measures of their intended concepts. These foundational results, along with the subsequent analysis of construct reliability and discriminant validity, provide a sound basis for proceeding with the structural model analysis.

〈Table 1〉 Convergent validity

| Construct & item | | Parameter estimates | Standard errors | *T* values | *P* values |
|---|---|---|---|---|---|
| DL | DL1 | 1.000 | n/a | n/a | n/a |
| | DL2 | .972 | .088 | 11.049 | .000 |
| | DL3 | .953 | .095 | 10.056 | .000 |
| | DL4 | .913 | .100 | 9.105 | .000 |
| PU | PU1 | 1.000 | n/a | n/a | n/a |
| | PU2 | 1.192 | .077 | 15.520 | .000 |
| | PU3 | 1.154 | .077 | 14.986 | .000 |
| DIS | DIS1 | 1.000 | n/a | n/a | n/a |
| | DIS2 | 1.144 | .114 | 10.072 | .000 |
| | DIS3 | 1.220 | .120 | 10.185 | .000 |
| | DIS4 | 1.396 | .128 | 10.864 | .000 |
| | DIS5 | 1.438 | .132 | 10.855 | .000 |
| | DIS6 | 1.501 | .135 | 11.152 | .000 |
| | DIS7 | 1.558 | .135 | 11.524 | .000 |
| PEOU | PEOU1 | 1.000 | n/a | n/a | n/a |
| | PEOU2 | .989 | .065 | 15.138 | .000 |
| | PEOU3 | .774 | .064 | 12.163 | .000 |
| | PEOU4 | .931 | .064 | 14.518 | .000 |
| PC | PC1 | 1.000 | n/a | n/a | n/a |
| | PC2 | 1.241 | .096 | 12.877 | .000 |
| | PC3 | 1.111 | .092 | 12.116 | .000 |
| ITU | ITU1 | 1.000 | n/a | n/a | n/a |
| | ITU2 | 1.004 | .071 | 14.165 | .000 |
| | ITU3 | 1.007 | .073 | 13.812 | .000 |

** Note: The group-specific CFA results are available in Appendix for further detail*

(2) Construct reliability and discriminant validity analysis

The reliability and validity of the measurement model were thoroughly assessed. First, construct reliability was confirmed as all Cronbach's alpha values ranged from .777 to .893, and composite reliability (CR) values ranged from .765 to .895, both exceeding the conventional threshold of .70.

Next, convergent and discriminant validity were examined. The average variance extracted (AVE) is a key indicator for convergent validity, with a recommended value greater than .50. As shown in Table 2, the AVE values for all constructs met this criterion, with the exception of DL, which was slightly below at .454. However, according to Fornell and Larcker (1981), if the CR of a construct is above .70, the convergent validity can still be considered acceptable even if its AVE is below .50. Since the CR for DL is a robust .765, the convergent validity for all constructs was deemed satisfactory, confirming convergence validity.

Finally, discriminant validity was assessed using the Fornell-Larcker criterion. As detailed in Table 3, the square root of the AVE for each construct shown on the diagonal is greater than its correlation with any other

〈Table 2〉 Construct reliability and validity

| Construct | Cronbach's alpha (standardized) | Cronbach's alpha (unstandardized) | Composite reliability (rho_c) | AVE |
|---|---|---|---|---|
| DIS | .893 | .894 | .895 | .546 |
| DL | .777 | .774 | .765 | .454 |
| ITU | .830 | .829 | .826 | .615 |
| PEOU | .856 | .856 | .860 | .603 |
| PU | .864 | .864 | .867 | .683 |
| PC | .827 | .825 | .829 | .622 |

* *AVE = Average variance extracted*

〈Table 3〉 Discriminant validity: Fornell & Larker Criterion

| Construct | DIS | DL | ITU | PEOU | PU | PC |
|---|---|---|---|---|---|---|
| DIS | .739 | | | | | |
| DL | .652 | .673 | | | | |
| ITU | .471 | .659 | .785 | | | |
| PEOU | .418 | .641 | .520 | .777 | | |
| PU | .459 | .585 | .661 | .375 | .826 | |
| PC | .146 | .224 | .031 | .143 | .131 | .789 |

construct. This result confirms that each construct is sufficiently distinct, thereby establishing discriminant validity.

(3) Theoretical Model Fit

The fit of the measurement model was assessed using the entire sample. While the chi-square statistic was significant ($\chi^2$ = 611.577, df = 314, $p < .001$)—a typical result for studies with larger sample sizes—other key indices pointed to a strong model fit. Specifically, the normed chi-square ($\chi^2$/df) was 1.948, indicating an excellent fit. Moreover, the primary goodness-of-fit indices all met conventional thresholds, including the CFI (.923), TLI (.914), and RMSEA (.055). These results collectively support the conclusion that the measurement model fits the data well and provides a robust foundation for testing structural relationships.

4.2.2 Hypothesis test results

(1) Direct effect analysis

To verify the hypotheses, the study examined the direct and mediating effects among the variables using bootstrapping (sample size: 5,000). The results are shown in Tables 5 and 6 respectively. Significant differences in some of the paths were observed between the service and manufacturing companies (H2, H3, H6, H8). Most of the hypotheses were supported, except those hypothesizing that DIS directly affects ITU (H1) and that PC influences ITU (H7). This suggests that DIS alone may not accelerate ITU (Joo, 2018) and that the benefits of IIT outweigh PC (Hassandoust et al., 2021). We found that DL positively impacted both the PEOU of IIT (manufacturing: $t$=5.673, $p$=.000; services: $t$=6.313, $p$=.000) and the PU of IIT (manufacturing: $t$=3.405,

〈Table 4〉 Theoretical Model Fit

| Matrix | Estimated model | Null model |
|---|---|---|
| Chi-square | 611.577 | 4235.009 |
| Number of model parameters | 64.000 | 27.000 |
| Number of observations | 316.000 | n/a |
| Degrees of freedom | 314.000 | 351.000 |
| *P* value | .000 | .000 |
| ChiSqr/df | 1.948 | 12.066 |
| RMSEA | .055 | n/a |
| SRMR | .072 | n/a |
| TLI | .914 | n/a |
| CFI | .923 | n/a |

$p$=.001; services: $t$=4.107, $p$=.000), supporting H4 and H5, respectively. Further, PU positively influenced ITU in both groups, supporting H9 (manufacturing: $t$=5.735, $p$=.000; services: $t$=2.787, $p$=.000).

Group differences emerged by sector. In manufacturing, DIS significantly influenced PU ($t$=2.421, $p$=.017), supporting H2, while DL directly affected ITU ($t$=2.483, $p$=.014), supporting H3. In services, higher DL led to greater PC, but this was not a major concern in manufacturing. The service sector showed a greater inclination to adopt technology because it facilitates service operations ($t$=2.400, $p$=.018), highlighting the importance of PEOU in the current high demand for ITU.

〈Table 5〉 Results of the direct effect analysis

| Hypothesis | Path | Group | Parameter estimate | Standard error | *T* value | *P* value |
|---|---|---|---|---|---|---|
| H1 | DIS → ITU | Manufacturing | -.116 | .158 | .733 | .464 |
| | | Services | .026 | .112 | .230 | .818 |
| H2 | **DIS → PU** | **Manufacturing** | **.457*** | **.189** | **2.421** | **.017** |
| | | Services | -.034 | .133 | .259 | .796 |
| H3 | **DL → ITU** | **Manufacturing** | **.318*** | **.128** | **2.483** | **.014** |
| | | Services | .262 | .197 | 1.326 | .187 |
| H4 | **DL → PEOU** | **Manufacturing** | **.650***** | **.115** | **5.673** | **.000** |
| | | **Services** | **.985***** | **.156** | **6.313** | **.000** |
| H5 | **DL → PU** | **Manufacturing** | **.434**** | **.127** | **3.405** | **.001** |
| | | **Services** | **.706***** | **.172** | **4.107** | **.000** |
| H6 | **DL → PC** | Manufacturing | .151 | .094 | 1.614 | .108 |
| | | **Services** | **.346**** | **.119** | **2.900** | **.004** |
| H7 | PC → ITU | Manufacturing | -.070 | .066 | 1.061 | .290 |
| | | Services | -.131 | .073 | 1.781 | .077 |
| H8 | **PEOU → ITU** | Manufacturing | .051 | .072 | .719 | .473 |
| | | **Services** | **.271*** | **.113** | **2.400** | **.018** |
| H9 | **PU → ITU** | **Manufacturing** | **.641***** | **.112** | **5.735** | **.000** |
| | | **Services** | **.271**** | **.097** | **2.787** | **.006** |
| Control | **R&D Dept. → ITU** | Manufacturing | .050 | .098 | .517 | .606 |
| | | **Services** | **-.191*** | **.095** | **2.010** | **.046** |
| | Region → ITU | Manufacturing | -.079 | .079 | .993 | .322 |
| | | Services | .018 | .091 | .195 | .845 |
| | Gender → ITU | Manufacturing | .006 | .116 | .048 | .962 |
| | | Services | -.121 | .109 | 1.114 | .267 |

* $p < .05$, ** $p < .01$, *** $p < .001$

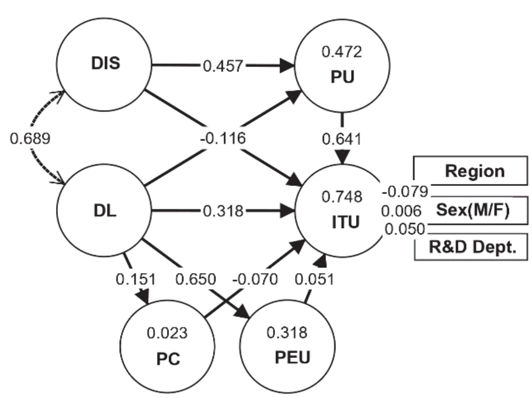
(2) Mediating effect analysis

The mediating effect analysis found that DL positively influences ITU through PU, supporting H10 in both sectors (manufacturing: $t$=2.262, $p$=.012, services: $t$=1.726, $p$=.042; Table 6) (Sayaf et al., 2022). However, the mediating effects of PEOU and PC on the DL - ITU relationship were not significant, leading to the rejection of H11 and H12, respectively. Conversely, DIS was found to have a significant complete mediating effect on the PU - ITU relationship, confirming H13. Additionally, the structural equation models in Figures 2 and 3 show that in both sectors, DIS and DL positively affect PEOU and PU, enhancing ITU, as evidenced by the good model fit and high R-squared values.

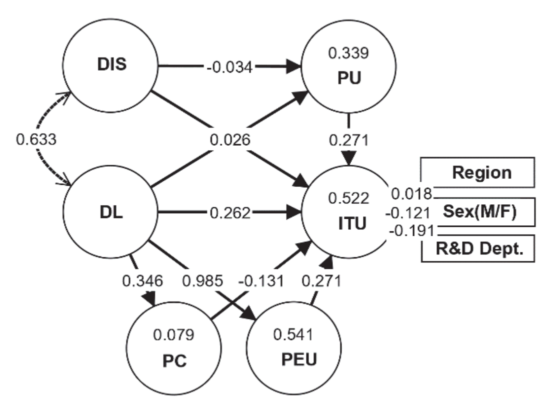
〈Table 6〉 Results of the mediating effect analysis

| Hypothesis | Path | Group | Original sample (O) | $T$ statistics (\|O/STDEV\|) | $P$ value |
|---|---|---|---|---|---|
| H10 | DL → PU → ITU | **Manufacturing** | **.278*** | **2.262** | **.012** |
| | | **Services** | **.191*** | **1.726** | **.042** |
| H11 | DL → PEOU → ITU | Manufacturing | .033 | .645 | .259 |
| | | Services | .267 | 1.410 | .079 |
| H12 | DL → PC → ITU | Manufacturing | -.011 | .738 | .230 |
| | | Services | -.045 | 1.081 | .140 |
| H13 | **DIS → PU → ITU** | **Manufacturing** | **.293*** | **1.852** | **.032** |
| | | Services | -.009 | .176 | .430 |

* $p < .05$, ** $p < .01$, *** $p < .001$




〈Figure 2〉 Research model (Result = Manufacturing)




〈Figure 3〉 Research model (Results = Services)

(3) Multi-group analysis

In this study, Following the application of the covariance-based structural equation model analysis to the theoretical model and path analysis, PLS-based analysis was conducted in parallel for additional in-depth analysis, such as multiple group analysis and importance performance map analysis. a three-stage procedure for analyzing the measurement invariance of composite models (MICOM) was employed to assess the feasibility of an MGA and examine the moderating effect of sector type. The results showed that, except for PU, the *p*-values supported the null hypothesis, indicating partial construction invariance for all the constructs except PU. This led to the third stage in which the mean and variance differences were compared and analyzed. The results showed acceptable mean differences between the company groups, with the ex-

〈Table 7〉 Results of the MICOM Testing Result

| MICOM Step 1: Pass | | | |
|---|---|---|---|
| MICOM Step 2: Partially Accepted | | | |
| Construct | Original correlation | Correlation permutation mean | Permutation p value |
| DIS | .999 | .997 | .847 |
| DL | .998 | .997 | .638 |
| ITU | .999 | 1.000 | .099 |
| PEU | .999 | .999 | .310 |
| PU | .999 | 1.000 | .036 |
| PC | .993 | .978 | .650 |
| R&D Dept. | 1.000 | 1.000 | .362 |
| Region | 1.000 | 1.000 | .409 |
| Gender | 1.000 | 1.000 | .187 |

| MICOM Step 3 | | | | |
|---|---|---|---|---|
| Construct | Original difference | | Permutation *p* value | |
| | mean | variance | mean | variance |
| DIS | .184 | -.263 | .052 | .059 |
| DL | .034 | .136 | .370 | .224 |
| ITU | .007 | -.053 | .487 | .392 |
| PEU | -.151 | -.061 | .099 | .340 |
| PU | .008 | -.315 | .491 | .044 |
| PC | -.091 | -.099 | .210 | .268 |
| R&D Dept. | -.242 | -.344 | .000 | .000 |
| Region | .051 | .001 | .231 | .231 |
| Gender | -.080 | -.372 | .041 | .041 |

ception of PU, which was statistically suitable for group comparisons.

The MGA results revealed the significant difference in the effect of PEOU on ITU (H7) and the mediating effect of DL between PEOU and ITU (H11). Notably, PEOU significantly influenced ITU in service companies, but not in manufacturing companies. Additionally, the path through which DL influenced PEOU before affecting ITU showed a significant moderating effect between the groups. Although this path was not statistically significant in either group, it appeared significant in the service company group at the 90% confidence level, indicating the need for further empirical validation. The results of the MICOM procedure are presented in Table 7 and the MGA results are presented in Table 8.

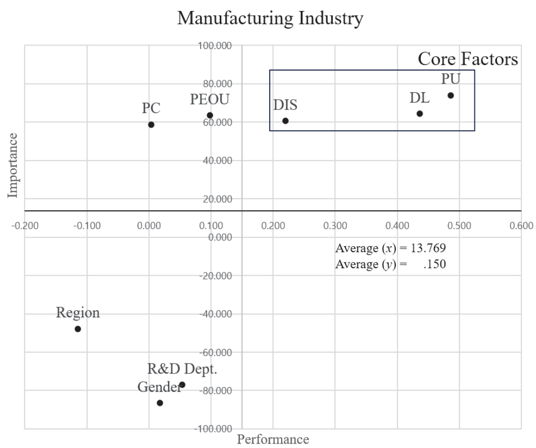
(4) Importance-performance map analysis

In an IPMA conducted to identify the factors affecting ITU in technology-based companies, the key variables were analyzed in the manufacturing (Figure 4) and service sectors (Figure 5), with ITU set as the dependent variable. The performance and importance of these variables were plotted on a quadrant map. We found that PU, DL, and DIS were significant in both sectors. In manufacturing, PU was the most critical (importance=.486, performance=74.047), followed by DL and DIS. Conversely, in services, DL was the most critical (importance=.378, performance=63.635), followed by PEOU and PU, with PEOU having more influence in services than in manufacturing. Digital transformation is vital for technology-based companies, with DL playing a significant

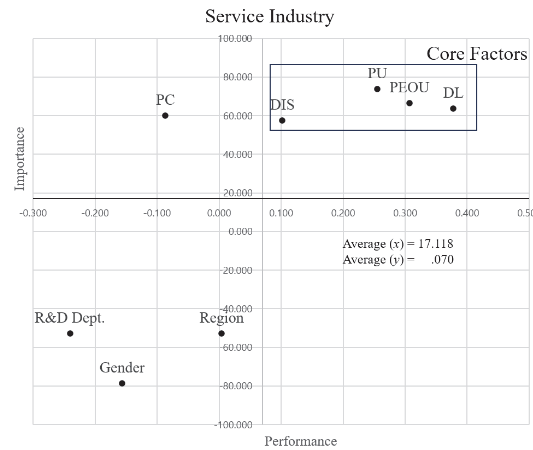
〈Table 8〉 Results of the MGA

| Hypothesis | Path | Difference | One-tailed *p* value | Two-tailed *p* value |
|---|---|---|---|---|
| H1 | DIS → ITU | -.005 | .518 | .482 |
| H2 | DIS → PU | .177 | .062 | .062 |
| H3 | DL → ITU | .085 | .263 | .263 |
| H4 | DL → PEOU | -.047 | .694 | .306 |
| H5 | DL → PU | .027 | .419 | .419 |
| H6 | DL → PC | -.088 | .734 | .266 |
| H7 | PC → ITU | .076 | .210 | .210 |
| **H8** | **PEOU → ITU** | **-.209*** | **.957** | **.043** |
| **H9** | **PU → ITU** | **.231*** | **.021** | **.021** |
| H10 | DL → PU → ITU | .071 | .102 | .102 |
| **H11** | **DL → PEOU → ITU** | **-.115*** | **.961** | **.039** |
| H12 | DL → PC → ITU | .019 | .184 | .184 |
| **H13** | **DIS → PU → ITU** | **.123**** | **.006** | **.006** |

* $p < .05$, ** $p < .01$, *** $p < .001$




〈Figure 4〉 IPMA results (manufacturing)




〈Figure 5〉 IPMA results (services)

role. However, PC does not significantly affect technology adoption. In services, IIT's PEOU is crucial, whereas in manufacturing, the value provided by technology and focus on research and development take precedence (Kinkel et al., 2022). For these companies, manufacturing trends toward automation and enhancing the perception of technology value (i.e., PU) are more crucial for ITU than PEOU.

(5) Moderating effect of PC

The results varied by sector when examining the moderating effect of PC on DL and its impact on PU and ITU. While no significant effects were found in manufacturing, increased PC and DL negatively affected the PU of IIT in the service sector (Table 9). This suggests that service companies should offer compliance education and security measures alongside DL training to improve ITU. Notably, manufacturing companies adopting a service-oriented approach showed a positive inclination toward IIT. We also found in a PLS-SEM prediction analysis (Table 10) that all the exog-

〈Table 9〉 Results of the moderating effect analysis

| Hypothesis | Path | Group | Original sample | Sample mean | *P* value |
|---|---|---|---|---|---|
| 14 | PC * DL → PU | Manufacturing | -.121 | -.115 | .069 |
| | | **Services** | **-.164**** | **-.160** | **.001** |
| 15 | PC * DL → PU → ITU | Manufacturing | -.590 | -.059 | .091 |
| | | **Services** | **-.042*** | **-.041** | **.016** |

* $p < .05$, ** $p < .01$, *** $p < .001$

〈Table 10〉 Results of the prediction analysis

| PLS-SEM LV prediction | | | | | CVPAT | | |
|---|---|---|---|---|---|---|---|
| Construct | Group | $Q^2$ prediction | RMSE | MAE | Average loss difference | t value | *P* value |
| ITU | Manufacturing | 0.268 | 0.874 | 0.675 | -0.137 | 2.185 | 0.030 |
| | Services | 0.155 | 0.937 | 0.714 | -0.081 | 1.496 | 0.137 |
| PEOU | Manufacturing | 0.210 | 0.906 | 0.703 | -0.114 | 2.513 | 0.013 |
| | Services | 0.261 | 0.875 | 0.677 | -0.152 | 2.744 | 0.007 |
| PU | Manufacturing | 0.319 | 0.843 | 0.653 | -0.170 | 3.659 | 0.000 |
| | Services | 0.143 | 0.943 | 0.741 | -0.107 | 1.865 | 0.064 |
| PC | Manufacturing | -0.006 | 1.014 | 0.790 | 0.003 | 0.185 | 0.853 |
| | Services | 0.012 | 1.011 | 0.770 | -0.011 | 0.368 | 0.714 |
| Overall | Manufacturing | | | | -0.105 | 3.703 | 0.000 |
| | Services | | | | -0.093 | 2.495 | 0.014 |

enous variables (except for items related to ITU and DIS in manufacturing and PC in services) significantly predicted ITU in both sectors, with high path value predictability and lower RMSEs and mean absolute errors than in a linear regression model. These results were in line with the findings of previous studies (Jang et al., 2021; Kinkel et al., 2022)

# Ⅴ. Conclusion

This study, grounded in the Technology Acceptance Model (TAM), empirically investigates the influence of DL, DIS, and PC on the adoption of IIT, and how these dynamics differ between the manufacturing and service sectors. To conduct a comprehensive analysis, these variables were mapped onto four key antecedent groups within the TAM framework: individual differences, social influence, system characteristics, and facilitating conditions. Our findings reveal distinct drivers of technology adoption in each sector, yielding the following academic, practical, and policy implications.

## 5.1 Summary and Discussion of Key Findings

The core finding of this study is that the pathway to IIT adoption is not a one-size-fits-all model; rather, industry characteristics act as a crucial moderating variable (Chatterjee et al., 2021).

First, DL and PU were reaffirmed as universal and pivotal drivers of technology adoption across both industries. The mediating path of DL, PU, ITU was particularly significant in both sectors, suggesting that the most critical mechanism for adoption is the enhancement of an employee's digital competence, which elevates their perception of a technology's usefulness, ultimately leading to a higher intention to use.

Second, there were fundamental differences in the determinants of technology adoption between the manufacturing and service sectors. In manufacturing, a technology's PU was the most dominant factor determining usage intention. The influence of DIS was significant only through the pathway of enhancing PU. This implies that the manufacturing context prioritizes the evaluation and acceptance of technology based on clear objectives of productivity and efficiency gains. In contrast, the IPMA revealed that DL was the most critical variable in the service sector, where PEOU also exerted a significant direct impact on usage intention. This highlights that in the complex, interactive environment of the service industry, the ability to handle technology confidently and easily is as important as its utility. It is noteworthy that the direct effect of DL on ITU (H3) is not significant for services. This may be because work in the service industry is more atypical and requires more complex interactions than in manufacturing. This suggests that in these environments, rather than simply confidence in high DL triggering technology use, the effect of DL follows a more fully mediated path through PEOU and PU, where the PU and PEOU of the technology in question are perceived to be specific.

Third, the moderating role of PC was significant only in the service sector in this study. Here, for employees with higher DL, increased PC negatively affected their perception of the technology's usefulness. This suggests that in the service industry, where handling customer data is essential (Tether, 2005). This suggests that while digital literacy training enhances employee competence, it may simultaneously increase sensitivity to privacy concerns, potentially reducing perceived usefulness.

Fourth, one of the interesting findings of this study is that PC do not have a direct effect on ITU as H7 rejected in both sectors. This can be interpreted in terms of the 'Privacy Calculus Theory', i.e., users judged that the apparent benefits of adopting IIT which means higher PU and PEOU outweighed the potential risks of privacy exposure, suggesting that PC was not a direct deterrent to technology adoption. Instead, PCs can be understood to exert their influence in a more subtle and indirect way that undermines the PU of the technology among the service industry's digitally literate population.

## 5.2 Implications of the Study

### 5.2.1 Theoretical Implications

First, this study empirically extends the contingency perspective of the Technology Acceptance Model (TAM). By moving beyond universal technology acceptance theories, it clearly demonstrates how a macro-level variable like 'industry type' moderates the core pathways and influence of key determinants, thereby re-emphasizing the importance of contextual analysis in technology acceptance research.

Second, it illuminates the multifaceted role of DL (Jang et al., 2021). The findings show that DL can simultaneously play a positive role by enhancing PEOU and PU, and a negative role by increasing PC, which then diminishes PU. In the context of Privacy Calculus Theory, the findings indicate that employees with high digital literacy are more likely to perceive greater risks, which offsets the benefits associated with technological usefulness. This presents new possibilities for interpreting the influence of DL through the lens of Privacy Calculus Theory (Carlsson and Nilsson, 2023) and reveals the complex mechanisms through which DL affects technology adoption.

Third, this research clarifies the influence pathway of DIS. It demonstrates that DIS does not directly impact usage intention but instead acts as a key variable that is fully mediated by PU, driven by the need to enhance collaborative performance in environments with high task interdependence (Sayaf et al., 2022). This contributes a specific, theoretically grounded explanation of how a technical feature of DIS translates into user adoption behavior via PU.

Ultimately, these findings enrich the TAM framework by demonstrating how individual differences (e.g., DL) interact with system characteristics (e.g., DIS) under the overarching boundary condition of the industrial context, leading to varied adoption pathways.

### 5.2.2 Practical and Managerial Implications

First, tailored digital transformation and employee training strategies for each industry are imperative. A uniform approach is inefficient. Manufacturing firms introducing new technology should focus on demonstrating how this technology increases productivity and facilitate related DIS. Conversely, service firms should prioritize training to enhance employee DL while selecting solutions that maximize PEOU. Notably, DL training in the service sector must include content on data privacy compliance and security measures. To develop these capabilities, expanding workforce training programs in higher education and fostering professional educators to reskill and upskill existing employees are recommended. The rise of AI tools since the early 2020s has made practical, solution-based, short-term training more feasible than traditional conceptual education. This shift suggests that enhancing DL is more accessible and encourages companies to find cost-effective customized training programs that can be quickly implemented in the workplace without significant time and cost investments (Chiu et al., 2022). Additionally, autonomous training tailored to individual companies is recommended (Jang et al., 2021). From a governmental perspective, strengthening promotional policies to support the education market is considered valuable.

Second, government R&D and digital transformation support policies should be differentiated by industry. For the manufacturing sector, it is necessary to expand support beyond advanced automation to include the adoption of Autonomous Intelligent Technologies (AIT), physical AI, and other smart factory solutions. Encouraging participation in Proof-of-Concept (PoC) through the expansion of on-site PoC platforms and fostering a workforce to lead digital transformation could be effective alternatives. For the service sector, policy support for employee DL program development, user-friendly interface (UI/UX) improvements, and the adoption of enhanced information security solutions would be effective. To counteract this, service firms need to implement complementary trust-building measures. For instance, enhancing the transparency of personal information processing and running problem-solving workshops focused on leveraging technology securely rather than simple functional training can rebuild and strengthen PU, thereby fostering ITU even among privacy-aware employees.

Third, mediating factors must be strategically leveraged for successful technology adoption. The pathway from DL to ITU through PU was powerful in both sectors, which means that the process of actively persuading and allowing employees to experience how this technology benefits you and our organization will determine the success of digital transformation, far beyond simple training on how to use the tools. In the service sector, this could involve visualizing KPI data such as service speed improvement rates or increases in customer satisfaction before and after IIT implementation. In the manufacturing sector, introducing a standardized assessment model to diagnose and visualize the level of digital capability, while fostering a culture of sharing successful and failed PoC cases through workshops, would be beneficial.

### 5.3 Limitations of the Study and Future Research Directions

While this study is significant for highlighting the importance of industry-specific strategies for IIT adoption, it has limitations that suggest directions for future research.

First, this study has methodological limitations regarding generalizability and causality. As the data were collected from a single country, South Korea, caution is warranted when generalizing the findings to different cultural and economic contexts. Furthermore, the cross-sectional nature of the data limits our ability to make definitive causal claims. Future research could address these limitations by conducting comparative cross-cultural studies, which would necessitate rigorous testing of measurement invariance to ensure the constructs are comparable across different cultural groups as emphasized in recent methodological reviews (Leitgöb et al., 2023) and employing longitudinal analyses to track adoption dynamics over time.

Second, beyond the macro-level classification of manufacturing and services, further in-depth research is needed to explore how technology adoption factors vary within sub-sectors (e.g., B2B vs. B2C services, process vs. assembly manufacturing). Additionally, contrary to our findings, personal information issues are emerging in new forms within the manufacturing sector, such as data handling challenges for employees and partners in the B2B value chain (Tang et al., 2025). Comparative research on other diverse groups not covered in this study would also be meaningful.

Finally, as the paradigm of new intelligent information technologies like Generative AI accelerate and the industrial boundaries between manufacturing and services continue to blur with the advancement of physical AI, continuous research is required to investigate how the influence of the variables validated in this study may change, or whether new, critical variables emerge.

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# 〈Appendix〉

〈Table 1〉 Measures of the Construct

| Construct | | Measures | Sources |
|---|---|---|---|
| IV* | DIS** | (DIS1) Sharing knowledge among individual members of the organization | Venkatesh et al. (2003); Kim(2020) |
| | | (DIS2) Sharing knowledge with other teams | |
| | | (DIS3) Sharing knowledge across the organization | |
| | | (DIS4) Building knowledge repositories to make it easy for employees to search for new knowledge | |
| | | (DIS5) Building knowledge repositories to facilitate employee knowledge storage | |
| | | (DIS6) Building knowledge repositories to facilitate employee search and use of knowledge | |
| | | (DIS7) Building knowledge repositories to make it easier for employees to communicate with coworkers | |
| | DL** | (DL1) Actively using a variety of online communication tools at work | |
| | | (DL2) Knowing how to select digital tools and technologies for collaboration and communication processes | |
| | | (DL3) Having appropriate internet etiquette when interacting in Cloud technology environments and digital environments | |
| | | (DL4) Respects copyright and licensing rules and knows how to apply them to digital information and content | |
| MV* | PC** | (PC1) Utilizing IIT may expose company's sensitive information and put it at risk of being hacked | |
| | | (PC2) IIT is imperfect and subject to unforeseeable risks | |
| | | (PC3) IIT could put our company at risk as a whole | |
| | PU** | (PU1) IIT will be useful for my company | |
| | | (PU2) IIT will speed up the production of my company's products | |
| | | (PU3) IT will be more productive if IIT is implemented | |
| | PEU** | (PEU1) Learning to work with IIT will be easy | |
| | | (PEU2) IIT will be clear and easy to understand | |
| | | (PEU3) will Finding it easier to do my job after implementing IIT | |
| | | (PEU4) will quickly become familiar with how to use IIT after it is implemented | |
| DV* | ITU** | (ITU1) willingness to adopt the IIT | |
| | | (ITU2) willingness to try the IIT | |
| | | (ITU3) Intend to apply the IIT | |

* 〔Note〕 IV = Independent Variables, MV = Mediating ~, DV = Dependent ~
** 〔Note〕 DIS = Digital Information Sharing, DL = Digital Literacy, PC = Privacy Concerns, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, ITU = Intention to Use

〈Table 2〉 Characteristics of the sample

| Item | | N | Ratio(%) | Item | | N | Ratio(%) |
|---|---|---|---|---|---|---|---|
| Title | CEO | 3 | 0.9 | firm age | ~ 10 years | 78 | 24.7 |
| | partner | 39 | 12.3 | | | | |
| | manager ~ | 274 | 86.7 | | ~ 30 years | 158 | 50.0 |
| R&D Dept | Y | 205 | 64.9 | | 30 years ~ | 80 | 25.3 |
| | N | 111 | 35.1 | | | | |
| Gender | male | 261 | 82.6 | Region | Seoul | 96 | 30.4 |
| | female | 55 | 17.4 | | Gyeonggi | 51 | 16.1 |
| age | 20s | 4 | 1.3 | | In-cheon | 12 | 3.8 |
| | 30s | 67 | 21.2 | | Daejeon | 12 | 3.8 |
| | 40s | 151 | 47.8 | | Chungchung | 21 | 6.6 |
| | 50s | 80 | 25.3 | | Daegu | 25 | 7.9 |
| | 60s | 14 | 4.4 | | Gyeongsang | 37 | 11.7 |
| firm type | Manufacturing | 157 | 49.7 | | Busan | 19 | 6.0 |
| | Services | 159 | 50.3 | | Ulsan | 12 | 3.8 |
| No. of employee | ~300 | 175 | 55.4 | | Gwangju | 8 | 2.5 |
| | | | | | Honam | 11 | 3.5 |
| | 300~ | 141 | 44.6 | | Gangwon | 8 | 2.5 |
| | | | | | Jeju | 4 | 1.3 |

〈Table 3〉 Convergent validity (Group Specific CFA Result)

| Construct & item | | Parameter estimate | | Outer loading | | *T* value | | *P* value | |
|---|---|---|---|---|---|---|---|---|---|
| | | Manufacturing | Services | Manufacturing | Services | Manufacturing | Services | Manufacturing | Services |
| DL- | 1 | 1.000 | 1.000 | 0.708 | 0.657 | - | | | |
| | 2 | 0.996 | 0.930 | 0.798 | 0.651 | 8.917 | 6.813 | 0.000 | 0.000 |
| | 3 | 0.894 | 1.012 | 0.665 | 0.665 | 7.301 | 6.932 | 0.000 | 0.000 |
| | 4 | 0.931 | 0.880 | 0.633 | 0.566 | 7.058 | 5.839 | 0.000 | 0.000 |
| PU | 1 | 1.000 | 1.000 | 0.823 | 0.78 | - | | | |
| | 2 | 0.974 | 1.349 | 0.769 | 0.925 | 9.622 | 11.981 | 0.000 | 0.000 |
| | 3 | 1.059 | 1.161 | 0.792 | 0.831 | 9.821 | 11.231 | 0.000 | 0.000 |
| DIS | 1 | 1.000 | 1.000 | 0.527 | 0.701 | - | | | |
| | 2 | 1.073 | 1.182 | 0.546 | 0.752 | 5.444 | 9.109 | 0.000 | 0.000 |
| | 3 | 1.204 | 1.206 | 0.608 | 0.726 | 5.756 | 8.73 | 0.000 | 0.000 |
| | 4 | 1.715 | 1.160 | 0.783 | 0.756 | 6.512 | 8.697 | 0.000 | 0.000 |
| | 5 | 1.688 | 1.259 | 0.781 | 0.758 | 6.454 | 8.819 | 0.000 | 0.000 |
| | 6 | 1.708 | 1.341 | 0.786 | 0.817 | 6.441 | 9.401 | 0.000 | 0.000 |
| | 7 | 1.734 | 1.417 | 0.822 | 0.857 | 6.598 | 9.794 | 0.000 | 0.000 |
| PEOU | 1 | 1.000 | 1.000 | 0.815 | 0.796 | - | | | |
| | 2 | 1.048 | 0.932 | 0.82 | 0.747 | 11.259 | 10.008 | 0.000 | 0.000 |
| | 3 | 0.726 | 0.826 | 0.65 | 0.767 | 7.877 | 9.353 | 0.000 | 0.000 |
| | 4 | 0.916 | 0.952 | 0.8 | 0.799 | 10.417 | 10.229 | 0.000 | 0.000 |
| PC | 1 | 1.000 | 1.000 | 0.712 | 0.777 | - | | | |
| | 2 | 1.277 | 1.220 | 0.901 | 0.864 | 8.571 | 9.573 | 0.000 | 0.000 |
| | 3 | 1.158 | 1.086 | 0.741 | 0.725 | 8.421 | 8.744 | 0.000 | 0.000 |
| ITU-- | 1 | 1.000 | 1.000 | 0.789 | 0.834 | - | | | |
| | 2 | 1.092 | 0.940 | 0.815 | 0.727 | 10.571 | 9.538 | 0.000 | 0.000 |
| | 3 | 0.952 | 1.072 | 0.767 | 0.786 | 9.594 | 10.094 | 0.000 | 0.000 |