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Determinants of digital technology adoption in innovative SMEs

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A B S T R A C T

Despite the increasing adoption of digital technology, small and medium enterprises (SMEs) continue to lag behind larger firms. This study integrates the technology, organization, and environment (TOE) framework with Rogers' diffusion of innovation (DOI) theory to investigate the factors influencing SMEs' digital technology adoption. Data from 419 SMEs was analyzed using partial least squares structural equation modelling (PLS-SEM), followed by artificial neural network (ANN) analysis to rank the importance of the variables identified.

The PLS-SEM results show that technological, organizational, and environmental factors directly impact adoption. The supported variables include adoption costs, top management support, human resources, digital culture, and trading partner pressure. Some factors indirectly impact adoption through top management support. This study also found that SMEs' international orientation moderates the relationship between digital culture and adoption behavior. The ANN results identify that the most important predictors, ranked from the most to the least influential, are digital culture, international orientation, top management support, trading partner pressure, human resources, and adoption costs.

This research contributes to the theoretical discourse on technology adoption by integrating the TOE framework with Rogers' DOI theory. It highlights that no single TOE element functions in isolation. The findings provide practical guidance for SME managers, stressing the need to improve organizational factors, such as, human resources, digital culture, and top management support. Governments may use these findings to identify ways to support SMEs' digital technology adoption, particularly by offering subsidies to reduce costs, which remain a barrier.

Introduction

Although digital technologies (DT) are increasingly being integrated into business systems, small and medium enterprises (SMEs) are reported to be currently lagging behind larger businesses in adopting such technologies, even those relevant to their operations (Pingali et al., 2023). This may leave SMEs unable to compete with larger firms, risking loss of market share if they cannot respond to disruptive digital innovations, thereby jeopardizing their ongoing viability (Rakshit et al., 2021). Scholars have observed that the factors influencing DT adoption differ between large firms and SMEs. For instance, SMEs are often constrained by knowledge gaps, which restrict their ability to fully capture the benefits of DT (Eller et al., 2020; Marzi, Marrucci et al., 2023). Additionally, SMEs face financial resource disadvantages, because adopting DT commonly necessitates significant financial investment (Ghobakhloo et al., 2022).

The diffusion and adoption of digital innovations are widely recognized in the literature as a fusion of organizational and information systems (IS) strategies (Vial, 2019). This intersection has attracted considerable attention from both practitioners and scholars, prompting extensive research into its mechanism (Chauhan et al., 2023). However, the associated studies have certain related limitations that indicate a research gap in this context. First, current studies predominantly focus on technology adoption in larger enterprises or more general business settings, often overlooking the unique economic interests and distinct challenges faced by SMEs (Roffia & Mola, 2022). Unlike their larger counterparts, SMEs typically have smaller workforces with limited knowledge, and limited financial resources (Ashiru et al., 2023), yet have more agile decision-making processes (Su et al., 2023). This discrepancy is significant, because findings from research on larger firms, while valuable, may not be entirely extrapolated to SMEs (Justy et al., 2023). In this context, SMEs are relatively under-researched, and there is a need to better understand the factors leading to their adoption of digital technology. Prior research has largely centered on developed

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countries, with limited focus on the uptake of IT-related technology by SMEs in developing nations (Mkansi, 2022). SMEs in developing countries arguably face more challenges than those in developed countries, such as a lack of digital infrastructure, institutional voids, and ineffective regulations (Skare & Soriano, 2021). Thus, they may be more reliant on government assistance to tackle knowledge- (Maroufkhani et al., 2020) and infrastructure-related challenges (Shukla & Shankar, 2022) in adopting new technology.

Second, past research in IT-related adoption primarily focuses on firms' inclination toward certain technology adoption (e.g., enterprise resource planning, cloud computing, the Internet of things, big data analytics); whereas studies that explore this intention at the aggregate level are somewhat scarce (Lee et al., 2021), even though their number has recently begun to increase (Lee et al., 2021; see also Shukla & Shankar, 2022; Chauhan et al., 2023). The current competitiveness in the market, stemming from globalization, the COVID-19 pandemic, rapid technology development, and changes in consumer behavior, has equipped firms with multiple DTs and paired them together simultaneously to unleash the combinatorial effects of enhancing the spillover effects of technological innovation (Pingali et al., 2023; Oduro et al., 2023). Systematic reviews by Ghobakhloo et al. (2022) and Ramdani et al. (2022) have identified common predictors across various DTs, suggesting that despite their diverse applications, these technologies share similar underlying characteristics and can be considered single entities influenced by theories like technology acceptance model, diffusion of innovations, resource-based view, and the technology-organization-environment framework.

Third, in terms of statistical analyses, past studies mostly rely on logistic regression (e.g., Ferreira et al., 2019) or partial least squares structural equation modeling (e.g., Tiwari et al., 2023). With the growing need to better understand which indicator is the most influential – or indeed the least influential – in terms of affecting firms' decisions to adopt new technology, relying solely on a given traditional statistical method may not be entirely effective (Singh et al., 2023). Thus, the application of an artificial neural network is warranted, where such an application could examine nonlinear relationships, enabling an understanding of which factors are most significant in influencing outcomes when multiple factors coincide (Abbasi et al., 2021). Additionally, most studies in the field of technology adoption have focused on the direct relationships between factors affecting technology adoption and its outcomes, often disregarding the role of moderators (Alsaad et al., 2017; Mohtaramzadeh et al., 2018). Investigating moderating factors could provide deeper insights into how these effects influence the causal relationships between variables, offering a more contextualized understanding (Oliveira et al., 2019) and facilitating theoretical refinement (Maroufkhani et al., 2023).

Based on the gaps identified in the literature above, this study aims to answer the following research questions:

1. What are the significant factors influencing digital technology adoption among small and medium enterprises?
2. What is the hierarchical order of these significant factors in terms of their influence on digital technology adoption among small and medium enterprises?
3. How do moderating factors influence digital technology adoption among small and medium enterprises?

By answering the above research questions, this study advances the digital technology adoption literature by: 1) revealing the order of significant variables influencing SMEs' decisions to adopt DT based on their importance; 2) examining DT as a collective concept rather than individually; 3) exploring less-frequently examined factors such as digital culture; 4) guiding policymakers and SMEs managers to enhance DT adoption in Indonesia in particular, and in broader contexts; and 5) examining the role of moderating factors, particularly international orientation, in influencing the adoption of DT.

Literature review

To understand the broader context of this study, it is essential to outline the key concepts and frameworks that underpin this research. This process involves detailing the concept of DT, the role of SMEs within the national context, and the diffusion of DT among SMEs, which are elaborated upon in the following sub-sections.

Overview of digital technology (DT)

The term digital technology refers to a set of technologies associated with digital transition that extend beyond organizational boundaries (Ghobakhloo, 2020). Some scholars suggest that DT represents a collection of intelligent innovations that define the current technological paradigm (Pedota et al., 2023). The implementation of these DTs can digitize and streamline a firm's value creation process, thereby bolstering competitiveness, enhancing productivity, and fostering digital innovation (Papadopoulos et al., 2020). Recognized as a significant asset for business transformation due to their disruptive potential and systemic organizational impact (Skare & Soriano, 2021), DTs are increasingly being incorporated into business systems to capitalize on their transformative power (Feliciano-Cestero et al., 2023).

The current global societal shock, a term coined by scholars to describe the profound impact stemming from the political and economic climate, has been regarded as a catalyst in expediting firms' digital technology transitions (Justy et al., 2023). For instance, firms were forced to adopt DTs to allow them to resume normal business routines amidst the ongoing measures that still restrict their worker movement (Crespo et al., 2023). A recent study reveals that firms with increased revenue during COVID-19 were associated with the use of DTs in their operations, while enterprises that did not engage with DT generally faced declining turnover (Ashiru et al., 2023).

The DTs included in this study are commonly referred to by the abbreviation SMACIT, which stands for social, mobile, analytics, cloud, and the Internet of things (Vial, 2019). In particular, this term covers cloud computing, artificial intelligence, big data analytics, block chain, the Internet of things, and mobile applications. These DTs radically change conventional firm strategy by allowing tasks to be achieved across time, location, and function. Akpan et al. (2022) concur that these state-of-the-art DTs not only suit the needs of SMEs, enabling them to thrive in the fourth industrial revolution and during the COVID-19 crisis, but also serve as strategic resources that enhance their competitive advantage and performance in the current business environment. Fabian et al. (2023) observe that these technologies have become ubiquitous and easily accessible to SMEs.

Overview of small and medium enterprises (SMEs)

Although some studies describe SMEs as 'laggards' in adopting digital technology, they nevertheless have certain advantages over large enterprises. For instance, SMEs can swiftly adapt to changes in their environment due to their flexible management practices (Justy et al., 2023). The reduced bureaucratic structure of SMEs facilitates reorganization and reconfiguration, proving advantageous in the digital environment (Su et al., 2023). Their flat organizational structure also leads to more efficient workflows than those seen in larger firms. Importantly, SMEs generally exhibit lower levels of organizational resistance to change compared to large enterprises, a significant barrier that often prevents larger firms from embracing new innovations (Broccardo et al., 2024). Given these factors, the potential for improving DT adoption among SMEs is considerable.

In Indonesia, SMEs are pivotal to the country's economic activities, employing over 97 % of the workforce and contributing >60 % of its GDP in 2019 (Ministry of Cooperative & Micro, Small & Medium Enterprises [MCMSME], 2021). They have been chosen for this research because they exemplify conditions prevalent in many developing countries, where SMEs play a crucial role in the economy, yet whose DT adoption remains low. The Ministry of Finance (2023) reports that only 17 million, or a mere 25 %, of Indonesian SMEs have embraced online platforms. Additionally, Indonesia's population is spread across 7000 islands, highlighting the importance of DT for SMEs to access the growing domestic market and remain competitive. By 2045, Indonesia is expected to become the world's fourth-largest economy (Secretary Cabinet, 2017). Studying this context could offer lessons for other nations with similar levels of technological integration and economic conditions.

This study adopts the Indonesian government's definition of SMEs, in alignment with its focus on Indonesia. The government classifies SMEs into three categories, micro, small, and medium enterprises (MSMEs) based on yearly turnover and asset value, as stipulated in Micro, Small, and Medium Enterprises Law No 20 (2008), as shown in Table 1, below. A firm must satisfy both criteria (value of assets and annual turnover), which are expressed in Indonesian rupiah (IDR), to be considered an SME. However, for consistency with the existing literature, the term SMEs is used, which is more universally recognized.

Table 1
Indonesian SMEs by category.

No.	Category	Value of assets (IDR)	Annual turnover (IDR)
1	Micro enterprises	0–50 million	0–300 million
2	Small enterprises	50–500 million	300 million–2.5 billion
3	Medium enterprises	500 million–10 billion	2.5–50 billion

Source: Micro, Small, and Medium Enterprises Law No 20 (2008).

Digital technology diffusion in small and medium enterprises – theoretical framework

To gain deeper insight into the factors influencing DT adoption among SMEs, it is essential to explore the theoretical frameworks that provide a structured approach to examining these determinants. This study combines the technology–organization–environment framework and Diffusion of Innovation theory to create a robust foundation for analyzing the adoption of DT within SMEs, which will be discussed in the following sub-sections.

The technology–organization–environment (TOE) framework

The TOE framework is regarded as the quintessential model to reveal factors that promote or inhibit IT-related adoption among firms, because its three dimensions cover all the factors necessary for successful technology adoption (Sun et al., 2024). The framework identifies several key predictors of the likelihood of certain innovations, namely technological, organizational, and environmental, which can present both opportunities and constraints to the adoption of new innovations (Tornatzky & Fleischer, 1990). Technological factors pertain to the characteristics of the technology itself, influencing a firm's decisions to adopt, including adoption costs, perceived benefits, perceived risks, compatibility, and complexity of technological innovation, which are mostly derived from Rogers' diffusion of innovation theory (Tiwari et al., 2023). Organizational factors are inextricably linked to and controlled by firms, such as human resources, top management support, the number of resources, and size. All these factors may make firms more receptive to innovation (Baker, 2012). Environmental factors are characterized as factors arising outside such firms' spheres, where firms do not have control over these factors, such as competitive pressure and government regulation (Maroufkhani et al., 2020). The TOE framework is considered progressive because it can incorporate different elements from state-of-the-art knowledge in specific research fields (Su et al., 2023). However, some scholars criticize the TOE framework for not incorporating important variables in its taxonomies (Toufaily et al., 2021). Thus, to avoid any bias from the application of the TOE framework, it is used as the overarching theoretical foundation to unify different constructs under a single umbrella in this study.

Diffusion of innovation theory (DOI)

Given the TOE's limitations, this study adds another theoretical lens to improve its framework, namely Rogers' DOI theory. DOI theory attempts to explain how and why an innovation, such as information, ideas, or products gains momentum and spreads within a social system over time via communication channels (Rogers, 2003). In this theory, an innovation is defined as an idea, practice, or object perceived as new by an individual or organization. In principle, the DOI assumes that the higher the individual's perception of five key elements, the greater the possibility of that individual adopting the innovation (Tiwari et al., 2023). The five elements are: (1) relative advantage, the extent to which the individual perceives the innovation to be superior to their current option; (2) compatibility, the degree to which the innovation aligns with the individual's existing values; (3) trialability, the extent to which the innovation can be tried out; (4) observability, the visibility of the innovation's outcomes to others; and (5) complexity, the perceived ease of use, or otherwise, of the innovation (Rogers, 2003). Diffusion of innovation theory is chosen to complement the TOE framework in this research because its constructs are identical to those of the TOE, except for the environmental context (Toufaily et al., 2021). Several studies have concluded and underscored that the combination of the TOE framework and DOI theory should provide a comprehensive framework for unraveling critical factors leading to technology adoption among SMEs (Maroufkhani et al., 2023), especially among those in developing countries (Chau et al., 2021).

Research model and hypotheses development

To examine the factors influencing DT adoption, this study uses the TOE framework as a guideline to identify the structures underpinning the factors that affect DT adoption among SMEs. Due to the extensive number of factors that may either prevent or promote SMEs' adoption of DT from the literature, the application of the TOE framework should help to classify them into specific categories (Baker, 2012). Table 2, below, identifies determinants addressed in past research within the field of innovation adoption.

Technological context

Adoption cost (AC)

The cost of acquiring new technology is often reported as the primary obstacle to firms' ability to engage with technological innovation, especially for SMEs, which inevitably face resource constraints (Eller et al., 2020). Advanced DTs entail significant financial outlays, primarily due to the initial investment required for their acquisition, which is often paid upfront. In addition to this initial outlay, there are ongoing maintenance costs to consider (Skare et al., 2023). SMEs are often hesitant to adopt new technology due to significant required investments and their relative lack of resources (Marzi, Manesh et al., 2023). The cost to acquire DT is almost inevitably a decisive factor before SMEs engage with new technology (Ghobakhloo & Ching, 2019; Moghavvemi et al., 2021; Park & Kim, 2021; Sharma, Singh et al., 2024). Hence, it could conceivably be hypothesized that:

H1. Adoption cost negatively affects DT adoption intention.

Perceived benefits (PB)

Iacovou et al. (1995) define PB as the extent to which an organization recognizes the potential benefits of adopting an innovation. In this study, PB refers to the degree to which SMEs believe DT as providing greater benefits compared to their traditional business practices. Swani (2021) claims that a firm's intention to adopt new technology increases concurrently with the improvement of benefits they can realize from such adoption. When effectively incorporated, DTs offer utilitarian

Table 2
Determinants identified based on literature review.

Context	Variable identified in this study	Similar variable from past studies	Significant effect	Insignificant effect
Technology	Adoption cost	Cost	Sharma, Singh et al. (2024)	Wong et al. (2020)
		Investment cost	Moghavvemi et al. (2021)	
		Financial investment	Park and Kim (2021)	
		Perceived costs	Ghobakhloo and Ching (2019)	Ilin et al. (2017)
	Perceived benefits	Relative advantage	Sharma, Singh et al. (2024); Tiwari et al. (2023); Wong et al. (2020); Albar and Hoque (2019)	Chen et al. (2023)
		Perceived usefulness	Abed (2020)	
		Perceived benefits	Pappas et al. (2021); Park and Kim (2021)	
		Perceived value	Ghobakhloo and Ching (2019)	
	Compatibility	Compatibility	Tiwari et al. (2023); Maroufkhani et al. (2023)	Chen et al. (2023); Park and Kim (2021); Albar and Hoque (2019)
		Incompatibility	Moghavvemi et al. (2021)	
		Perceived compatibility	Ghobakhloo and Ching (2019)	
	Complexity	Complexity	Sharma, Singh et al. (2024); Tiwari et al. (2023); Maroufhani et al. (2023); Moghavvemi et al. (2021); Wong et al. (2020)	Chen et al. (2023); Albar and Hoque (2019)
Organization	Human resources	Employee capability	Sharma, Singh et al. (2024)	
		Technological capabilities	Park and Kim (2021)	
		Technology competence	Pappas et al. (2021)	Tiwari et al. (2023); Chen et al. (2023)
		Knowledge competency	Ghobakhloo and Ching (2019)	Ilin et al. (2017)
	Top management support	Top management support	Sharma, Singh et al. (2024); Chen et al. (2023); Maroufhani et al. (2023); Abed (2020); Deng et al. (2020); Albar and Hoque (2019)	Tiwari et al. (2023)
		Management support	Park and Kim (2021)	
		Upper management support		Wong et al. (2020)
	Digital culture	Organizational culture	Albar and Hoque (2019)	
		Digital organizational culture	Martínez-Caro et al. (2020)	
	International orientation	International orientation	Cho et al. (2023)	
Environment	Trading partner pressure	Vendor support		Sharma et al. (2024b)
		Trading partner pressure	Chen et al. (2023)	Tiwari et al. (2023)
		Partner adoption		Park and Kim (2021)
	Competitive pressure	Competitive pressure	Tiwari et al. (2023); Chen et al. (2023); Wong et al. (2020)	Sharma, Singh et al. (2024)
		Competition	Pappas et al. (2021)	
		Competitor adoption		Park and Kim (2021)
		Lack of critical mass	Moghavvemi et al. (2021)	
		Competitive environment		Albar and Hoque (2019)
	Government regulatory support	Regulatory support		Wong et al. (2020)
		Regulatory pressure	Tiwari et al. (2023)	
		Government support policy	Park and Kim (2021)	
		Government regulatory support	Ilin et al. (2017)	
	Government resource support	Government resource support	Ilin et al. (2017)	
		Government support		Chen et al. (2023)

benefits for SMEs, such as providing better access to skills and talent, expanding market share, assisting firms in developing new products, services, or management (Ramdani et al., 2022), and promoting firms' efficiency through better communication and collaboration (Li et al., 2022). These benefits are recognized as key drivers to DT adoption (Marzi, Marrucci et al., 2023).

Past studies have discovered that perceived benefits were the essential impetus of innovation adoption because the adoption of new technology is based on commercial advantages (Abed, 2020; Park & Kim, 2021; Pappas et al., 2021; Tiwari et al., 2023; Sharma, Singh et al., 2024). Additionally, PB might motivate firms' top management to support the adoption of new technology. This suggests that, due to potential advantages, top management is likely to facilitate adoption (Wong et al. 2020). From this perspective, top management support may mediate the relationship between PB and DT adoption. Thus, it leads to the following hypotheses:

H2a. Perceived benefits positively affect digital technology adoption intention.

H2b. Perceived benefits positively affect top management support.

Compatibility

Compatibility refers to the degree to which an innovation is seen as consistent with an individual's current values, prior experiences, and the demands of adopters (Rogers, 2003). The idea of compatibility is relevant for the diffusion of new technologies because it assists in mitigating potential uncertainties associated with adopting new technological solutions (Moghavvemi et al., 2021). This may be because firms are confronting various challanges when implementing new technology, such as data integration, storage, analysis, and sharing (Kumar et al., 2022). When the new technology aligns with a firm's current values, it promptly encourages top management to support its adoption (Duan et al., 2019). In contrast, if new technology is perceived as incompatible, top management tends to decline it due to extensive learning and adjustment required (Maroufkhani et al., 2023). Compatibility appeared to positively affect IT-related adoption among SMEs in various countries, including Iran (Ghobakhloo & Ching, 2019), Vietnam (Chau et al., 2021), and India (Tamvada et al., 2022; Tiwari et al., 2023). In addition, compatibility also influences top management support for such initiatives among Iranian SMEs (Maroufkhani et al., 2023). Thus, it leads to the following hypotheses:

H3a. Compatibility positively affects digital technology adoption intention.

H3b. Compatibility positively affects top management support.

Complexity

Complexity refers to how an individual perceives the ease of use of an innovation. Essentially, this perception is inversely proportional to the possibility of adopting the innovation (Rogers, 2003). The easier it is for organizations to apply a new innovation, the more likely they are to engage with such technology. Conversely, a high degree of complexity can make it difficult for organizations to understand and adopt new innovations Advanced DT is considered a complex IT innovation in which SME managers might assume its adoption to be somewhat arduous (Tamvada et al., 2022). Thus, it is logical for SME managers to assume DT may not be implemented within their current business systems, especially when the technology is considered relatively new, leading to resistance to adoption. Such a perception might arise owing to the combination of a lack of training (Moghavvemi et al., 2021) and insufficient knowledge in the use of IT-related technology (Roffia & Mola, 2022). Complexity appeared to be a key inhibitor in some studies for the adoption of different technology among SMEs in various countries, including Iran (Maroufkhani et al., 2020), Malaysia (Moghavvemi et al., 2021), South Africa (Mkansi, 2022), and India (Tamvada et al., 2022; Tiwari et al., 2023). Thus, it can be hypothesized:

H4. Complexity negatively affects digital technology adoption intention.

Organizational context

Human resources (HR)

Tamvada et al. (2022) contend that the ongoing advancement of DT introduces complex challenges related to their operation and maintenance. Additionally, DTs necessitate a cohesive business strategy, integrating them to attain a firm's overarching objectives (Liu et al., 2023). Unlike the previous business environment that mostly viewed firms' employees as DTs' operators, the modern digital business landscapes necessitate firms' human resources not only to operate but also collaborate with DTs to achieve a more beneficial outcome (Vial, 2019), thereby making firms' employees an integral part of business transformation (Li et al., 2022).

To this end, the human element is crucial to embrace digital initiatives. The literature suggests that firms with proficient IT knowledge can absorb advanced technologies more quickly and harness them effectively compared to those lacking such knowledge (Huy et al., 2012). Put differently, a lack of internal expertise regarding IT knowledge is considered one of the major impediments to engaging with new technologies. Previous studies found a correlation between HR and new technology adoption among SMEs (Oliveira et al., 2019), Greek SMEs (Pappas et al., 2021), and Chinese SMEs (Chen et al., 2023). Hence, the following hypothesis is posted:

H5. Small and medium enterprises' human resources positively affect DT adoption.

Digital culture (DC)

Digital culture refers to the shared assumptions and overall knowledge regarding organizational practices in a digital context (Martínez-Caro et al., 2020). It can be viewed as a means by which a firm can start planning for digital strategies in a quickly evolving environment, and has become an intrinsic part of the new business model, which has imprinted itself on digital innovation (Leal-Rodríguez et al., 2023). Some studies report that DC has a positive relationship with firms' behavior in adopting certain technology (Albar & Hoque, 2019), digitization (Martínez-Caro et al., 2020), contributes positively to the degree of digitalization (Zangiacomi et al., 2020) and digital processes in the firm (Proksch et al., 2021), and has a positive association with firms' digital transformation (Guy, 2019). This association can be attributed to the fact that while individuals within organizations might use DT in diverse ways and attribute different meanings to it, a strong DC helps establish a common standard. In contrast, lack of DC has been identified as one of the most significant barriers to firms' engagement with advanced technologies (Raj et al., 2020).

Although many studies have attempted to reveal the role of DC in influencing the uptake of DT, they have mostly employed large organizations as their research background. As Dasgupta and Gupta (2019) caution, the culture among large and small organizations might be different, it is crucial to conduct studies to reveal whether DC has a similar impact on technology acceptance among SMEs as it has in large enterprises. Hence, the following hypothesis is created:

H6. Small and medium enterprises' digital culture positively affects digital technology adoption intention.

Top management support (TMS)

Top management in an organization has been considered the 'chief architect' of the firm's actions and the prime decision makers, making their endorsement a critical element in many firms' decisions (Popli et al., 2022). Maroufkhani et al. (2020) define TMS as the degree to which the upper echelons in an organization understand and encourage the uptake of technology for business purposes, where positive attitudes toward change can enhance the adoption process. Top management often orchestrates the establishment of essential IT infrastructure and the integration and re-engineering of business processes to facilitate technological adoption (Baabdullah et al., 2021).

Since the 1960s, TMS has been postulated in the literature and highlighted as a vital component in the adoption of technology in the organization that may work either to advocate the adoption or against the adoption (Oliveira et al., 2019). Studies indicate that more supportive the top management's involvement within the organization concerning adopting new technology, the stronger the possibility that the adoption will take place (Swani, 2021). TMS has been discovered as a primary determinant that affects IT-related adoption among SMEs in Saudi Arabia, Iran, Australia, and China (Albar & Hoque, 2019; Deng et al., 2020; Maroufhani et al., 2023; Chen et al., 2023). Accordingly, the following hypothesis is proposed:

H7. Top management support positively affects digital technology adoption intention.

Environmental context

Trading partner pressure (TPP)

Trading partner pressure refers to a mandate given by trading partners to their distributors to engage with particular technologies (Tiwari et al., 2023). In general, large firms and SMEs typically follow different decision-making paths when considering the adoption of new technology from a supply chain perspective. Large firms often adopt new technology to enhance efficiency and security within the supply chain. SMEs, particularly from the supply chain viewpoint, tend to align with their suppliers' mandates because the benefits of adoption are more pronounced for large enterprises when their trading associates throughout the distribution chain also engage with the same technological spectrum (Abed, 2020). Therefore, trading partners generally require their distributors to adopt a specific technology they have implemented to achieve a competitive edge (Marzi, Marrucci et al., 2023).

From the SMEs' perspectives, pressure from trading partners is a crucial driver for the adoption of DT. These partners often equip SMEs with the necessary preliminary knowledge for utilizing DT effectively, which makes SMEs more receptive to its adoption (Maroufkhani et al., 2020). Within the industry ecosystem, small firms are considered to have less coercive power and are often obliged to adhere to their suppliers' requirements (Abed, 2020). Thus, TPP has been seen as a potent predictor of technology adoption, especially among SMEs. TPP has been found to be a determinant factor behind various IT initiatives among SMEs in Australia, Saudi Arabia, and China (Deng et al., 2020; Abed, 2020; Chen et al., 2023). Thus, this guides the following hypothesis:

H8. Trading partner pressure positively affects digital technology adoption intention.

Competitive pressure (CP)

The current business environment is seen as being turbulent and intense, stemming from various factors, including the availability advanced technology, changing customers' consumption, and globalization (Hock-Doepgen et al., 2021). According to Zhu et al. (2006), CP is the extent of influence that firms experience due to the competition in the market. This pressure is defined by the possibility of losing customers or market share as the competition intensifies (Ghobakhloo & Ching, 2019). Firms often respond to the competition by adopting DT to be competitive in the industry landscape, and many firms try to become the first movers in adopting DT to achieve the benefit from a first mover advantage (Shetty & Panda, 2023).

Swani (2021) reveals that firms tend to follow their competitors in their efforts regarding new technology adoption due to concerns about market displacement when competitors have already adopted certain technologies, initiating a bandwagon cycle. The more firms that adopt DT, the greater the pressure on those who have not yet adopted it to do so (Shetty & Panda, 2023), because increased adoption amplifies competitive pressure to conform (Su et al., 2023). Competitive pressure has been found to be a factor leading to technology adoption among firms in various countries, including Malaysia (Wong et al., 2020), Greece (Pappas et al., 2021), China (Chen et al., 2023), and India (Tiwari et al., 2023). Thus, this guides the following hypothesis:

H9. Competitive pressure positively affects digital technology adoption intention.

Government resource support (GRESS)

Government support refers to the existence of government policies and efforts aimed at fostering technology adoption (Chau et al., 2021). The support available from the government can be diverse, and includes mediating IT infrastructure (Alsaad et al., 2021), offering direct or indirect funding, improving SMEs IT-related knowledge (Mkansi, 2022), providing experts to answer SMEs' queries (Park & Kim, 2021), and creating privacy and security regulations (Priharsari et al.,2023) Given the potentially extensive nature of government support, scholars have divided it into two categories: governmental policies related to resource support and those related to regulatory support (e.g., Ilin et al., 2017). GRESS includes consultation, seminars, training, and educational assistance provided by the government to enhance enterprise employees' knowledge of the use of specific technologies in their business activities (Zhang et al., 2023); creating internet infrastructures, such as base transceiver station (BTS) or satellites, are also included in this category (Priharsari et al., 2023). GRESS has been found to be a determinant in technology adoption among firms in Balkan countries (Ilin et al., 2017). Accordingly, the following hypothesis is enacted:

H10. Government resource support positively affects digital technology adoption intention.

Government regulatory support (GREGS)

GREGS encompasses government legislative regulation designed to create a positive economic climate to encourage technology adoption, for instance, by providing tax reductions, subsidies, reductions in telecom costs (Alsaad et al., 2021), and creating an appropriate legal environment (Park & Kim, 2021). Pingali et al. (2023) highlight that, due to challenges like unstable political systems, infrastructure, and regulatory issues faced by SMEs in developing countries, GREGS is essential to foster an environment conducive to technology adoption. GREGS has been argued to represent a driving factor behind South Korean firms and Chinese SMEs technology adoption (Park & Kim, 2021; Chen et al., 2023). Hence, it can be hypothesized:

H11. Government regulatory support positively affects digital technology adoption intention.

Moderating role of a firm's international orientation (IO)

Knight and Kim (2009) interpret IO as a firm's vision that assists in creating and harnessing resources to fulfil their objectives in the international realm. A high IO is characterized as firms that actively pursue opportunities within the international realm, considering the world as their market, articulating their international objectives across organizations, and enhancing the resources necessary for international activities (Moen et al., 2016). According to Crespo et al. (2023), IO embodies a managerial perspective that emphasizes a proactive culture, one which actively pursues opportunities overseas and devises strategies aimed at succeeding in global markets.

Firms with high international strategy often take proactive steps to engage with new technological innovation to acquire an extensive perspective of the international markets (Kyriakou & Loukis, 2019). They do this to ensure their products meet the requirements or preferences of international markets (Ballerini et al., 2023). Digital technologies provide firms with the agility to navigate the market, because they amass valuable customer data that aid in predicting emerging trends, thereby fostering enhanced product and service innovation (Reim et al., 2022). Furthermore, according to Freixanet et al. (2021), IO positively induces firms' innovation through greater use of DTs.

Despite the significance of IO in predicting DT uptake, most IT-related adoption studies have primarily examined the direct relationship between IO and firms' intentions to adopt DT (e.g., Cho et al., 2023). In practice, the degree of firms' IO may affect their organizational factors, such as human resources and digital culture. This is because IO is linked to the adoption of strategies aimed at reducing competitive risks and enhancing business growth (Crespo et al., 2023). Prior research has shown that a firm's internationalization moderates the relationship between certain types of innovation (e.g., sustainable operation) and direct variables (e.g., Liu et al., 2020). Building from these perspectives, HR and DC might be moderated by firms' IO. This leads to the following hypotheses:

H12a. International orientation moderates the relationship between human resources and digital technology adoption intention.

H12b. International orientation moderates the relationship between digital culture and digital technology adoption intention.

Control variables

Research in management and IT-related studies suggests that certain factors can potentially affect firms' decision to adopt new technology (e.g., Marzi, Marrucci et al., 2023; Oduro et al., 2023). A detailed examination of these factors can assist in identifying external influences that might distort the outcomes (Pedota et al., 2023). Accordingly, this study will control for sector, location, and firm size to ensure a more accurate analysis.

Research model

Based on the discussion above, Fig. 1, below, illustrates the relationship among the variables. The proposed research framework integrates the TOE framework with Rogers' DOI theory to provide a clearer understanding of the factors influencing SMEs' adoption of DT. In total, there are 12 constructs that were identified from the literature that influence SME new technology adoption that can be classified into technological, organizational, and environmental contexts. Each hypothesis explores a distinct relationship, contributing to a hierarchical arrangement of these variables. The detailed research framework and the 12 constructs are conceptualized in Fig. 1.

Research methodology

Instruments and pilot test

After reviewing the literature, 58 questions were selected from previously validated studies to investigate the various factors (as dependent or moderating variables) that influence SMEs' intentions to adopt DT (detailed in Appendix). These items were scored on a five-point Likert scale from 'strongly disagree' to 'strongly agree.'

All questions in the survey, along with the participant information statement, were carefully translated into Indonesian to make it convenient for the participants to express their views. A reverse translation back into English was performed by a professional translator to ensure that the survey's meanings were not lost due to the translation process. To ensure the survey's clarity and objectivity, and to minimize language bias, a pilot study involving 30 SMEs was carried out prior to the broader distribution of the survey.

Participants in the pilot study were asked to complete the questionnaire and provide feedback where possible. They affirmed the clarity of the questions and instructions. Cronbach's alpha was employed to ensure the reliability of the survey instrument, and all values were within the acceptable range defined by Hair et al. (2019). Following this validation, the questionnaire was distributed to a broader group of potential participants for data collection.

Data collection

The email containing the survey link was addressed to SME managers or owners because they are the most qualified individuals to explain DT adoption in their firms. Employees could also fill out the survey, provided that they had a mandate to act on a manger's/owner's behalf to do so. The information about SMEs (e.g., names, e-mail address, location, and sector) was acquired from Statistic Indonesia's database, which is publicly available. To expand the level of engagement from the broader SME industry, SMEs' information was also sought from different government agencies with their approval. All SMEs that received the questionnaire meet the Indonesian government's definition of SMEs, as outlined in Table 1 above. Due to SMEs being located in dispersed geographical areas, stratified sampling was performed first to minimize sampling errors compared to pure random sampling (Khan et al., 2015).

To achieve this, the data were divided based on the location and sector where the SMEs operate, thereby creating sub-populations. Then, the number of SMEs in each sub-population is counted, and normal random sampling is carried out to ensure that every SME in each sub-population has an equal chance of being selected (Ghauri et al., 2020). Following Marzi, Manesh et al. (2023) recommendations, this study did not differentiate SMEs based on sector or location. This approach was taken to generate a holistic perspective on DT adoption across various SME industries, thereby reducing potential bias that could arise from focusing on a single sector.

To minimize the potential of social desirability bias, this study

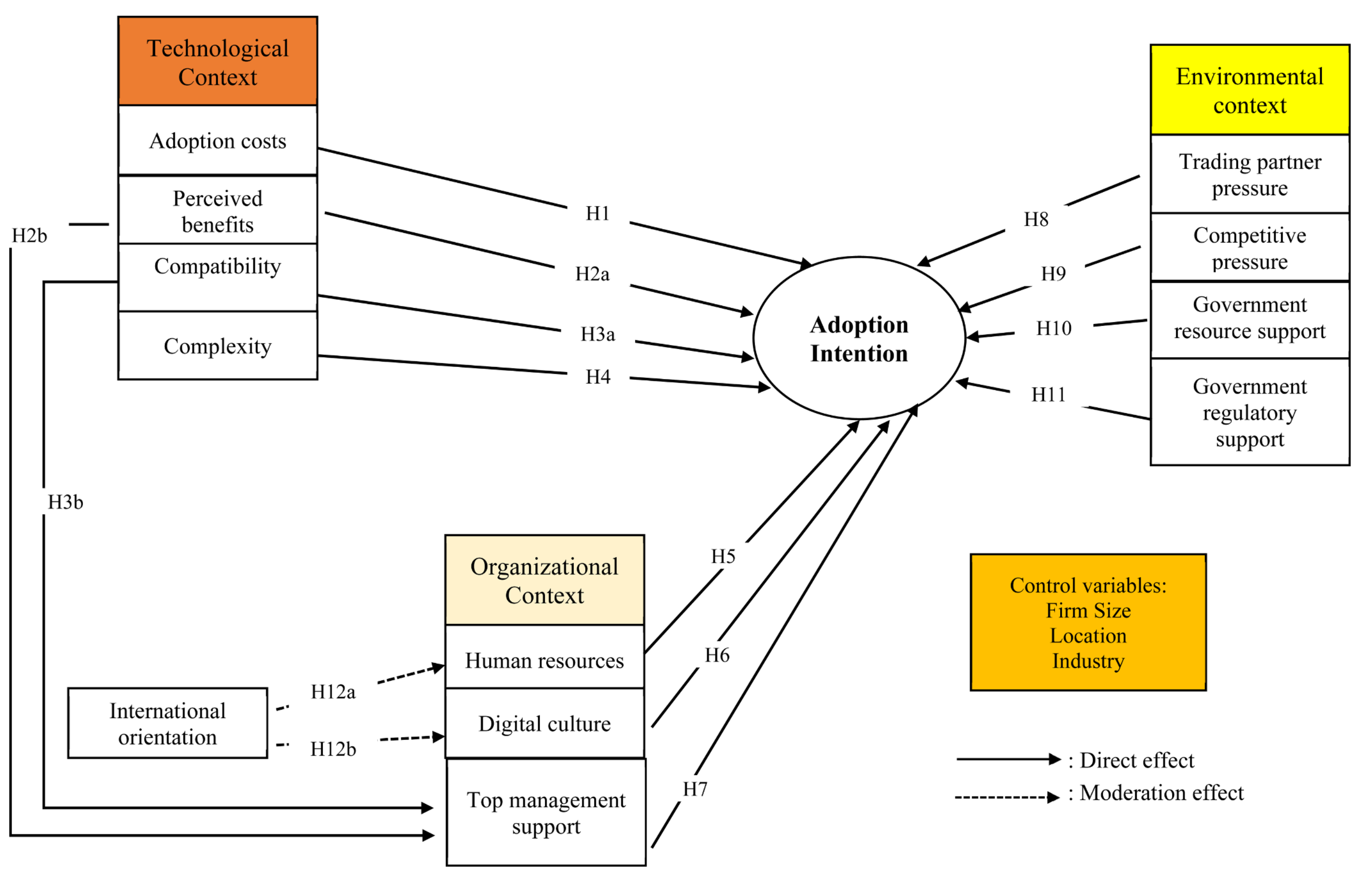

Fig. 1. Research framework.

ensured confidentiality and framed questions around the broader behaviors of the organizations and their members. Since the questions were not geared toward individual actions or outcomes, they were less prone to such bias. Additionally, to prevent bias, screening questions were employed to confirm respondents' eligibility, such as being at least 18 years old and verifying that their firms qualify as SMEs under Indonesian Law. Only participants who met these criteria were allowed to proceed with the survey.

The survey link was disseminated to 10,000 SME managers/owners via Qualtrics in June 2022. Of the 426 responses received, seven were discarded due to identical answers, giving a 4.2 % response rate. The demographic characteristics of the respondents are presented in Table 3. Most respondents were business owners (68.02 %), followed by employees (19.09 %) and managers (12.89 %). A substantial proportion of respondents were micro firms (57.76 %), followed by small (35.32 %), and medium firms (6.92 %). These figures are consistent with Statistic Indonesia's report (2018), which showed that the majority of SMEs in Indonesia are considered micro-enterprises, followed by small and medium enterprises. The majority of respondents come from the manufacturing sector (41.05 %), followed by the services sector (36.75 %) and the agriculture sector (22.20 %). These figures also in line with Statistic Indonesia's report (2018), which reported that SMEs in Indonesia are dominated by the manufacturing sector, followed by services, and then agriculture. Table 3 shows that 79.24 % of responses came from developed provinces, and 20.76 % from less-developed ones. Gender distribution is nearly equal, with slightly more females. An independent *t*-test was conducted on the mean responses of two groups' mean responses of early and late respondents to several constructs (Armstrong & Overton, 1977). The results indicate that there were no statistically significant differences between these groups.

Analytical method

Partial least squares structural equation modeling (PLS-SEM) approach

Partial least squares structural equation modeling was selected for its flexibility in handling normal and non-normal data distributions, which is particularly advantageous given the data characteristics commonly found in entrepreneurship studies (Douglas et al., 2020) and firm behavioral research (e.g., Chen et al., 2023). These fields frequently involve non-normally distributed data, making PLS-SEM a suitable choice because it does not rely on the assumption of normal data distribution (Hair et al., 2020). Moreover, PLS-SEM is particularly favorable for studies involving complex models, because it tends to achieve model convergence when a large number of latent variables are present. Because this study includes control variables, numerous latent variables, along with direct and moderating factors, resulting in a complex model, the use of PLS-SEM is relevant to ensure model convergence. Partial least squares structural equation modeling is useful for developing theoretical frameworks (Hair et al., 2017) and is therefore more aligned with theory exploration than confirmation (Dash & Paul, 2021). Given that this study combines two theories that incorporate diverse elements from state-of-the-art knowledge, PLS-SEM is an appropriate choice as the theoretical framework is still being developed.

Additionally, PLS-SEM can deliver reliable results even with small and medium sample sizes (Hair et al., 2020), making it particularly beneficial in research fields where obtaining large samples is challenging (Cheah et al., 2023). Since this study's sample size is limited due to difficulties in accessing small business data in developing countries (Soluk et al., 2021), PLS-SEM is an accurate analytical method for these circumstances. Finally, PLS-SEM is flexible for analyses involving formative or reflective constructs (Dash & Paul, 2021). The use of PLS-SEM is suitable in this regard because this study employs indicators grounded in prior IT-related adoption research, this study operationalizes all constructs reflectively, aligning with the literature's precedent. The analysis was conducted using SmartPLS 4.0.9.9 (Ringle et al., 2024).

Artificial neural network (ANN) approach

Artificial neural network (ANN) was employed to complement PLS-SEM, because it can determine the predictive capacity of independent variables and rank them based on their importance on certain outcomes (Abbasi et al., 2021), which is relevant to addressing research question number 2 of this study. Artificial neural network is frequently used to quantify the importance of each independent construct that has been proved to be statistically significant from previous analyses through sensitivity analysis (Lee et al., 2022). To predict the analysis outcomes, ANN uses a feed-forwarded-backward-propagation (FFBP) algorithm, where inputs are loaded in a forward path and projected errors are relocated in a reverse manner (Taneja & Arora, 2019). ANN can learn from the data, allowing the researchers to obtain more accurate predictions that contribute to robust research findings (Abbasi et al., 2021), and it is suitable for concluding the predictive power of any bias (Sharma, Joshi et al., 2024). Due to its many advantages, some scholars suggest applying ANN measures to offset the limitations of PLS-SEM, particularly its inability to handle non-linear relationships (e.g., Leong et al., 2020). In this study, the neural network analysis was conducted using the SPSS V.26 neural network module (IBM, 2019).

Results

Measurement model

The reliability of the measures was assessed through the Cronbach's alpha, Dijkstra-Henseler's rho_A, composite reliability (CR), and average variance extracted (AVE). All results exceeded the Hair's et al. (2019) recommendation for evaluation benchmarks with Cronbach's alpha, rho_A, and CR values above 0.7 and AVE values over 0.5, which can be seen in Table 4. The results of the factor loadings are presented in the Appendix, where the value for each indicator is above the minimum of 0.708 (Hair et al., 2019), except for PB2. According to Tajudeen et al. (2018), excluding an indicator is unnecessary if it does not impact the

Table 3
Respondent characteristics ($n = 419$).

Characteristic		Freq.	%	Characteristic		Freq.	%
Respondent's position	Owner	285	68.02	Firm age (years)	≤ 2	67	15.99
	Manager	54	12.89		2–5	57	13.60
	Employee	80	19.09		6–10	209	49.88
Firm size	Micro	243	57.76		> 10	86	20.53
	Small	148	35.32	Education	≤ High school	164	39.14
	Medium	28	6.92		Diploma	42	10.02
Firm sector	Services	154	36.75		Undergraduate	178	42.48
	Manufacturing	172	41.05		Postgraduate	35	8.35
	Agriculture	93	22.2				
Location	Less-developed provinces	87	20.76	Respondent's age	18–30	153	36.52
	Developed provinces	332	79.24		30 – < 40	141	33.65
Respondent's gender	Male	207	49.40		40 – <50	92	21.96
	Female	212	50.60		> 50	33	7.88

Table 4
Construct reliability and validity.

	Cronbach's alpha (α)	rho_A	Composite reliability	Average variance extracted (AVE)
AC	0.829	0.843	0.878	0.59
AI	0.91	0.91	0.944	0.848
COMPB	0.86	0.862	0.899	0.641
CP	0.838	0.893	0.879	0.594
CPLXTY	0.79	0.819	0.875	0.701
DC	0.872	0.873	0.912	0.723
GREGS	0.898	0.909	0.925	0.711
GRESS	0.902	0.907	0.927	0.717
HR	0.923	0.937	0.945	0.811
IO	0.908	0.908	0.936	0.785
PB	0.815	0.819	0.871	0.575
TMS	0.865	0.868	0.902	0.649
TPP	0.86	0.882	0.897	0.636

Notes: AC = adoption costs, AI= adoption intention, COMPB = compatibility, CP = competitive pressure, CPLXTY = complexity, DC = digital culture, GREGS = government regulatory support, GRESS = government resource support, HR = human resources, IO = international orientation, PB = perceived benefits, TMS = top management support, TPP = trading partner pressure.

AVE or CR. Therefore, since the omission of PB2 did not affect the AVE and CR outcomes, it was retained.

Discriminant validity was evaluated using the Fornell and Larcker (1981) criterion. Table 5 shows that inter-variable correlations were below the square root for each variable, indicating the requirement for discriminant validity is met. Additionally, the Heterotrait-Monotrait (HTMT) ratio was employed to assess discriminant validity. A potential threat to discriminant validity is indicated by an HTMT value exceeding 0.9 for very similar indicators or 0.85 for distinct constructs (Henseler et al., 2015). As shown in Table 6, all HTMT ratios are below the customary threshold of 0.85, except for GRESS, which stands at 0.883. Considering GRESS and GREGS both assess elements of government regulation and are closely related, the more lenient threshold of 0.9 is appropriate. Therefore, the discriminant validity is not present in the current model.

To examine the presence of common method bias, Harman's single factor test was conducted using SPSS V.26. Such bias is indicated if a single factor accounts for over 50 % of the variance (Podsakoff et al., 2003). The test results showed that the sum of squared loadings for the first factor explained 26.27 % of the variance, which falls below the threshold. Thus, common method bias is not considered to be a concern in this study.

Structural model

Fig. 2 shows the structural model outcomes derived from the PLS-SEM analysis, evaluated through non-parametric bootstrapping with 5000 iterations. The determination of the acceptance or rejection of the hypothesis is based on the cut-off value of $p < 0.05$ (two-tailed). Multicollinearity among the formative indicators was assessed using the variance inflation factor (VIF). As shown in Table 7, all VIF values fall under 3.3 (Kock, 2015), signifying that multicollinearity does not pose a problem in this research. The research model included three control variables and the analysis showed that these control variables did not significantly influence SMEs' intention to adopt DT. Given that this study's focus is not on the control variables, the discussion is limited to the main research model.

Hypotheses testing

A total of 11 direct effects were analyzed, with five hypotheses found to be statistically significant: AC, TMS, DC, HR, and TPP, all of which influence firms' intention to adopt DT. The supported hypotheses are primarily from the organizational context (TMS, DC and HR), with one supported hypothesis from technological (AC) and environmental (TPP) contexts. Meanwhile, PB, compatibility (COMPB), complexity (CPLXTY), CP, GRESS, and GRESS were not statistically significant in affecting SMEs' intention to adopt DT. Regarding indirect effects, which include moderating and mediating variables, four hypotheses were tested. The results supported the hypotheses of COMPB and PB positively affect TMS, and that IO moderates the relationship between DC and the intention to adopt DT.

Moderating factor result

Figs. 3 and 4 present the result of IO as a moderator between DC and HR with SMEs intention to engage with DT. Fig. 3 indicates that IO moderates the relationship between firms' DC and DT adoption. Fig. 4 shows that IO does not moderate the relationship between HR and DT adoption, as all three lines appear to be parallel.

Artificial neural network (ANN)

The ANN approach is similar to the neuron, synapse, and axon structure of the human brain; thus, it is regarded as suitable for exploring a deeper understanding of certain phenomena through a learning process that emulates the human decision-making system (Singh et al., 2023). ANN is capable of self-learning and adaptation which could produce input and output neurons that are corresponding in advance. This learning process is known as 'training.' Thus, essentially, ANN uses artificial intelligence to generate a solution of a given complex group of problems (Sharma, Joshi et al., 2024).

Two hidden layers were adopted in the ANN architecture (known as

Table 5
Fornell and Larcker.

	AC	AI	COMPB	CP	CPLXTY	DC	GREGS	GRESS	HR	IO	PB	TMS	TPP
AC	**0.768**												
AI	0.21	**0.921**											
COMPB	0.317	0.425	**0.801**										
CP	0.197	0.412	0.475	**0.77**									
CPLXTY	0.45	0.217	0.372	0.273	**0.837**								
DC	0.182	0.643	0.503	0.444	0.255	**0.85**							
GREGS	0.11	0.316	0.418	0.404	0.314	0.456	**0.843**						
GRESS	0.116	0.295	0.34	0.373	0.257	0.436	0.8	**0.847**					
HR	0.148	0.296	0.476	0.357	0.166	0.434	0.422	0.388	**0.901**				
IO	0.128	0.607	0.391	0.316	0.186	0.638	0.358	0.395	0.324	**0.886**			
PB	0.303	0.324	0.71	0.381	0.313	0.397	0.325	0.248	0.343	0.296	**0.758**		
TMS	0.22	0.536	0.593	0.463	0.199	0.533	0.32	0.257	0.51	0.473	0.524	**0.805**	
TPP	0.202	0.452	0.499	0.601	0.272	0.479	0.476	0.454	0.474	0.399	0.357	0.473	**0.798**

Notes: AC = adoption costs, AI= adoption intention, COMPB = compatibility, CP = competitive pressure, CPLXTY = complexity, DC = digital culture, GREGS = government regulatory support, GRESS = government resource support, HR = human resources, IO = international orientation, PB = perceived benefits, TMS = top management support, TPP = trading partner pressure.

Table 6
Discriminant validity (HTMT).

	AC	AI	COMPB	CP	CPLXTY	DC	GREGS	GRESS	HR	IO	PB	TMS	TPP	IO x HR	IO x DC
AC															
AI	0.232														
COMPB	0.364	0.479													
CP	0.241	0.429	0.533												
CPLXTY	0.562	0.25	0.444	0.337											
DC	0.207	0.719	0.581	0.481	0.301										
GREGS	0.126	0.345	0.477	0.461	0.367	0.514									
GRESS	0.135	0.321	0.384	0.426	0.295	0.49	0.883								
HR	0.165	0.318	0.534	0.396	0.189	0.48	0.461	0.419							
IO	0.138	0.667	0.441	0.327	0.212	0.714	0.393	0.435	0.347						
PB	0.349	0.371	0.84	0.435	0.378	0.468	0.385	0.29	0.393	0.344					
TMS	0.255	0.603	0.683	0.496	0.227	0.609	0.36	0.282	0.565	0.53	0.618				
TPP	0.232	0.485	0.56	0.701	0.325	0.525	0.533	0.516	0.52	0.429	0.407	0.525			
IO x HR	0.046	0.064	0.101	0.047	0.091	0.074	0.067	0.079	0.129	0.189	0.043	0.114	0.122		
IO x DC	0.054	0.358	0.091	0.109	0.093	0.345	0.029	0.039	0.053	0.378	0.065	0.254	0.048	0.15	

Notes: AC = adoption costs, AI= adoption intention, COMPB = compatibility, CP = competitive pressure, CPLXTY = complexity, DC = digital culture, GREGS = government regulatory support, GRESS = government resource support, HR = human resources, IO = international orientation, PB = perceived benefits, TMS = top management support, TPP = trading partner pressure.

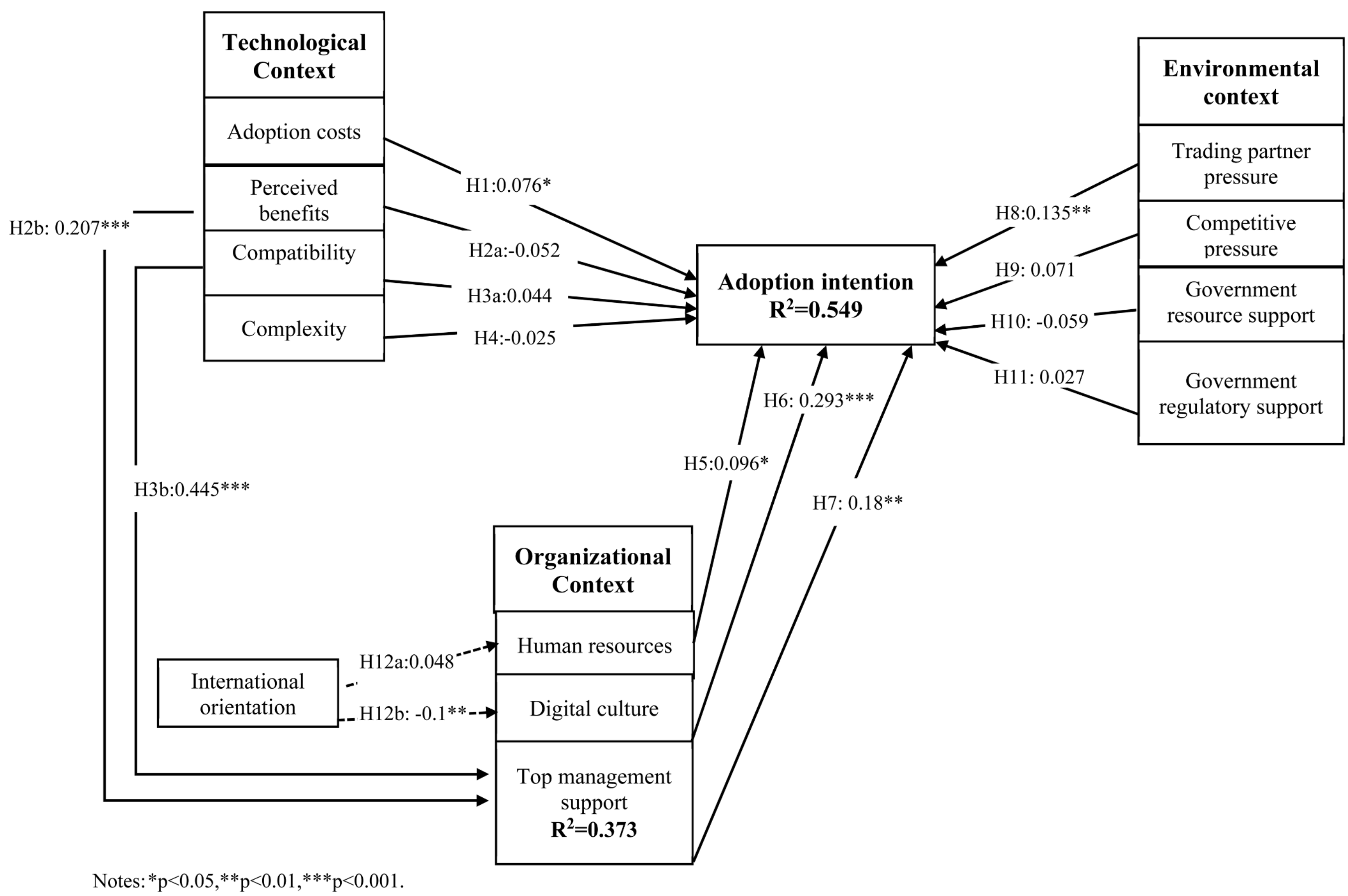

Fig. 2. Structural model assessment.

a deep ANN architecture) as opposed to a single hidden layer (known as a shallow ANN) to improve the precision of nonlinear associations with the model, because it has a stronger deep learning ability via two hidden layers (Abbasi et al., 2021). The tenfold cross-validation process was applied to address the overfitting issue by differentiating the number of hidden nodes from one to ten (Sharma et al., 2021). The default IBM SPSS neural network module was used for data allocation, with 70 % of the data for training the neural network and the remaining 30 % for evaluating the prediction accuracy of the trained model. The hyperbolic tangent is selected for the activation function for both the hidden layer and output layer because it converts real-valued arguments into the range (−1,1) and can be applied to all units in the hidden layers (IBM, 2019).

Previous studies assert that only significant independent variables can be used in ANN models as opposed to the whole constructs (e.g., Leong et al., 2020); therefore, this study only considered the significant independent variables from PLS-SEM analysis. The six statistically significant predictors from the PLS-SEM analysis, namely: AC, TMS, HR, DC, IO, and TPP, were used in the input layer. Meanwhile, DT adoption as the dependent variable was used in the output layer. The DT adoption

Table 7
Structural relationship and hypotheses testing.

Paths	β	Sample mean (M)	STDEV	T statistics	P-values	VIF	R-square	Supported
Direct effects								
H1: AC → AI	0.076	0.079	0.039	1.978	0.048	1.348	0.549	Yes
H2a: PB → AI	−0.052	−0.051	0.054	0.964	0.335	2.142		No
H3a: COMPB → AI	0.044	0.043	0.064	0.683	0.494	2.824		No
H4: CPLXTY→ AI	−0.025	−0.023	0.046	0.545	0.586	1.491		No
H5: HR → AI	−0.096	−0.094	0.043	2.249	0.025	1.644		Yes
H6: DC → AI	0.293	0.291	0.056	5.193	0	2.331		Yes
H7: TMS → AI	0.18	0.178	0.059	3.056	0.002	2.184		Yes
H8: TPP → AI	0.135	0.136	0.055	2.449	0.014			Yes
H9: CP → AI	0.071	0.071	0.047	1.493	0.136	1.786		No
H10: GRESS→ AI	−0.059	−0.057	0.06	0.991	0.322	3		No
H11: GREGS → AI	0.027	0.023	0.068	0.4	0.689	3.188		No
Indirect Effects								
H2b: PB → TMS	0.207	0.21	0.057	3.662	0	2.015	0.373	Yes
H3b: COMPB → TMS	0.445	0.447	0.051	8.734	0	2.015		Yes
H12a: IO HR→AI	0.048	0.047	0.041	1.181	0.238	1.097		No
H12b: IO DC → AI	−0.1	−0.102	0.036	2.787	0.005	1.357		Yes

Notes: AC = adoption costs, AI= adoption intention, COMPB = compatibility, CP = competitive pressure, CPLXTY = complexity, DC = digital culture, GREGS = government regulatory support, GRESS = government resource support, HR = human resources, IO = international orientation, PB = perceived benefits, TMS = top management support, TPP = trading partner pressure.

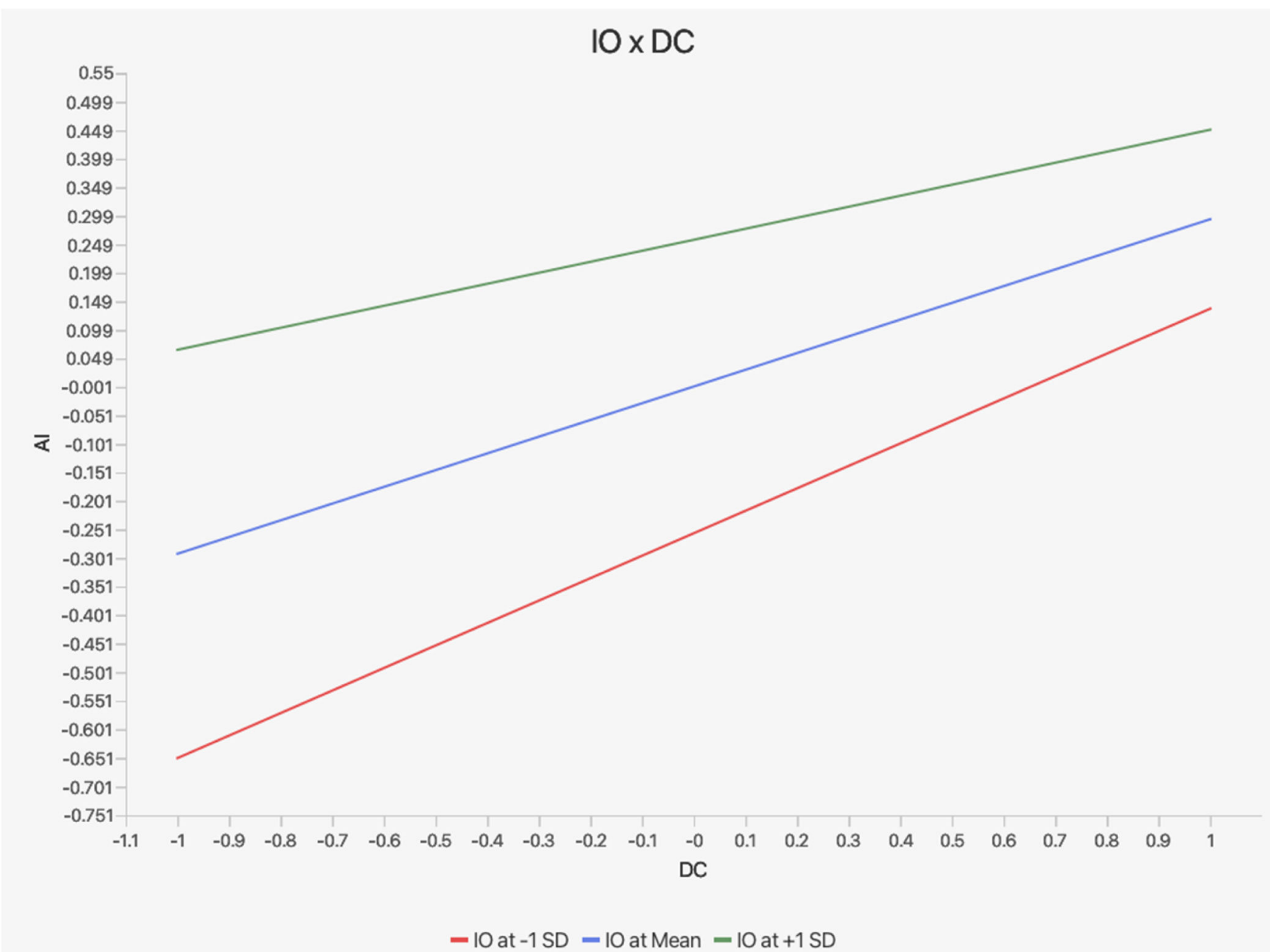

Fig. 3. The effect of IO on the relationship between DC and DT adoption.

as the dependent variable was used in the output layer. Fig. 5 depicts a diagram of ANN based on the significant variables in this study.

Validation

Root mean square error (RMSE) was applied to validate the ANN findings. Fig. 6, below, shows that the values of RMSE are between 0.1

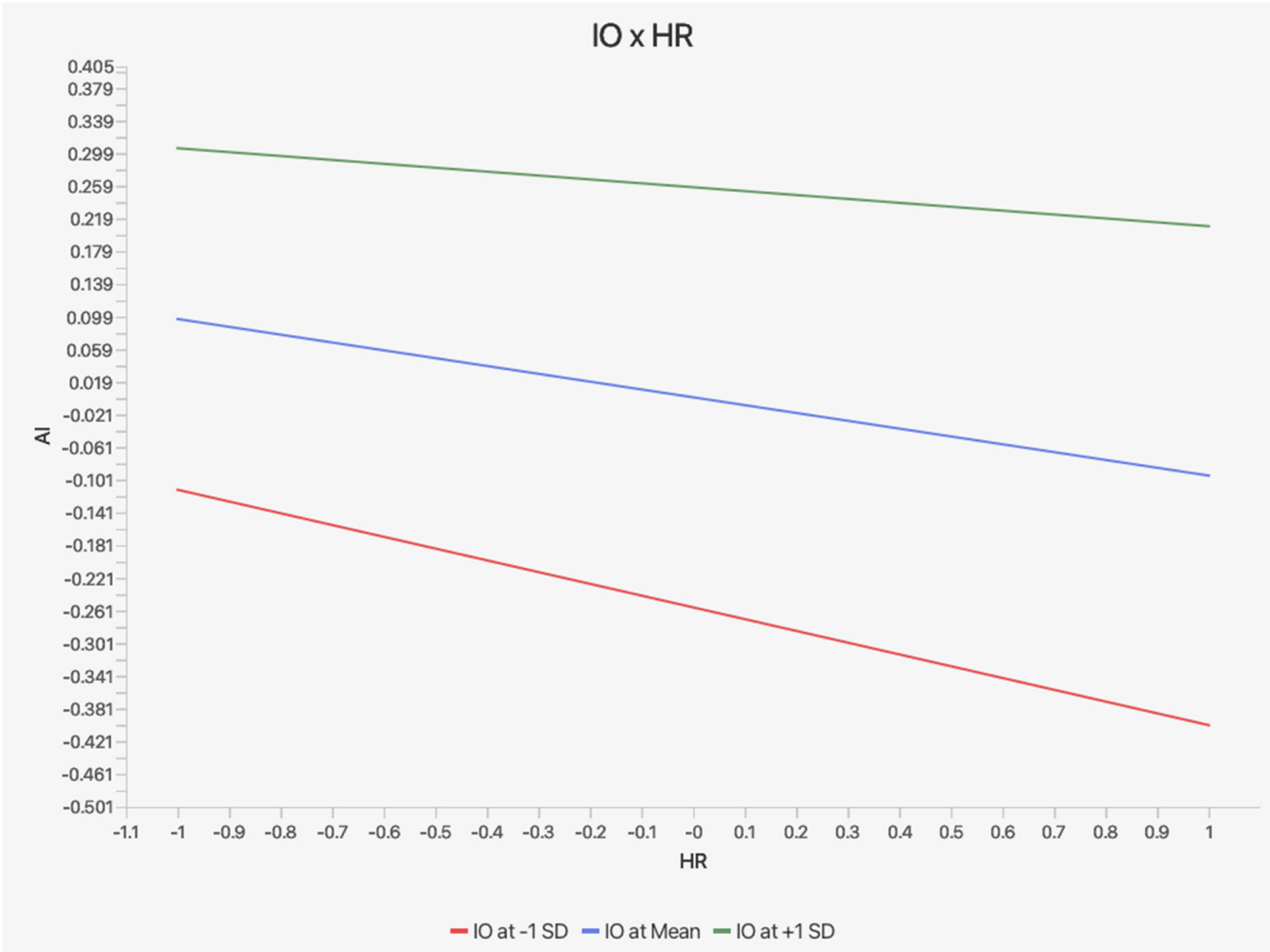

Fig. 4. The effect of IO on the relationship between HR and DT adoption.

and 0.25 for training and testing tests, close to 0 and below the 0.5 threshold (Sharma, Joshi et al., 2024). This suggests that the model is accurate and reliable, and captures the relationships between independent variables and dependent variable.

Sensitivity analysis

This study employed sensitivity analysis to measure the predictive strength of each input neuron. It evaluates the variations in the dependent construct by changes in the associated independent constructs, highlighting the model's reliance on specific independent variables (Lee et al., 2022). For comparative analysis, the importance of each neuron was normalized by dividing its values by the highest importance value in the network, resulting in percentage terms (Leong et al., 2020). Table 8 below shows that the most important predictor of DT adoption is DC (100 %), followed by IO (84 %), TMS (72 %), TPP (60 %), HR (36 %); with AC being the least influential factor at 27 %.

Fig. 7 below was developed to provide a better depiction of the hierarchal level of variables affecting firms' decision to adopt DT.

Discussion

This study attempts to identify the factors that influence SMEs to adopt DT in their businesses. The results obtained from PLS-SEM and ANN confirm the impact of each investigated factor leading to DT adoption, although the extent of their influence may vary. This study highlights that the factors originating from the organizational context exert a more substantial impact on SMEs' decisions to accept DT, given that all associated variables are statistically significant. This analysis suggests that the centrality of DT adoption is influenced more by organizational context than by environmental or technological ones. Polisetty et al. (2024) note that the technological, organizational, and environmental contexts continually interact within the same reality, influencing the causal relationship with new technology. Consequently, outcomes from one context may have a more significant impact than others. Expanding on this, Agrawal (2024) argues that the organizational context is more critical during the early stages of technology adoption, where lack of regulatory support and prevalent technological uncertainty often diminish the impact of technological and environmental factors. Sun et al. (2024) emphasize that despite the interplay of technology, organizational, and environmental factors being important, the most pivotal aspect is the strategic mindset of the decision makers who often evaluate their organization's capabilities before deciding to engage with new technology.

The PLS-SEM results show that digital culture (H6) has a significant effect on DT adoption. The ANN results demonstrate that DC holds the highest (100 %) relative importance, outweighing other supported variables in SMEs' adoption of DT. Despite the scarcity of research on the role of DC in technology acceptance, this finding aligns with those of Martínez-Caro et al. (2020), who assert that DC contributes positively to multinational firms' business digitalization. This finding might be explained by the fact that firms with strong DC can seamlessly integrate DT into their strategies, adopt agile governance, foster flexible digital

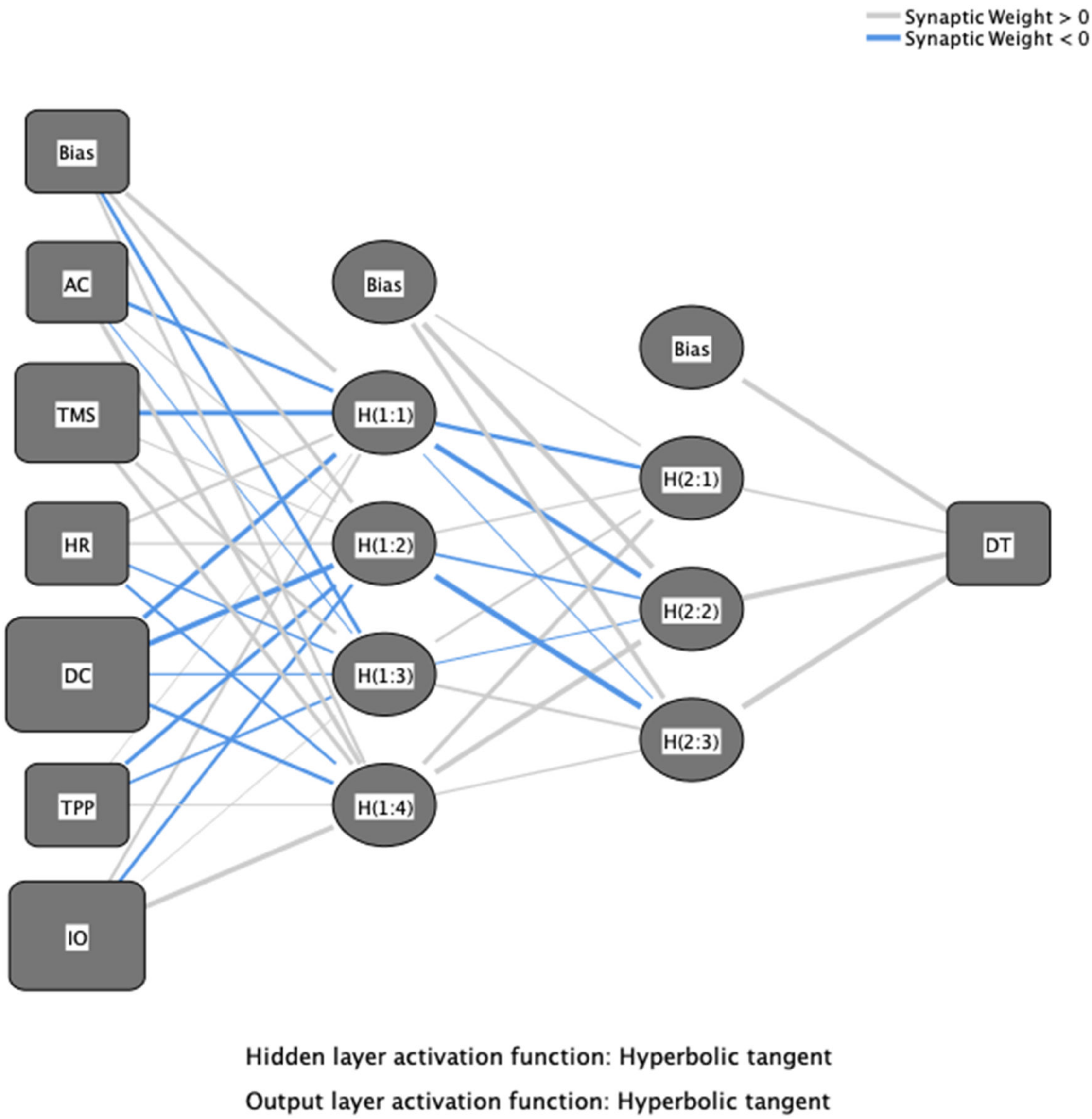

Fig. 5. Artificial neural network diagram.

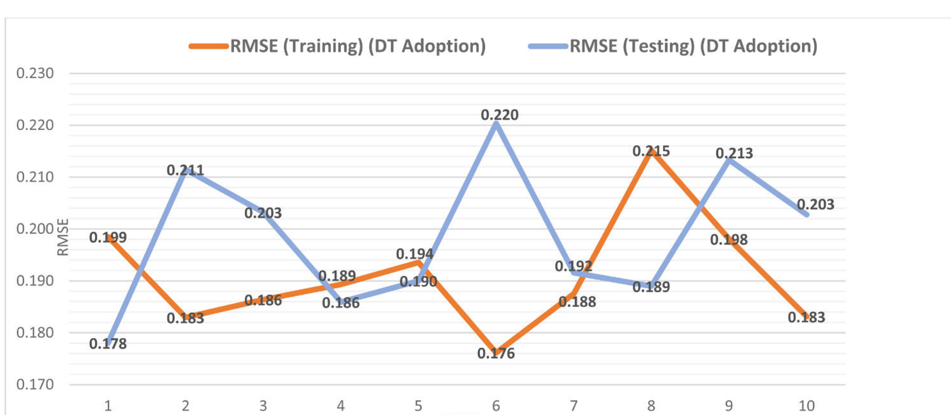

Fig. 6. The values of RMSE for training and testing.

platforms (Proksch et al., 2021), and establish efficient monitoring processes (Oduro et al., 2023), collectively furthering the achievement of their strategic objectives (Leal-Rodríguez et al., 2023).

TMS (H7) is a significant factor in DT adoption, supporting the prevailing literature that highlights its crucial role in successful technology integration within SMEs (Sharma et al., 2024b), large

Table 8
ANN model results.

Ann models	AC	TMS	HR	DC	TPP	IO
ANN1	0.114	0.184	0.119	0.242	0.122	0.221
ANN2	0.046	0.256	0.117	0.138	0.246	0.196
ANN3	0.089	0.227	0.096	0.091	0.342	0.155
ANN4	0.06	0.243	0.099	0.324	0.066	0.208
ANN5	0.041	0.162	0.077	0.398	0.132	0.19
ANN6	0.091	0.141	0.139	0.234	0.145	0.249
ANN7	0.082	0.121	0.071	0.308	0.165	0.254
ANN8	0.063	0.225	0.072	0.321	0.128	0.192
ANN9	0.071	0.141	0.081	0.27	0.15	0.286
ANN10	0.06	0.202	0.08	0.304	0.091	0.264
Average importance	0.072	0.190	0.095	0.263	0.159	0.222
Normalized Importance (%)	27	72	36	100	60	84

Notes: AC = adoption costs, TMS = top management support, HR = human resources, DC = digital culture, TPP = trading partner pressure, IO = international orientation.

corporations (Swani, 2021) and firms in general (Oliveira et al., 2019). The ANN findings revealed that top management has the third-highest (72 %) relative importance, implying its significance for SMEs' DT adoption. This finding may be because adopting DT necessitates managerial acumen to digitize and integrate business processes both vertically (across the value chain) and horizontally (across departments) to ensure effective communication, automation, and connectivity (Oduro et al., 2023). Top management typically devises a clear digital transformation strategy delineating the objectives of a digital transformation process, facilitating the implementation of DTs within their SME (Baabdullah et al., 2021), and delegating responsibilities to their employees (Pingali et al., 2023).

The significant effect of HR (H5) on DT adoption, as evidenced in the PLS-SEM analysis, is consistent with the findings across various business types. For instance, Oliveira et al. (2019) highlight the importance of HR in technology innovation adoption within firms at large, while both Pappas et al. (2021) and Chen et al. (2023) specifically underscore its critical role in DT adoption among SMEs. Given that human resources are the primary users of DT, it is crucial for firms to ascertain their workforce's proficiency with such technology prior to its adoption. The ANN analysis shows that HR ranks fifth, at 36 %, indicating less influence than other supported variables in this study. This may be due to the prevalence of young, well-educated, and digitally literate employees among SMEs' workforces in this study.

The PLS-SEM analysis reveals a significant effect of trading partner pressure (H9) on DT adoption, with the ANN results indicating that trading partner pressure has the fourth highest relative importance (60 %). This finding concurs with antecedent studies, such as those conducted by Abed (2020) and Chen et al. (2023), which assert that TPP is a determinant in SMEs' adoption of new technology. One possible reason behind this outcome could be that SMEs can improve their relationships by utilizing the same technology platforms as their suppliers, creating fluid partnerships, and unveiling new opportunities. Furthermore, the PLS-SEM results indicate that AC (H1) negatively influences the adoption of DT. This finding confirms strands of the literature that suggest factors relating to financial resources, including the costs associated with adopting new technology, are a roadblock to SMEs' new technology implementation (e.g., Mkansi, 2022). Broccardo et al. (2024) observe that small businesses, usually operating with limited resources, frequently encounter a substantial upfront commitment when considering the adoption of new innovation. The ANN outcomes suggest AC is the least influential factor, accounting for only 27 %. This could be due to advancements in DT alleviating financial barriers to SMEs, such as the availability of pay-as-you-go access and declining DT costs, reducing the need for large initial outlays (Han & Trimi, 2022).

Surprisingly, perceived benefits (H2a) were not a decisive factor in SMEs' adoption of DT. This finding diverges from the consensus in the existing literature on technology adoption, such as that conducted by Park and Kim (2021), who found PB to be a determinant behind technology uptake by large firms. However, this finding is consistent with recent studies conducted by Chen et al. (2023) and Polisetty et al. (2024), which also found no relationship between PB and firms' new technology uptake. The reason could be that SMEs have restrained expectations about how DT might benefit their businesses. These expectations are shaped mostly by their competitors' adoption patterns and industry-specific situations. As technology adoption in the industry increases, SMEs' motivation to embrace such technology might diminish, largely because the outcomes may not meet their initial expectations. However, the PLS-SEM results indicate that PB positively influences TMS (H2b), aligning with the study by Wong et al. (2020). The rationale might be that while top management recognizes the benefits of DT, mere adoption may not in itself significantly enhance business practices. It is the strategic integration of these technologies, covering organizational structure, key personnel actions, and control systems, that realizes their full potential (Ocloo et al., 2020).

Compatibility (COMPB) does not influence the adoption of DT in this study. This is evidenced by the minimal impact observed in H3a (p-value > 0.05) from the PLS-SEM analysis This finding contrasts with strands of the literature, including research conducted by Moghavvemi et al. (2021) and Chau et al. (2021), that claim new technology adoption among SMEs is influenced by the degree of compatibility of the new

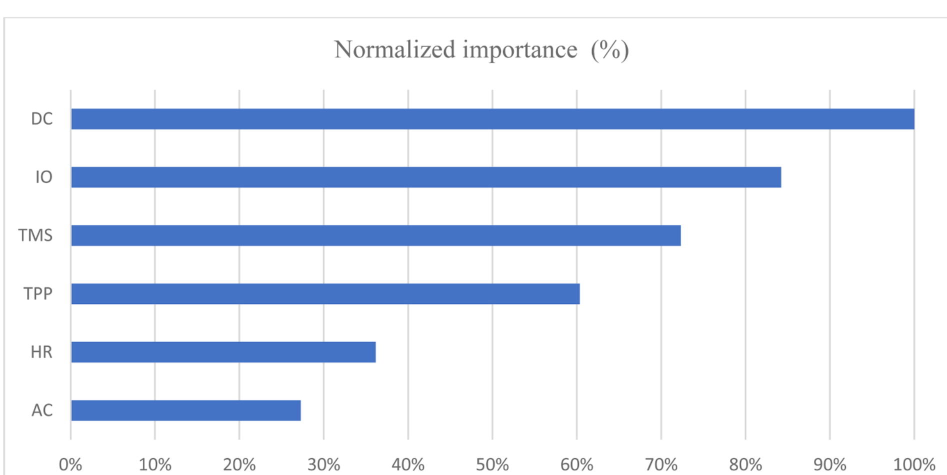

Fig. 7. Normalized importance chart.

technology with firms' current practices. However, this finding is consistent with studies conducted by Chen et al. (2023) and Maroufkhani et al. (2020), who suggest that integrating new technology appears to be more straightforward for SMEs than large enterprises, given the former's generally greater agility in adapting to changes. A likely reason is that advancements in DT have made it well-suited to current business practices, signaling that alterations to their operations are unnecessary. However, the PLS-SEM results suggest that COMPB positively influences TMS (H3b). This finding could be because adopting new technology affects nearly all business areas (Rakshit et al., 2021). Upper management often leads this change, preferring technologies that integrate smoothly and minimize disruption to the organization and its workforce.

The outcomes from the PLS-SEM analysis indicate that complexity (CPLXTY) (H4) does not significantly influence the adoption of DT. This finding contradicts several earlier studies, such as the work by Wong et al. (2020), who identified a significant relationship between CPLXTY and new technology adoption by firms. Nonetheless, this finding is congruent with previous research by Chen et al. (2023) who found no such correlation within Chinese SMEs. This finding also aligns with a meta-analysis performed by Chauhan et al. (2023), which found that CPLXTY has a negligible impact on the adoption of innovative technology. It is possible that SMEs find DTs are easily used because they represent advancements of technologies that SMEs have previously encountered. Hund et al. (2021) explain that the origins of new digital innovations can often be traced back to some form of previous DT, indicating they are an evolution from their predecessors. With their growing interaction with DTs, firms are believed to have a higher level of familiarity and proficiency in utilizing these DTs than ever before, overcoming any technical limitations associated with them and develop the capability to prepare for the next phase of adoption (Baabdullah et al., 2021; Su et al., 2023).

The PLS-SEM results indicate that CP (H9) is not a determinant of DT adoption. This finding contradicts the results of Wong et al. (2020) and Swani (2021), who found that CP positively influences firms' intention to adopt DT; however, it aligns with Maroufkhani et al. (2020), who conclude that competitive pressure has an insignificant effect on SMEs' new technology initiative. A possible explanation is that the current level of competition has not reached an intensity that would impact SMEs' market shares. The extensive adoption of DT among firms intensifies the pressure on those who remain non-adoptive because it creates a sense of urgency for firms to adopt new technologies to stay ahead of their competitors (Swani, 2021). The Ministry of Finance (2023) reveals that only 17 million, or merely 25 %, of Indonesian SMEs have embraced online platforms. This indicates that DT has not yet reached a critical mass within the SME ecosystem in Indonesia. Additionally, SMEs often operate in a niche market, where the level of competition is generally less intense (Shemi & Procter, 2018).

The PLS-SEM outcomes show that GRESS (H10) and GREGS (H11) do not significantly affect DT adoption. This finding is inconsistent with previous findings within the IT-related adoption stream, such as Ilin et al. (2017), who claim that SMEs' intention to adopt new technology is influenced by government support. However, this study's findings agree with Chen et al. (2023) and Wong et al. (2020), noting that government resource support and regulatory support has no effect on DT adoption. A potential reason for this could be that government support, in both its scope and scale, is deemed insufficient and does not address fundamental needs like infrastructure in developing countries. In fact, Indonesia is still confronted with such infrastructure shortcomings. For example, most of Indonesia's Internet traffic is routed through Singapore, resulting in higher subscription costs and slower connection speeds (Priharsari et al., 2023). Another reason might be that current regulations do not effectively reduce the barriers SMEs face when adopting new technologies, possibly due to insufficient consultation with a broad range of SME stakeholders during the regulatory creation process.

International orientation (IO) only moderates the nexus between DC and DT adoption (H12b), rejecting H12a. This finding implies that when SMEs possess a strong IO, the influence of DC on the adoption of DT is low. In contrast, when SMEs have a weak IO, DC significantly impacts DT adoption. This finding could be because SMEs with a pronounced IO frequently encounter diverse innovative technological strategies due to intense global competition. Without international engagement, such insights could remain hidden, and SMEs might not be able to access multiple global markets quickly without the assistance of DTs (Zahoor et al., 2023). However, to tap into these benefits, SMEs must adjust their behavior, fostering a digital-centric culture that would allow them to enhance their dynamic capabilities through DTs in tandem with their internationalization strategies (Feliciano-Cestero et al., 2023). Crespo et al. (2023) identify a correlation between a firm's digital orientation and its internationalization strategy, suggesting that a strong digital culture within firms leads to enhanced international orientation. Conversely, SMEs with weak international orientation appear to lack experience in international practices, necessitating the deliberate development of the firm's digital culture to catalyze DT adoption. Thus, when a firm's international orientation is weak, the effect of digital culture on DT adoption is strong. Overall, this study sheds light on how IO can act as a moderating factor in the adoption of DT, highlighting the imperative of embedding it within SMEs' decision-making processes.

Conclusions

This study has revealed factors influencing DT adoption among SMEs by combining the TOE framework and Rogers' DOI as the theoretical lens. The TOE framework acts as the primary theoretical foundation, consolidating various constructs under one conceptual umbrella. While the TOE framework can integrate diverse elements derived from cutting-edge knowledge in specific research domains, the DOI complements the TOE by offering an in-depth view of technology adoption; this is due to the DOI's focus on technological attributes (Chauhan et al., 2023). In analyzing the data, a two-stage PLS-SEM and ANN analysis was conducted to enhance the predictive power and robustness of research outcomes. Additionally, variables that are rarely examined, such as digital culture and international orientation, were included. In brief, the PLS-SEM outcomes reveal that the supported hypotheses are mainly derived from the organizational context (e.g., TMS, HR, and DC), whereas the supported hypotheses from technological and environmental contexts are AC and TPP, respectively.

Meanwhile, the ANN outcomes show that the most critical predictors of DT adoption are DC, IO, TMS, TPP, HR, and AC. In terms of indirect effects, which include moderating and mediating variables, four hypotheses were examined. The findings support the hypotheses that both COMPB and PB have a positive effect on TMS, and that IO moderates the relationship between DC and the intention to adopt DT. Thus, SME managers attempting to engage with DT might consider factors emanating from the organizational context, because these factors appear to exert a greater degree of influence over DT adoption than others. Policymakers could create policies to subsidize the cost of DT uptake and provide training to increase SMEs' knowledge.

Theoretical contributions

This study offers multiple theoretical contributions. First, to understand the nature of the uptake of DT in Indonesian SMEs, this study evolved to adopt a different set of assumptions. The primary ontological assumption was that DTs are not a single entity, but rather a collection of various technologies facilitated by information and communication technology. This perspective arises because the DT landscape has shifted towards more seamless integrated technologies, and the fact that all forms of DT appear intertwined with one another (Su et al., 2023; Pedota et al., 2023).

Second, this study combined the TOE framework with Rogers' DOI as the theoretical lens to expose factors leading to the adoption of DT. The empirical findings of this study reinforce the idea that combining the TOE framework with Rogers' DOI leads to improved model predictability by providing a more detailed perspective on technology adoption, mainly through DOI's emphasis on technological characteristics. Third, this study integrated elements seldom examined before, advancing knowledge in the technology adoption field. DC and IO are elements that emerged as important determinants of SMEs' adoption of DT, but they appeared to be understudied. Fourth, employing moderating factors proved to be of utility in deepening our understanding of the conditions and mechanisms that influence particular outcomes. It has been demonstrated that IO moderates the relationship between DC and SMEs' intention to adopt DT. Fifth, from a methodological standpoint, this study illustrated the complementarity of PLS-SEM and ANN analyses in the context of DT adoption. PLS-SEM is used to analyze the relationship between variables in the conceptual model; whereas ANN is employed to determine the predictive capacity of independent variables and rank them based on their importance on certain outcomes. Understanding which indicator exerts a greater degree of influence over DT adoption than the others will assist managers or other stakeholders in focusing on and channeling the resources they have toward the significant determinants that occupy the top rankings in the listing, rather than depleting the resources they have for all variables (Abbasi et al., 2021).

Practical implications

This study underlines the importance of several findings from which SME managers and policymakers could benefit. First, COMPB and CPLXTY appeared to be less significant factors in the adoption of DT; thus, SMEs should not be concerned with issues related to COMPB and CPLXTY when deciding on such an adoption. SMEs can seek assistance from external solutions to overcome challenges associated with their intention to engage with DT, with the availability of these solutions continually increasing. Second, this study demonstrates that organizational context appears to substantially impact SMEs' decisions to accept DT. Thus, managers interested in adopting DT should improve factors from the organizational context, including HR, DC, and TMS. Third, this study highlighted the practical implications for SMEs with varying degrees of IO. Interventions to encourage DT adoption among SMEs should be tailored according to their level of international engagement. Specifically, for SMEs primarily focused on domestic markets, enhancing their DC is a key strategy, because this has been identified as a pivotal step in accelerating digital transformation; thus, government-sponsored seminars and training should promote the development of a digital culture. Integrating these educational efforts with initiatives to boost SME exports could assist in the creation of digital capabilities alongside international ventures. Fourth, policymakers might consider financial incentives such as tax breaks or direct funding to offset the significant costs of DTs for SMEs, despite their decreasing costs.

Fifth, differentiating between types of government support based on resources and regulations, as in this study, is useful in helping policymakers to tailor support for specific contexts. Targeted interventions could boost DT adoption among SMEs, particularly in developing countries.

Limitations

This study has some limitations. First, this study is quantitative in nature, as a methodological approach. Given the dynamic business landscape, influenced by the COVID-19 pandemic and rapid socioeconomic and technological shifts, this study might not be able to incorporate recent developments that are not yet reflected in the extant literature. Second, this study engages with SMEs in Indonesia in general without specifying the industries. As Ferreira et al. (2019) explain, the factors that affect new technology adoption can be different across the SME sector. Hence, this study could not identify the determinants of digital technology adoption for specific SME industries. Third, nearly 80 % of respondents were SMEs located in developed provinces, with only a small percentage from less-developed areas. This geographic imbalance may lead to bias, limiting the applicability of the results to SMEs in rural areas, where factors affecting innovation adoption, such as the digital divide (Albar & Hoque, 2019) and infrastructure deficiencies (Priharsari et al., 2023), may differ from urban areas. Fourth, this study used the TOE framework without introducing a new taxonomy. Previous research has shown that managers' personal characteristics (e.g., level of education, age, gender) may influence their adoption intention (Al Hadwer et al., 2021).

Directions for future research

Future research might consider the use of a mixed-methods exploratory approach. This approach could gather information that may not otherwise be readily available in the current literature due to advancements since earlier research was published. Such information could then be quantitatively validated using a wider participant base, enhancing the generalizability of the findings. Future studies could investigate the factors that affect DT adoption within each SME sector, revealing more specific factors pertinent to each industry. Similarly, future studies could examine the factors influencing DT adoption in rural SMEs and assess how these factors differ from those affecting urban SMEs. Finally, it may be advantageous for future studies to expand the TOE framework to incorporate SME managers' personal attributes to allow for a more accurate prediction of adoption. This expansion may provide more comprehensive insights into the drivers of digital technology adoption beyond the current TOE framework, and lead to an enhanced understanding of SMEs' decision-making processes.

CRediT authorship contribution statement

Faiz Faiz: Writing – original draft, Investigation, Formal analysis. **Viet Le:** Writing – review & editing, Supervision, Conceptualization. **Eryadi K Masli:** Writing – review & editing, Supervision, Conceptualization.

Declaration of competing interest

The authors have no conflicts of interest to disclose.

Appendix

Appendix
The constructs, operational measure, and factor loadings.

Construct	Items	Description	Loadings
AC (Mohtaramzadeh et al., 2018; Ghobakhloo & Ching, 2019; Wong et al., 2020)	AC1	Cost of investment to acquire digital technologies is high	0.739
	AC2	Digital technologies require additional costs for staff training	0.799
	AC3	Digital technologies require maintenance and operational costs	0.796
	AC4	The cost of integrating digital technologies with existing information management is high	0.714
	AC5	The expected cost of reengineering business processes around digital technologies is high	0.788
PB (Wong et al., 2020; Swani, 2021; Chau et al., 2021)	PB1	Adoption of digital technologies increases our firm's sales	0.736
	PB2	Adoption of digital technologies reduces operating costs	0.686
	PB3	Adoption of digital technologies allows simplification of operating procedures	0.788
	PB4	Adoption of digital technologies provides timely information for decision making purposes	0.804
	PB5	Adoption of digital technologies increases customer satisfaction	0.77
COMPB (Chau et al., 2021; Swani, 2021)	COMPB1	Digital technologies are compatible with our firm's information technologies infrastructure	0.767
	COMPB2	Digital technologies are consistent with our firm's beliefs and values	0.813
	COMPB3	Digital technologies are consistent with current firm's business process	0.837
	COMPB4	Digital technologies are suitable with customers' preferences	0.813
	COMPB5	Digital technologies can easily be adapted with the existing distribution channel	0.772
CPLXTY (Alsaad et al., 2017; Wong et al., 2020)	CPLXTY1	Learning how to operate digital technologies is not simple	0.783
	CPLXTY2	Adoption of digital technologies requires a lot of mental effort	0.857
	CPLXTY3	I believe that the use of digital technologies requires ample experience	0.868
HR (Abed, 2020; Huy et al., 2012)	HR1	Our employees are proficient in using computer or other IT-related devices	0.872
	HR2	Our employees are knowledgeable about digital technologies	0.888
	HR3	Our employees are competent about digital technologies	0.935
	HR4	Our employees are well trained in digital technologies	0.906
DC (Martínez-Caro et al., 2020)	DC1	The teams collaborate functionally in the initiatives for the innovation and digital transformation	0.872
	DC2	There is a clear orientation to digital technology changes inside the company's culture	0.865
	DC3	The culture of digital innovation and change takes part as a natural process within the Company	0.845
	DC4	The organization shares with the staff the digital strategy, taking into consideration their suggestions	0.817
IO (Birru et al., 2019)	IO1	The prevailing organizational culture at our firm is conducive to active exploration of new export opportunities	0.836
	IO2	Top Management develops human and other resources for achieving our goals in international markets	0.919
	IO3	Top management tends to see the world, instead of just Ethiopia, as our firm's marketplace.	0.902
	IO4	Management continuously communicates its mission to succeed in international markets to firm employees	0.884
Construct	Items	Description	Loadings
TMS (Alsaad et al., 2017; Abed, 2020; Swani, 2021)	TMS1	Top management in our firm is interested in adopting digital technologies	0.784
	TMS2	Top management in our firm considers digital technologies adoption important	0.784
	TMS3	Top management in my firm is willing to accept risks when adopting digital technologies	0.794
	TMS4	Top management in my firm has allocated necessary resources to allow digital technologies adoption	0.831
	TMS5	Top management in my firm establishes goals and standards to monitor the adoption of digital technologies	0.833
TPP (Mohtaramzadeh et al., 2018)	TPP1	Our suppliers and trading partners are pressuring us to adopt digital technologies	0.811
	TPP2	Our trading partners are demanding the use of digital technologies to do business with them	0.826
	TPP3	Our main trading partner decide on what information systems applications are to be exchanged with my firm	0.823
	TPP4	Adopting digital technologies will provide opportunity to collaborate with trading partners	0.761
	TPP5	Our trading partners decide on the rules and regulations for using digital technologies in order processing	0.765
CP (Alsaad et al., 2017; Ghobakhloo & Ching, 2019; Wong et al., 2020)	CP1	Our firm is under pressure from competitors to adopt digital technologies	0.727
	CP2	Our firm thinks we lose our customers if we do not adopt digital technologies	0.778
	CP3	Some of our competitors have already adopted digital technologies	0.815
	CP4	Our firm thinks we lose our market share to digitalised counterparts	0.732
	CP5	We feel that it is a strategic necessity to introduce digital technologies in order to compete in the market	0.795
GREGS (Mohtaramzadeh et al., 2018; Ocloo et al., 2020; Wong et al., 2020;)	GREGS1	The government has provided support to ensure digital technologies are affordable	0.783
	GREGS2	The government has provided a clear direction of nation's digital technologies adoption	0.87
	GREGS3	The laws and regulations that exist today are sufficient to protect the use of digital technologies	0.857
	GREGS4	The government has created legal considerations for digital technologies adoption	0.872

(continued on next page)

Appendix (*continued*)

Construct	Items	Description	Loadings
	GREGS5	In general, we receive enough information about digital technologies laws and regulation from the government	0.833
GRESS (Ilin et al., 2017; Ocloo et al., 2020)	GRESS1	The government has provided public infrastructure readiness that support digital technologies adoption	0.836
	GRESS2	The government has provided training and education programs to encourage digital technologies adoption	0.866
	GRESS3	The government has provided adequate consulting services for use digital technologies	0.878
	GRESS4	The government has provided financial support to encourage digital technologies adoption	0.847
	GRESS5	The government is offering tax incentives to boost digital technologies adoption	0.806
AI (Davis, 1989)	AI1	Have an intention for adoption	0.899
	AI2	Have a certain plan for adoption	0.932
	AI3	Have a strong commitment to adoption	0.93
Control:			
Size		Firms were grouped by their size (micro, small, and medium) according to Indonesian Law	
Location		Firms were classified by their location in developed and developing provinces, as determined by their GDP according to Statistics Indonesia	
Industry		Firms were divided by their industry (agriculture, services, and manufacturing)	

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