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Beyond technology adoption: How critical factors drive business performance through digital transformation

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A B S T R A C T

In the age of digitalization and artificial intelligence, companies in the manufacturing sector face new opportunities to improve their business performance (BP). However, they also face significant challenges in achieving a successful digital transformation (DT). In this context, this study analyzes how critical factors (AW, OP, RD, and TC) drive DT and how DT influences the BP of manufacturing companies. Based on the resource-based view (RBV) and dynamic capabilities theory (DCT), this research develops and empirically tests a conceptual framework using data from a survey of 175 formal manufacturing firms located in Peru. The data were analyzed using the partial least squares structural equation modeling (PLS-SEM) approach. The results indicate that AW, OP, RD, and TC significantly influence DT. While the direct effects of these factors on BP are less consistent, DT exerts a strong and significant impact on BP and mediates the relationship between the critical factors and performance outcomes. These findings highlight the strategic role of DT as a mechanism through which critical factors translate into improved BP in manufacturing firms.

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1. Introduction

In recent decades, DT has generated major changes in manufacturing companies driven by technological advances, increased competitiveness, the transformation of customer behavior, and labor market intensity (Oncioiu et al., 2025). In this context, DT has driven development at the business level, managing to transcend information in time and space and become part of conventional production components (S. Zheng & Zhou, 2025). Likewise, its effectiveness for the upgrading and reorganization of manufacturing companies has been evidenced (Fu, 2022; Johns, 2022). One of the most influential consequences of DT is its impact on employment and is also recognized as an essential strategic priority (Omol, 2024; Sobczak, 2025). Digitalization has favored the emergence of new jobs and the increased demand for professionals specialized in data processing, artificial intelligence (AI), digital security, and systems engineering (Brussels et al., 2018). Likewise, DT enables the creation of innovation mechanisms, allowing companies to focus on customer experience, resource efficiency, workforce management, cost reduction, and quality supervision (Santos & Martinho, 2020). Ultimately, companies must not only adapt to new technologies but also incorporate them into their core strategies and processes (Cannas, 2021; Kim & Kim, 2023). However, these advantages bring significant challenges that limit the adoption of DT in numerous companies (Levallet & Chan, 2019). This situation is particularly visible in Latin America, where a gap persists in the adaptation of new technologies compared to other developed countries. According to the Banco Mundial (2024), companies in Latin America and the Caribbean invest in digital solutions at 27.75%, while companies in East Asia and the Pacific invest with an increase of 54%, using digitalization to improve communication with customers, suppliers, and workers, with the aim of accelerating processes and increasing efficiency. Additionally, according to EY GLOBAL (2023), the countries with the highest digital

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maturity index (DMI) include Ecuador with 64.67 points (pts), Chile 62.73 pts, Mexico 62.11 pts, and Peru 60.32 pts, being the country with the lowest score and showing a decline of at least 3 pts compared to the 2021 index.

In the Peruvian case, the manufacturing sector shows moderate growth. The Ministerio de la Producción del Perú (MP, 2023) reports a DMI of 54% for this sector, representing a positive level, although with room for improvement. This positive change is supported by Industry 4.0 oriented toward Industry 5.0, which arises from the implementation of new technologies (Yao et al., 2024). Recent studies show that these technologies are enabling manufacturers in emerging countries to improve their productivity, customization, and supply chain performance (Zafar et al., 2024). However, these advantages represent new challenges for companies (Johansson et al., 2020), such as limited understanding of associated technologies, the lack of a precise and efficient digital strategy, and a DT action plan (Buer et al., 2018; Carolis et al., 2017; Kane et al., 2015). Furthermore, the complexity of DT brings multiple conceptions and different levels of maturity among companies (G. Kane, 2019). Along these lines, companies face serious problems in integrating digital technologies into conventional processes due to the absence of information, high costs, and the lack of specialized technical competencies that hinder the effective adoption of DT (Javadi & Chirumalla, 2024; Peng & Tao, 2022; Sanders et al., 2016). To address these challenges, it is imperative to identify the critical factors that contribute to the effective adoption of DT, which remains an underexplored field of research (Jordan Strategy Forum, 2024). Recent literature in this field has generated general knowledge about critical factors applicable to different sectors (Deepu & Ravi, 2021; Oyetade & Zuva, 2025; Sony et al., 2021; Wang & Su, 2021; Zheng et al., 2025). While there are studies oriented toward small and medium-sized enterprises (SMEs) (Kahveci, 2025; Becker et al., 2025; Matarazzo et al., 2021; Rupeika-Apoga et al., 2022; Zhang et al., 2022) and large industrial companies (Steiber et al., 2021), a notable gap is evident in research tailored to the unique needs of manufacturing companies (Chang & Chen, 2025; Vogelsang et al., 2018), and particularly, in understanding how these factors influence BP (Bindeeba et al., 2025), specifically in the context of emerging economies such as Peru.

This research aims to address this gap by focusing on four critical factors with the potential to impact DT: awareness, readiness, operations, and technology, as well as their influence on BP in manufacturing companies. Additionally, the mediating role of DT in these relationships is examined. To guide the research, the following questions were posed:

RQ1: How do critical factors impact the adoption of DT in manufacturing companies?
RQ2: What mediating role does DT play in the relationship between critical factors and business performance?
RQ3: To what extent does DT influence business performance?

Finally, most of the research conducted has been carried out in developed and developing economies, and across diverse sectors (Guo et al., 2025; Zhang & Chen, 2025), such as the textile sector (Bermeo-Giraldo et al., 2025), manufacturing and services (Bhatia & Kumar, 2022), construction (Zhong et al., 2025), financial services (Aytuna & Özkaya, 2026), and electronics manufacturing (Huang et al., 2025). DT researchers have suggested that there is an evident absence of context in these findings and of a more specialized sector, and that it should be based on a more exhaustive analysis with a broader scope (Vial, 2019). This article addresses this deficiency by examining a previously unexplored context: the Peruvian context, which differs from studies centered on Western Europe.

2. Theoretical Foundations and Hypotheses

To develop a new construct or measurement model, it is necessary to fulfill three aspects: (1) clearly define the conceptual domain, (2) specify the appropriate measurement model, and (3) provide evidence that the items measure the construct or model (MacKenzie et al., 2011). First, the conceptualization of DT is presented based on an exhaustive literature review.

2.1. Digital Transformation

The origins of DT are situated with the emergence of computers and the progressive digitalization of companies' operational processes (Terras, 2011). The current trend of DT is attributed to Industry 4.0, initially driven from Germany, in the context of the Fourth Industrial Revolution and the expansion of the digital economy. Particularly, Industry 4.0 was consolidated as a central component of Germany's High-Tech Strategy (2020), aimed at promoting innovation and competitiveness in the manufacturing industry (S. Kim et al., 2021). In turn, DT gained greater visibility as a study phenomenon from 2013 onward, during a period characterized by the acceleration of the digital economy (Omol, 2024).

In this scenario, companies have been motivated to change their value creation processes to sustain their competitiveness through the introduction of numerous digital technologies (Imran et al., 2021). However, DT has generated notable repercussions in both the academic environment and business practice; despite being widely debated and examined in the literature, there is still no unified and global definition (Osmundsen et al., 2018). This is due, in part, to it being a relatively new concept approached from diverse theoretical perspectives, which suggests (Fichman et al., 2014), that it may be too broad to be explained by a single theory. Consequently, various scholars predominantly view it as a strategy (Matt et al., 2015), paradigm shift (Piccinini et al., 2015), process (Loebbecke & Picot, 2015), or business model (Remane et al., 2017). Generally

speaking, DT is commonly described as an organizational transformation driven by, supported by, or enabled through digital technology, generating changes in the development of organizational activities (Haffke et al., 2016; Heilig et al., 2017).

The conceptualization of DT in the literature is often used analogously with the concepts of digitization and digital innovation. Although there are some similarities, it is crucial to establish distinctions among the three terms (Haffke et al., 2017). According to (Hinings et al., 2018), digitization is defined as "the use of digital technologies to innovate a business model and provide revenue streams and value generation mechanisms in industrial ecosystems" (p. 12), while digital innovation for (Nambisan et al., 2017) is defined as "the use of digital technology throughout the innovation process" (p. 223). According to (Morakanyane et al., 2017), who in their study based on a systematic literature review aimed at addressing the conceptualization, define DT as "an evolutionary process that leverages digital capabilities and technologies to enable business models, operational processes, and customer experiences to create value" (p. 437).

Although DT has been described as a radical change rather than an evolutionary process, it is suggested that the evolutionary process is a more integrative term, reflecting how DT evolves over time, and each time such evolution takes place, the impacts generate major changes in the organization (Janowski, 2015). Within the conceptualization of DT, our research places special emphasis on its evaluation. Considering that DT brings organizational changes at both structural and technological levels in an organization (Garzoni et al., 2020; Verhoef et al., 2021), its measurement is of relevant importance for understanding current DT practices. Now, current literature highlights that the measurement of DT is divided into two main streams. The first stream focuses on the organization as the unit of analysis and proposes measurement mechanisms centered on the insertion and deployment of digital technologies (Lombardi & Secundo, 2021; Rialti et al., 2020). The second literature stream is oriented toward the schemes and frameworks currently available to evaluate DT (Agostino & Costantini, 2022). The present study will focus on performance measurement frameworks for the quantification of DT. To develop this framework, consideration will be given to (Almajali et al. (2025) and Canetta et al. (2018), who develop indicators such as people, technology, processes, customers, strategy, and investment that seek to evaluate DT in the manufacturing industry sector.

2.2. Theoretical Foundation of the Study

2.2.3. Resource-Based View

To study how critical factors impact DT (and, consequently, favor business performance), this study is grounded in the Resource-Based View (RBV) (Barney et al., 2001), Dynamic Capabilities Theory (DCT) (Teece et al., 1997), and the ARTO model. While these theories are different, they provide convergent approaches that, building upon one another, offer a solid perspective for understanding: (i) how critical factors impact digital technologies that operate as key resources, (ii) how companies adapt and restructure in an agile manner to respond to changing environments; and (iii) how these actions are articulated with the needs of key stakeholders to favor business performance. Regarding the RBV, it originates with Penrose (1959), proposing that the firm can be understood as a set of resources, and is later formalized and popularized by Wernerfelt (1984) in his study "resource-based view of the firm." From this perspective, a firm's competitive advantage originates from valuable, rare, unique, and difficult-to-replicate resources and capabilities that can be controlled (Barney, 1991).

The theoretical assumptions of the RBV highlight that a firm's resources constitute basic units of analysis for understanding performance differences among companies. Furthermore, in the DT context, this implies that digital technologies and tools can operate as strategic resources, whose development and deployment increase the possibility of achieving improvements in performance and operational success (Nayak et al., 2023). This study will employ the RBV framework to analyze how manufacturing firms use digital technology to enhance their performance. Digital tools, such as mobile payment platforms, inventory control systems, websites, and digital marketing tools, play an important role. When integrated with already established capabilities, such as skilled labor and management expertise, these resources become valuable assets for the firm (Utonga et al., 2026). As evidenced by (da Silva et al., 2025; Díaz-Arancibia et al., 2024), manufacturing firms can achieve a competitive advantage and improve their performance by integrating digital technologies across their operations, streamlining processes, increasing customer engagement, and expanding market reach. These capabilities enable firms to reduce costs, improve customer service and product offerings, and create competitive advantages that are consistent with the RBV perspective (Utonga et al., 2026). However, the RBV provides a very static approach, limited in explaining how companies continuously adapt and transform with their resources and capabilities in the face of technological changes (Barney et al., 2001); this deficiency will be mitigated through the integration of DCT.

2.2.4 Dynamic Capabilities Theory

DCT extends the RBV by suggesting that a firm's inherent capabilities can seek new opportunities and secure resources in changing environments (Teece et al., 1997), which is crucial for achieving differentiation from competitors and being able to increase business performance (Eisenhardt & Martin, 2000). The Dynamic Capabilities Theory (DCT) provides a crucial perspective for understanding digital transformation (DT) in manufacturing firms. According to Teece et al. (1997), dynamic capabilities are defined as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (p. 516). Prior literature on DT remains in a stage of development and exploration regarding the mechanisms that enable firms to seize the opportunities offered by digital technologies to improve performance. The

evidence highlights the critical role of three key dynamic capabilities—sensing, seizing, and reconfiguring—which act as enablers of a firm's DT. Therefore, manufacturing firms must possess strong dynamic capabilities, including the ability to sense and shape opportunities, seize them, and reconfigure or transform their resource base in alignment with a well-defined business strategy, so that they can drive and achieve DT and remain competitive in a digital environment (David J., 2014). The capability to seize opportunities involves making strategic decisions about identified opportunities, which should then be exploited through new products, processes, services, or an integration of these options (Ghosh et al., 2022).

In the era of AI and digitalization, the value of digital technologies is not relevant merely by acquiring them, but rather from the organizational capability to integrate them, combine them, and know how to use them at the opportune moment for strategic purposes. Thus, DCT is oriented toward describing how companies evolve and readjust the key resources identified by the RBV, with the aim of constantly optimizing business performance in dynamic contexts. While the RBV and DCT focus on the dynamics of resources and capabilities, the ARTO model incorporates an approach through four variables: awareness, readiness, technology, and operations. According to (Chirumalla et al., 2025), it is argued that DT consists of established and multidimensional stages that integrate emerging digital technologies into organizational processes, strategies, and culture, enabling companies to create value for key stakeholders, such as organizational adaptability and improvement of production systems (resources and capabilities). Within this framework, the integration of the RBV, DCT, and the ARTO model offers a more robust explanation of how critical factors drive DT in companies, and how this process translates into improvements in business performance and the strengthening of competitive advantage (Chirumalla et al., 2025).

2.3 Hypothesis Development

2.3.1 Digital Transformation and Business Performance

DT is an emerging field due to the acceleration of technological advances in recent decades, and even more so in the business realm. The exploration of previous research has created an in-depth analysis of the association between DT and different performance outcomes. Studies have demonstrated that the use of digital technologies in the manufacturing sector improves company performance (Wongwas et al., 2024); organizational performance (Khin & Ho, 2019), environmental performance (Yadav et al., 2024); supply chain performance (Oncioiu et al., 2025); operational performance (Hanandeh et al., 2023); and innovation performance (Agrifoglio et al., 2017; Soetjipto et al., 2022). However, the association between DT and BP in the context of emerging countries continues to constitute a challenge for the academic world, as it requires further research.

Available studies suggest that DT tends to increase operational performance in some way. Moreover, digital technologies tend to increase customer experience, optimization, and processes, as well as increase market share (Zaki, 2019). The use of the internet, Internet of Things (IoT), big data, business data analytics (BDA), cloud computing, and artificial intelligence (AI) can reduce resource consumption through efficient management, elevating operational performance and optimizing overall effectiveness (Chirumalla et al., 2025). As a result, DT can increase the quality of services and products, generating greater satisfaction among stakeholders. Furthermore, DT can generate favorable effects on the performance of small, medium, and micro enterprises when there is a minimum base of technology adoption and they transition toward higher technological levels, replacing obsolete technology and strengthening competitiveness (Bindeeba et al., 2025).
Therefore, it is essential that DT and its inherent advantages safeguard companies' actions to minimize their operating costs and optimize efficiency. Based on these arguments, we propose the following hypotheses:

H_1: *Critical factors positively impact Digital Transformation.*
H_{1a}: *Awareness positively impacts Digital Transformation.*

Awareness, as the first variable of the ARTO model, is important in a company because it encompasses all the processes that must be followed to make decisions regarding the initial phase of DT. On the other hand, awareness integrates a set of critical factors that support it: external support, organizational structure, organizational culture, organizational strategies, and the accessibility of the workforce with sufficient capabilities (Schumacher et al., 2019). In the context of Industry 4.0, awareness plays an important role because it is oriented toward the evaluation of benefits and risks of digitalization, including consideration of staff qualifications to address the incorporation of new emerging technologies (Schumacher et al., 2019). Therefore, it is expected that higher levels of awareness will translate into a more decisive and structured adoption of DT initiatives.

H_{1b}: *Readiness positively impacts Digital Transformation.*

Once the requirements of DT and the considerations of the factors that support it have been established, it is necessary to mention "Readiness" as the second variable of the ARTO model. This variable explains how companies must be prepared to operate in accordance with their DT objectives, supported by six factors: organizational structure, organizational culture, organizational leadership, organizational strategies, employee capabilities, and infrastructure investments. That is, companies must undertake a comprehensive reconfiguration to explicitly evaluate their readiness for DT during this phase. Thus, this stage is fundamental where modifications are implemented to articulate the company's capabilities with the demands required

by the transformation (Mittal et al., 2019). Consequently, having a higher level of readiness increases the possibility of implementing DT effectively by aligning internal capabilities with the demands of the transformation process.

H_{1c}: *Technology positively impacts Digital Transformation.*

While “Awareness”" and “Readiness” address the decision-making process and the degree of organizational preparedness for DT, “Technology” as the third variable, encompasses the selection of new technologies that are appropriate and align with the company's DT objectives. However, technology focuses on the determination and incorporation of emerging technologies, where the variable is supported by factors such as: the characteristics, selection, and integration of digital technologies, and infrastructure investments. Given this, the selection of new technologies that ensure the effectiveness of the DT process is essential. The selection of suitable technologies for the company not only increases operational efficiency but also reduces the loss of time and strategic resources, preventing dissatisfaction among key stakeholders and strengthening the transformation trajectory (Temel & Ayaz, 2019).

H_{1d}: *Operations positively impacts Digital Transformation.*

Once the company selects the technology and it is implemented and used to optimize its processes, the fourth variable, “Operations,” plays a key role, as it focuses on the immediate practice and management of these technologies within the company in order to achieve the proposed DT objectives. The variable is based on several factors, such as data security, data governance, and production system design. It should be noted that the incorporation of different technologies in a company brings with it a large amount of data and information. The success of DT requires timely evaluation mechanisms, secure communication, and uninterrupted and reliable storage of information (Merhar et al., 2019).

H_2: *Digital transformation plays a mediating role in the relationship between critical factors and business performance.*
H_{2a}: *Awareness significantly influences business performance.*

“Awareness” is based on the following elements: external support, organizational culture, organizational structure, organizational strategies, and employee accessibility, which are highly determinant for initiating and guiding DT (W. Zhang et al., 2023). A company that contains the mentioned elements internally and with a perspective toward DT satisfies the necessary conditions to configure an optimal environment for DT. Furthermore, culture must be a central axis for generating innovation and flexibility, and the structure must drive efficiency in decision-making, while strategies must be aligned with digital objectives (Nausch et al., 2020). Likewise, companies must have a high rate of availability of qualified employees with technological competencies, specifically in senior management to address awareness risks. Therefore, competencies are necessary to succeed in decision-making and to efficiently anticipate the DT process (Choi et al., 2017). Consequently, it is expected that awareness drives DT and that, through it, efforts are oriented toward improving BP.

H_3: *Digital transformation plays a mediating role in the relationship between readiness and business performance.*
H_{3a}: *Readiness significantly influences business performance.*

“Readiness” significantly enhances a company's DT, shaping its impact on BP According to (Buer et al., 2021), senior management and leadership must empower employees through a set of specific training programs and courses, amending them with essential capabilities and knowledge for participation in the transformation, along with infrastructure investments that ensure the sustainability of digital initiatives. Furthermore, the company must have solid strategies with a clear vision to achieve success in the DT process (Jaskó & Ruppert, 2025). Planning and coordination are also essential, ensuring that all actions are articulated with the strategies. Ultimately, the "Readiness" variable must develop an opportune environment to ensure successful DT in the company and that it has the necessary conditions in terms of both internal capabilities and strategic management. Therefore, it is expected that a higher level of readiness will drive DT and that this, in turn, will contribute to BD.

H_4: *Digital transformation plays a mediating role in the relationship between technology and business performance.*
H_{4a}: *Technology significantly influences business performance.*

“Technology” has increasingly been consolidated as a primary factor of digitalization in the manufacturing sector, driving greater BP as a consequence of the identification and use of appropriate technology. Companies should strive to choose technologies that are intuitive to use, sustainable, and long-lasting, ensuring they are functional and easily accessible for their needs (Pirola et al., 2020). When analyzing technology adoption as part of the company's operations to favor DT, these processes require total supervision of the functioning of technologies with existing systems and processes, and also toward the investment in infrastructure required for their implementation (Jung et al., 2020). Finally, companies must consider the most opportune technology, for example; for (Babu et al., 2021; Indra & Tanaya, 2024; Madduri et al., 2022), cloud computing, the use of Big Data, and digital technologies (tablets, smart devices) that not only satisfy immediate needs but also guide them toward growth and adaptability in a progressively more digital environment. Ultimately, it is expected that technology will influence BP through the contribution of DT.

H_5: *Digital transformation plays a mediating role in the relationship between operations and business performance.*
H_{5a}: *Operations significantly influence business performance.*

The inclination toward the "Operations" variable favors DT, developing an impact on BP. Data security management is important as it relates to protecting information obtained, stored, evaluated, and processed within a system. Senior management has the task of configuring the strategy that safeguards the maximum security of the information acquired and of the company (Soori et al., 2023). Likewise, production design allows leveraging technologies to improve efficiency in material use and the improvement of final product quality. Furthermore, data governance begins with the collection of information from various sources within the same system; then the information is thoroughly examined for interpretation before information storage. Naturally, data capture becomes a real challenge in companies' process toward successful DT. Therefore, the adequate extraction of information becomes a central axis, as it is a senior management tool for making better decisions (Bevilacqua et al., 2017). Consequently, the importance of success in DT lies in data security, data governance, and system design, and that, through these, it affects BP.

H_6: *Digital Transformation positively impacts business performance.*

Various previous studies have extensively examined the existing link between digital technologies and BP Recent studies have demonstrated that the use of technologies across different industries and company sizes positively impacts BP in the retail industry (Wongwas et al., 2024), agriculture (Giraldo et al., 2025), large companies (Feng et al., 2025), and in SMEs (Kim & Kim, 2023; Mushtaq et al., 2023). However, the link between digital technologies and business performance in the manufacturing industry remains a research gap that requires further analysis and evaluation. The literature suggests that DT positively increases BP by favoring greater economic income, profitability, and return on investment, as well as improvements in customer experience, market share, and process efficiency (Salamah, 2023). Likewise, the modernization of machinery and modern equipment can improve the efficiency and effectiveness of operational processes, reinforcing the company's economic performance (Zomer et al., 2020). DT also drives labor performance, as devices, the Internet of Things (IoT), and the use of virtual reality technology by workers allow the company to track the distance of components and send real-time information during tasks involving the handling of components, materials, and equipment (Manavalan & Jayakrishna, 2019).

3. Materials and methods

3.1 Research Formalities

This research adopted a quantitative approach with a cross-sectional design (Sampieri & Torres, 2018) and an explanatory level, with the objective of: (i) explaining how critical factors impact DT, (ii) analyzing the mediating effects of DT on the association between critical factors and BP, (iii) determining how DT influences the BP of manufacturing companies. Based on the literature review, 11 critical factors were identified and grouped into four variables: awareness, readiness, technology, and operations, reported as relevant determinants of DT. Consequently, the study seeks to understand how these variables affect the DT of manufacturing companies and how both critical factors and DT impact BP.

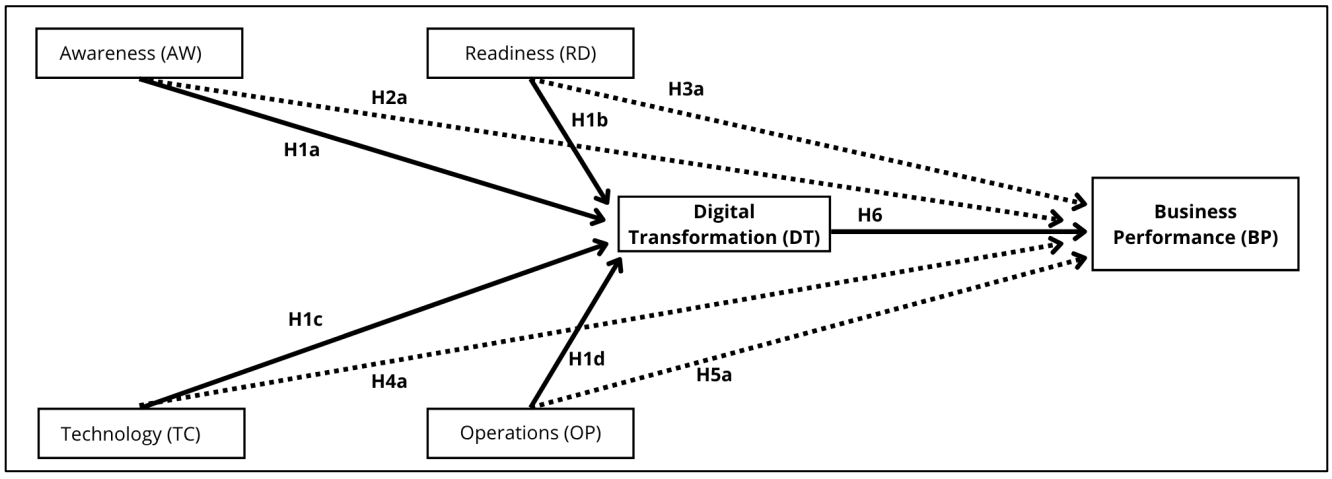

Fig. 1. Conceptual model of the research.

Therefore, the following conceptual model presented in Fig. 1 emerges, structured around the following constructs: awareness, encompasses the decision-making dynamics for the initial stage of DT; readiness, is defined as the willingness to act in accordance with DT objectives; technology, reflects the selection of appropriate technologies that are subject to DT objectives; operations, focuses on the use of technologies and the management of time for adopted technologies; DT, understood as a

gradual progress that capitalizes on the company's digital competencies and technologies; BP, measures a company's ability to achieve its financial objectives and human capital management.

3.2. Instrument Design and Validation

A questionnaire was developed to measure each of the model's constructs, which is reflected in Fig. 1. For its development, the procedures proposed by (Horna, 2012) were followed with the purpose of ensuring a reliable and valid measurement instrument. Likewise, scales validated by the literature were used with the exception of the constructs (Readiness, Awareness, Operations, and Technology), which have been recently addressed within the framework of the ARTO model and, therefore, there is not yet consolidated evidence of validated scales and items in the existing literature. Consequently, the corresponding questionnaire items for these constructs have been developed and validated, following the steps used by (Diamantopoulos & Winklhofer, 2001; Petter et al., 2007). Below, the process followed for the development of the questionnaire will be described. Overall, the questionnaire items were formulated as closed-ended questions to optimize the response rate. The questionnaire used two types of questions: (i) rating questions, using a Likert-type scale, and (ii) categorical questions. The instrument consisted of two sections. Section 1 contains instructions such as the purpose of the study and a paragraph detailing participation and confidentiality of the information obtained; additionally, general characteristics of the company and the respondent were collected, such as the respondent's position, company seniority, main economic activity of the company, and the number of employees. Section 2 includes the questionnaire instructions, as well as the structure containing the 31 statements with their respective scales, see Appendix A.

Table 1
Construction of the training model questionnaire.

Construct	N°	Item	Source	Selected
Awareness (AW)	1	The company receives external support.	(Chirumalla et al., 2025)	Yes
	2	The company promotes a culture that is open to change.	(Wagire et al., 2021)	Yes
	3	The company facilitates the use of new technologies.	(Santos & Martinho, 2020)	Yes
	4	The company anticipates which technologies it should adopt.	(Chirumalla et al., 2025)	Yes
	5	Digital transformation is part of the company's strategy.	(Santos & Martinho, 2020)	No
	6	Staff have the knowledge and skills to use technologies.	(Santos & Martinho, 2020)	Yes
	7	The company needs to modernize technologically.	(Chirumalla et al., 2025)	Yes
Readiness (RD)	1	The company's work organization allows the installation of new machines.	(Santos & Martinho, 2020)	Yes
	2	Staff adapt to new, modern machines.	(Wagire et al., 2021)	Yes
	3	Leaders support the use of digital technologies.	(Chirumalla et al., 2025)	Yes
	4	The company has a phased plan to implement technology.	(Chirumalla et al., 2025)	Yes
	5	Staff are ready to learn new technologies.	(Schumacher et al., 2019)	Yes
	6	The company has space and internet access to modernize equipment.	(Buer et al., 2021)	Yes
	7	The company uses digital technology to organize and monitor work.	(Schumacher et al., 2019)	No
	8	The company has the funds and personnel to begin technological modernization.	(Chirumalla et al., 2025)	Yes
Technology (TC)	1	Current machines/software are easy to use.	(Temel & Ayaz, 2019)	Yes
	2	Before investing, the company assesses whether the technology improves work processes or revenues.	(Chirumalla et al., 2025)	Yes
	3	Digital tools fit the way we work.	(Temel & Ayaz, 2019)	Yes
	4	Resources are allocated to upgrade and repair equipment/systems.	(Buer et al., 2021)	Yes
	5	Investment is made in physical and technological infrastructure to support digitalization.	(Buer et al., 2021)	No
	6	Current equipment is sufficient for the company's work.	(Chirumalla et al., 2025)	Yes
Operations (OP)	1	The company protects its information to prevent losses.	(Santos & Martinho, 2020b)	Yes
	2	Customer and sales information is well organized and can be retrieved quickly.	(Temel & Ayaz, 2019)	Yes
	3	The workshop/production is organized to leverage technology.	(Chirumalla et al., 2025)	Yes
	4	Technology makes workshop operations faster and more organized.	(Chirumalla et al., 2025)	Yes

Source: Author's own work.

Digital Transformation (DT): Based on the research conducted by (Canetta et al., 2018) on appropriate and validated items, DT is weighted as a reflective construct being evaluated on a Likert scale from 1 to 5, where 1 means “strongly disagree” and 5 “strongly agree”, consisting of 5 items.

Business Performance (BP): This is classified as a reflective construct and was developed using a five-point Likert scale (ranging from 1 meaning “strongly disagree” to 5 “strongly agree”) distributed across 4 items, adapted from the work of (Kim y Jin, 2024).

For the development of items for the constructs (Readiness, Awareness, Operations, and Technology), the 4 criteria proposed by Petter et al. (2007) were first used to determine their specification as formative constructs, then we proceeded to define the construct items. Subsequently, we defined 25 items: seven for Awareness, eight for Readiness, six for Technology, and four for Operations; these items are presented in Table 1. Next, we asked four experts in the field of DT (two academics and two professionals), each with more than ten years of experience in the subject, to review the items to establish their suitability and level of representativeness based on the elements to which they belong. Likewise, three items with the lowest scores were excluded from the list, obtaining a final version of 22 items: six for Awareness, 07 for Readiness, 05 for Technology, and 04 for Operations, as shown in Table 1, and will be measured using a five-point Likert scale (with a rating ranging from "strongly disagree" = 1 to "strongly agree" = 5). For all constructs, a minimum of four items is considered sufficient and reliable (Franke et al., 2008), as suggested by the literature.

The initial draft of the questionnaire underwent a review and refinement process by specialists (professionals and academics), with the objective of ensuring contextual and content validity. Subsequently, a pilot study of 30 randomly selected participants was conducted, aimed at verifying whether the statements are correct and comprehensible, as well as the feasibility of responding to the questionnaire. With the pilot test data, a preliminary analysis was performed in SmartPLS 4.1.1.6 software, where reliability was evaluated, and various statistical tests were used, such as composite reliability, Cronbach's alpha, convergent validity, discriminant validity, and other determining factors. During the pilot phase, participants had no difficulty responding to the questionnaire statements.
Likewise, control variables and factors that are subject to the DT and BP constructs, commonly used for this type of analysis, were included. Particularly, company size was measured with a scale based on the number of workers the organization has, while seniority was estimated through the years of operation the organization has (Almajali et al., 2025), which to some extent could influence the analyzed constructs. Additionally, some factors related to the constructs were controlled, such as the position held by the respondent in the company and the company's main economic activity (Guo & Xu, 2021).

4. Participants

The study population of this research consisted of companies in the manufacturing sector located in Peru, specifically in the city of Abancay, being the most important economic and social center of the Apurímac region Banco Central de Reserva del Perú (BCRP, 2024). According to the Superintendencia Nacional de Aduanas y de Administración Tributaria (SUNAT, 2023), at the beginning of February 2025, 209 formal companies in the manufacturing sector were registered in the study area. Subsequently, The questionnaire was administered starting in October 2025, over a period of two months, which involved contacting SUNAT.
Subsequently, during that period of time, a total of 175 valid questionnaires were obtained, which resulted in a response rate of 83.7%. Given the sampling responses, we proceeded to use the determination of sample error for finite population, with a sampling margin of error of 3%, assuming maximum variance (p=q=0.5) and 95% confidence. The resulting margin of error is low, which is considered ideal for a statistical study (Roldán & Fachelli, 2017). Study participation was voluntary and all responses were anonymous, reducing bias.
To verify the sufficiency of the sample size within the framework of Partial Least Squares Structural Equation Modeling (PLS-SEM), which establishes requirements for sample size, the considerations of (Hair et al., 2019) were taken into account to estimate sample sizes based on power analysis. Therefore, we used the inverse square root method calculation proposed by Kock & Hadaya (2018), which suggests 155 samples for a significance level of 5% ($\alpha = 0.05$) with a statistical power of 80% and an expected minimum path coefficient between 0.11 and 0.20. In a complementary manner, the "10 times rule" proposed by Barclay et al. (1995) was applied, where the minimum sample size should be 10 times the maximum number of paths leading to a construct anywhere in the proposed model.
Source: Author’s own work.
From all of the above, the final sample of 175 considered in the study is more than sufficient; furthermore, it meets the two analyses described previously in the paragraph and also complies with the postulate of Hair et al. (2021), who argues for the need for a sample size of 150 to 200 in order to obtain reliable parameter estimates and sufficient statistical power for models with complex mediation configurations. Therefore, it can be indicated that our final sample does comply with all best practice recommendations for PLS-SEM. Regarding the profile of respondents, as can be seen in **Table 2**, males are mostly the representatives of manufacturing companies at 63%, and only 37% are women. On the other hand, almost 39.4% of companies have been in the market for at least 1 to 3 years, and 33.7% have remained for 4 to 6 years. Finally, companies that have

approximately 1 to 10 employees represent 89.7%, and only 9.7% have 11 to 50 workers. These results provide relevant context and will be considered in the subsequent analysis, particularly in the interpretation of control variables.

Table 2
Statistical description of companies in the manufacturing sector.

Gender	**Frequency**	**%**
Male	110	62.9
Female	65	37.1
Total	175	100.0
Position in the Company	Frequency	%
Owner	96	54.9
Manager/Administrator	30	17.1
Production Manager	23	13.1
Sales/Commercial Manager	25	14.3
Other	1	0.6
Total	175	100.0
Company Seniority	Frequency	%
Less than 1 year	9	5.1
Between 1 and 3 years	69	39.4
Between 4 and 6 years	59	33.7
More than 7 years	33	18.9
Not specified / out of range	5	2.9
Total	175	100.0
Main Economic Activity	Frequency	%
Metal products for structural use	20	11.4
Furniture and wood products	33	18.9
Food products	51	29.1
Non-alcoholic beverages	12	6.9
Clothing and footwear	25	14.3
Printing and graphic arts	17	9.7
Glass/ceramics/concrete	12	6.9
Other	5	2.9
Total	175	100.0
Company Size (number of workers)	Frequency	%
1 to 10 workers	157	89.7
11 to 50 workers	17	9.7
51 to 200 workers	0	0.0
More than 200 workers	1	0.6
Total	175	100.0

5. Results

Partial Least Squares (PLS) analysis was applied using SmartPLS 4.1.1.6 to evaluate the measurement model proposed in the study. Below, the three foundations for choosing PLS-SEM will be presented. First, it was chosen because it is a widely used and validated technique in research related to accounting and digitalization (Singh et al., 2021). Second, the adoption of PLS-SEM instead of the Covariance-Based Structural Equation Modeling (CB-SEM) technique is justified because the proposed model incorporates both formative and reflective constructs and, additionally, works with a moderate sample size. Third, PLS-SEM is a technique that allows simultaneous evaluation of multiple associations between constructs; therefore, it optimizes the modeling process, which is relevant when it is necessary to maximize the predictive capacity of the proposed model (Henseler et al., 2014).

5.1. Common Method Bias (CMB)

Because the data were collected using a single method at a single point in time namely, a survey CMB needed to be assessed. to mitigate this risk, several procedural remedies described in the preceding paragraphs were implemented, along with statistical diagnostics such as Harman's single-factor test and the collinearity assessment. The results reported in Tables 5 and 3 indicate that the variance inflation factor (VIF) values are below the 3.0 threshold, suggesting that CMB does not pose a significant concern in this study (Kock, 2015). In addition, the analysis showed that the first factor accounted for only 23.30% of the total variance and that the indicators did not load onto a single dominant factor; because this value is below the critical 50% cutoff, there is no evidence of substantial CMB (Podsakoff et al., 2003).

5.2. Measurement model assessment

However, before testing the hypotheses (evaluating the structural model), it is necessary to examine both the overall model fit as well as the measurement model. In that sense, all the questionnaire information has been processed, and a result of 0.054 was obtained, being a maximum value for the model fit evaluation, where it achieved a Standardized Root Mean Square

Residual (SRMR) below the recommended threshold of 0.08 (Hu & Bentler, 1998). Likewise, the Normed Fit Index (NFI) is located at the threshold of 0.8 and 0.9 (Mulaik et al., 1989), having a minimum value of 0.769. Consequently, it is confirmed that the model presents a good fit. Given that the proposed model has two reflective constructs and four formative constructs, the analysis began with the reflective constructs (BP and DT). To examine the measurement model of these constructs, the five steps proposed by Hair y Alamer (2022) were followed: (1) determine outer loadings, (2) evaluate indicator reliability, (3) estimate internal consistency reliability, (4) examine the Average Variance Extracted (AVE), and finally (5) verify discriminant validity through HTMT.

First, outer loadings were evaluated as shown in Table 3, which, according to Hair et al. (2017), should exceed the threshold of 0.708. In their entirety, the indicators of the reflective constructs meet this criterion, with the exception of BP04, which has a loading of 0.673. However, this indicator will be retained in the model, due to the recommendations of Hair et al. (2021), since it exceeds the minimum value of 0.401. Second, the reliability of all outer loadings was estimated, where they widely exceed the value of 0.50 except for BP04, which was chosen to retain since it generates a minimal increase in AVE or in composite reliability. Third, the reliability and validity of the indicators of the reflective constructs in the measurement model were analyzed. To verify reliability, Cronbach's alpha and composite reliability indices were used as shown in Table 3, demonstrating a good measurement model (Cronbach's Alpha, Rho A, and CR > 0.7). It should be noted that for the validity of the measurement model, not only factor loadings (convergent validity) were examined, but also at the reflective construct level (discriminant validity). Fourth, to evaluate construct validity, AVE was explicitly analyzed, obtaining values above the threshold of 0.5, which is acceptable; therefore, the suggestions of Hair et al. (2021) have been followed.

Table 3

Reliability, Internal Consistency, and Convergent Validity Estimators for Model Constructs (Reflective Constructs).

Constructs	Indicators	Outer Loadings	Reliability	VIF	Cronbach's Alpha	Composite Reliability (rho_a)	Composite Reliability (rho_c)	Average Variance Extracted (AVE)
Digital Transformation (DT)	DT01	0.882	0,778	2,885	0.903	0.906	0.928	0.721
	DT02	0.832	0,692	2,205				
	DT03	0.784	0,615	1,851				
	DT04	0.881	0,776	2,969				
	DT05	0.863	0,734	2,556				
Business Performance (BP)	BP01	0.843	0,711	1,955	0.816	0.840	0.878	0.646
	BP02	0.873	0,762	2,133				
	BP03	0.811	0,658	1,750				
	BP04	0.673	0,453	1,362				

Recommended thresholds, CR ≥ 0,70, AVE ≥ 0,50.

Fifth and finally, for the reflective constructs, discriminant validity was analyzed through the Fornell-Larcker criterion proposed by Fornell & Bookstein (1982), as shown in Table 4. Based on this criterion, the AVE of each construct must be higher than the correlations between both constructs of the proposed model. Additionally, the heterotrait-monotrait ratio (HTMT) method proposed by Henseler et al. (2014) was used; as a result, the reflective constructs show a value of 0.779, which is lower than the maximum value of 0.90 as suggested by Henseler et al. (2014). Therefore, it is confirmed that both constructs are distinct concepts and discriminant validity is fulfilled.

Table 4

Discriminant Validity of Model Constructs (Reflective Constructs) Based on Fornell-Larcker.

Constructs	Business Performance (BP)	Digital Transformation (DT)
BP	0.804	
DT	0.667	0.849

Source: Author's own work.

Regarding the formative constructs of AW, OP, RD, and TC, an alternative approach was applied to demonstrate their validity as proposed by Hair y Alamer (2022), which includes: (1) evaluating convergent validity, (2) estimating indicator multicollinearity, (3) corroborating the size and statistical significance of indicator weights, (4) analyzing the size and significance level of indicator loadings, and finally (5) examining predictive validity. First, bootstrapping of 5,000 subsamples was performed to evaluate the convergent validity of the formative constructs. This procedure examines the degree of positive relationship of the substantive construct through a reflective measurement (single indicator) of the same concept (AW_G, OP_G, RD_G, TC_G). Consequently, each formative construct (AW, OP, RD, and TC) was evaluated. The results are visualized in Table 5, where values of ($\beta > 0.708$ and $R^2 > 0.50$) are observed for AW, RD, and TC. With the exception of the OP construct ($\beta = 0.695$ and $R^2 = 0.483$), values lower than the thresholds. However, the relationship was highly significant ($p < 0.001$), so in accordance with the recommendations of Hair et al. (2017), it was decided to retain the construct.

On the other hand, it was verified that the formative indicators do not present multicollinearity problems. The most commonly used statistical test for this purpose is the VIF; as shown in Table 5, all values do not exceed the value of (3.0) as recommended by (J. F. Hair et al., 2017). In this study, the maximum value obtained was 1.293.

Table 5
Outer Weights, Outer Loadings, and Variance Inflation Factor (Formative Constructs).

Constructs	Indicators	Outer Weights	Outer Loadings	VIF
Awareness (AW)	AW01	0.255	0.467	1.063
β = 0.822	AW02	0.323	0.500	1.066
R^2= 0.676	AW03	0.206	0.451	1.086
p < 0.001	AW04	0.392	0.563	1.050
	AW05	0.562	0.723	1.077
	AW_G	N/A	N/A	N/A
Readiness (RD)	RD01	0.326	0.477	1.073
β = 0.852	RD02	0.231	0.394	1.098
R^2= 0.726	RD03	0.454	0.635	1.208
p < 0.001	RD04	0.516	0.743	1.140
	RD05	0.194	0.485	1.132
	RD06	-0.028	0.417	1.293
	RD_G	N/A	N/A	N/A
Technology (TC)	TC01	0.175	0.476	1.118
β = 0.773	TC02	0.459	0.596	1.056
R^2= 0.598	TC03	0.552	0.711	1.092
p < 0.001	TC04	0.395	0.636	1.108
	TC_G	N/A	N/A	N/A
Operations (OP)	OP01	0.576	0.768	1.091
β = 0.696	OP02	0.514	0.708	1.076
R^2= 0.484	OP03	0.355	0.545	1.051
p < 0.001	OP_G	N/A	N/A	N/A

**: p < 0.05; ***: p < 0.001.

Likewise, we examined the outer weights to analyze the significance and relevance of the formative indicators, where they were evaluated according to their outer weights. In our research, after applying the bootstrapping process once again, the results in Table 5 show that most of the associated weights are significant, with the exception of AW02, OP03, RD02, RD05, RD06, and TC01. Following the recommendation of Hair et al. (2017) for formative models, we proceeded to review the corresponding outer loadings of these indicators. The results show that the associated outer loadings remain statistically significant (p < 0.05) and, additionally, no multicollinearity problems are observed (VIF < 3.0). Therefore, there is empirical support for retaining all of the indicators.

5.3. Structural model assessment

After verifying that the measurement models of both reflective and formative constructs present acceptable levels of quality in terms of reliability and validity, we proceeded to evaluate the presented structural model. The hypothesis testing reports are shown in Table 6 and Fig. 2; after that, we analyzed the significance of the path coefficients, which was evaluated through the bootstrapping process, taking into account a significance level of P < 0.05 and using percentile-based confidence intervals (Urreta & Rönkkö, 2018).

Table 6
Hypothesis Testing Results.

Hypothesis	Paths	Original Sample (O)	Standard Deviation (STDEV)	P Values	Observation
H_{1a}	AW → DT	0.507	0.044	p < 0,001	Significant
H_{1b}	RD → DT	0.458	0.054	p < 0,001	Significant
H_{1c}	TC → DT	0.306	0.050	p < 0,001	Significant
H_{1d}	OP → DT	0.206	0.048	p < 0,001	Significant
H_{2a}	AW → BP	0.176	0.072	p < 0,05	Significant
H_{3a}	RD → BP	0.008	0.073	0.914	Not significant
H_{4a}	TC → BP	0.086	0.068	0.207	Not significant
H_{5a}	OP → BP	0.161	0.071	p < 0,05	Significant
H_6	DT → BP	0.504	0.097	p < 0,001	Significant
	Control Variables				
Company seniority	→ DT	0.004	0.043	0.919	Not significant
Company seniority	→ BP	0.022	0.058	0.712	Not significant
Number of workers	→ DT	-0.034	0.035	0.350	Not significant
Number of workers	→ BP	0.103	0.069	0.133	Not significant

**: $p < 0.05$; ***: $p < 0.001$.

The results in Table 6 and Fig. 2 reveal that critical factors such as AW (O = 0.507; p < 0.001), RD (O = 0.458; p < 0.001), TC (O = 0.306; p < 0.001), and OP (O = 0.206; p < 0.001) positively impact DT. These findings strongly support hypotheses H_{1a}, H_{1b}, H_{1c}, and H_{1d}, as presented in Table 6. Furthermore, it is confirmed that different manufacturing companies have a

higher probability of developing a successful adoption and implementation of digital technologies in the organizational structure through critical factors, with DT playing a major role in generating positive effects on business performance.

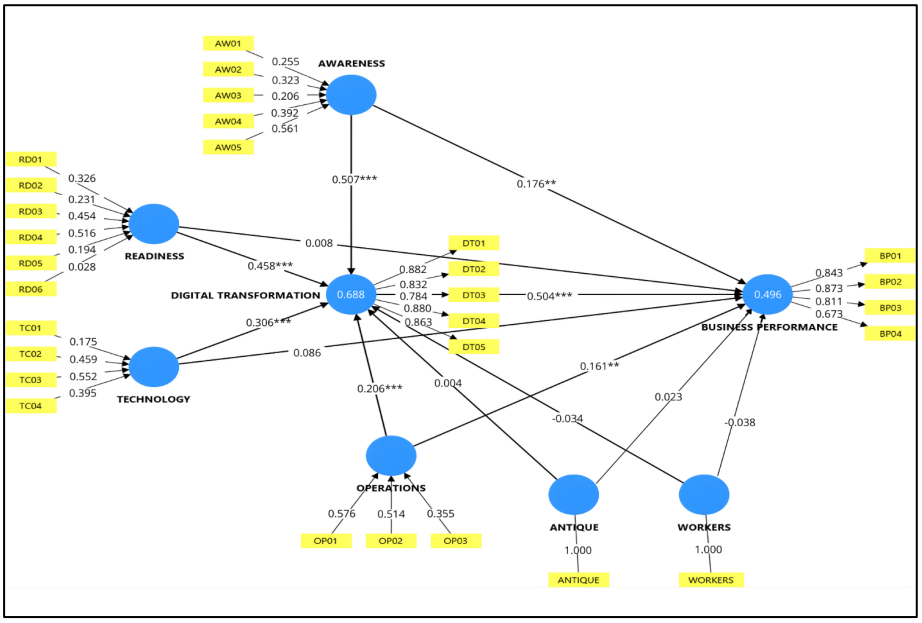

Fig. 2. Structural Model Results. **: p < 0.05; ***: p < 0.001.

While RD (O = 0.008; p > 0.1) and TC (O = 0.086; p > 0.1) do not have a significant effect on BP (rejecting hypotheses H_{3a} and H_{4a}). Therefore, it can be pointed out that not all critical factors significantly influence BP. Now regarding DT (O = 0.504; p < 0.001), it significantly and positively influences BP, supporting hypothesis H_6. This finding indicates that an effective implementation of digital technologies at the organizational level is associated with improvements in business performance, reflected in both economic results and labor outcomes. Now, regarding the control variables incorporated to support the robustness of the proposed model; the seniority variable (years of operation) does not report significant effects on DT (O = 0.004; p = 0.919) nor on BP (O = 0.022; p = 0.712). Similarly, the number of workers (variable) does not have a significant influence on DT (O = −0.034; p = 0.350) or on BP (O = 0.103; p = 0.133). These results suggest that the success of DT in companies does not depend on the years of operation in the market, much less on the number of workers, but rather on the companies' ability to adequately manage and implement DT (critical factors).

Table 7. Evaluation of Mediating Effects.

Hypothesis	Paths	Original Sample (O)	Standard Deviation (STDEV)	t Statistics	P Values	Observation
H_2	AW → DT → BP	0.256	0.051	5.061	p < 0,001	Significant
H_3	RD → DT → BP	0.231	0.052	4.463	p < 0,001	Significant
H_4	TC → DT → BP	0.155	0.038	4.107	p < 0,001	Significant
H_5	OP → DT → BP	0.104	0.028	3.647	p < 0,05	Significant
	Company seniority → DT → BP	0.003	0.020	0.162	0.872	Not significant
	Number of workers → DT → BP	0.020	0.017	1.198	0.231	Not significant

**: $p < 0.01$; ***: $p < 0.001$.

In this research, the bootstrapping test was employed to verify the mediation hypothesis. And in order to estimate the existence of substantial mediating effects Wetzels et al. (2009), P-values were considered, and if zero is located outside the lower and upper threshold of the confidence interval, the presence of an indirect influence is approved. As presented in Table 7, the results indicate that the indirect effect of AW on BP is greater, being significant and substantial (O = 0.256; p = 0.0000004), which suggests the mediating influence of DT; therefore, we confirm hypothesis 2. Now regarding the influence that RD generates on BP, it is significant (O = 0.231; p = 0.00001), where the mediating influence of DT is indicated, and hypothesis 3 is accepted.

Furthermore, the reports in Table 7 indicate the mediating influence of DT on the association between TC and BP, being significant (O = 0.155; p = 0.00004), supporting hypothesis H_4. And the results also suggest the mediating influence of DT on the relationship between OP and BP with a value of (O = 0.092; p = 0.00027), being significant; therefore, H_5 is approved. In conclusion, it can be affirmed that DT plays a fundamental role (confirming itself as the determining driver), as it acts as a critical mediator through which the critical factors (AW, RD, TC, and OP) statistically impact the BP of Peruvian manufacturing companies.

5.4. Predictive power

In the present study, the explanatory power and predictive relevance of the structural model were assessed using the R^2 and Q^2_predict statistics. Following Wetzels et al. (2009), the coefficient of determination (R^2) can be interpreted as substantial (0.75), moderate (0.50), or weak (0.25). As shown in Table 8, AW, OP, RD, and TC jointly exert a substantial effect, explaining 68.8% of the variance in DT, which indicates that the proposed model has strong explanatory power. Regarding BP, AW, OP, RD, TC, and DT together account for 49.6% of the variance, reflecting a moderate combined effect and underscoring the model's moderate explanatory capability for BP. Consistent with (Hair et al., 2017), these results suggest that the model demonstrates adequate predictive capability and a high degree of explanatory power.

Table 8
Evaluation of the predictive capacity and relevance of the model.

Constructs	R^2	Q^2
DT	68,8	0.608
BP	49,6	0,311

Source: Author's own work.

To validate the model's predictive relevance, Q^2predict values were examined. According to (Hair et al., 2017), values greater than zero indicate predictive relevance. Q^2predict was obtained using the PLSpredict procedure in SmartPLS 4.1.1.6, yielding positive Q^2 predict values for all constructs. Specifically, digital transformation achieved a Q^2predict value of 0.608 and business performance 0.311. These results indicate that the model predicts digital transformation effectively through AW, OP, RD, and TC in manufacturing firms, and it also predicts business performance, albeit to a lesser extent.

6. Discussion

The findings of our analysis support the general hypothesis: critical factors positively impact DT. This is in line with the arguments of Vogelsang et al. (2018), who propose that the success of DT in companies depends on three dimensions: The organization is based on (long-term objectives, strategic market fit, culture, and Big Data management); the environment encompasses (connectivity, information transparency, value generation, and organizational norms); and finally, technology, which highlights (organizational infrastructure, data security, availability, selection, use, and adaptation of digital technologies). In a complementary manner, the study by Chang and Chen (2025) identifies three contexts that influence DT success: people, processes, and technology, which favors a more effective and efficient adoption of DT in companies. Likewise, the study by Pozzi et al. (2023) is related to the verified hypothesis, highlighting critical success factors such as: capacity, knowledge, and experience in quality, flexibility, senior management leadership, establishing teams interconnected with new technologies, DT project planning, technological training, and continuous improvement. These statements fully support the hypotheses that critical factors significantly influence DT.

The research results definitively confirm that critical factors positively influence DT, enabling companies to have a greater probability of success in the implementation and adoption of DT. Consequently, the reports verifiably show that AW has a statistically greater positive impact on DT (H_{1a}), while on BP (H_{2a}) it is less significant; likewise, DT acts as a mediator in the association between AW and BP (H_2), being highly significant. The study by Romero et al. (2025), who, in the Peruvian context, report that digital competencies and organizational culture have statistically direct effects on DT in companies. Consistently, Schumacher et al. (2019) maintains that a clear organizational strategy acts as a roadmap for DT implementation, along with the strengthening of competencies and knowledge in emerging technologies, as well as cybersecurity, notably improving DT adoption. Along the same lines, Senna et al. (2023), points out that the integration of systems at the organizational level, accompanied by a cybersecurity policy, substantially favors the success of DT projects; furthermore, it highlights the values, norms, and aptitudes that compose organizational culture, which must permeate all hierarchical levels to promote a collaborative vision and recognition of employees toward successful DT. These statements are consistent with the RBV, DCT, and the ARTO model, since the impact of DT on BP is solid by improving operational efficiency (Zhang, 2024). In a complementary manner, in their study, Feng et al. (2025), discovered the influence of technological aspects, government support, organizational changes and strategies on BP, allowing companies to have competitive sales in the market. On the other hand, the findings of this research show a positive and statistically significant impact of RD on DT (H1b). These reports align with the study by Santos & Martinho (2020), who highlight the role of organizational structure, culture, and strategy, in articulation with workforce skills, smart factories, and smart processes, favoring a successful implementation of DT in companies. Similarly, the study by Bohórquez y Herrera (2022), demonstrates that the elements of Big Data, operations, leadership and organizational strategy, culture, and people are fundamental for the effective incorporation of DT in companies. In relation to DT, it plays a substantial mediating role in the relationship between RD and BP (H3) of companies in the Peruvian manufacturing sector. These findings align with Imran et al. (2021), who propose that leadership, organizational structure, and culture act as key facilitators for developing successful DT initiatives throughout the company, generating positive effects on BP. Likewise, the research by Tan et al. (2025) supports the hypothesis by showing that factors such as strategy, leadership, organizational structure, environmental dynamism, and absorptive capacity significantly increase DT, strengthening its efficiency and effectiveness, and contributing positively to the BP of companies. Consistently, the study by Teng et al. (2022) confirms that DT strategies are associated with financial performance, highlighting that this effect operates

primarily through the mediating role of DT. Together, these results allow us to maintain that RD facilitates a successful implementation of DT at the organizational level and that, through this, positive effects are generated on the BP of companies, reflected in greater long-term profitability and improvements in labor performance.

Regarding the research results, it is demonstrated that TC significantly affects DT (H_{1c}), reinforcing the evidence provided by Buer et al. (2021), who maintain that the management of digital technologies (IT), aspects of digitalization, technologies and machines, are significantly associated with higher levels of DT in manufacturing companies. Along the same line, the research by Jung et al. (2020) reveals that the selection and integration of IT, including the deployment of mobile devices and IoT, and data processing through hardware, when articulated with a DT vision, show favorable results in DT. Likewise, the study by Bevilacqua et al. (2017) shows that investment in infrastructure and the implementation of IT, based on energy management in the IoT integrated into a manufacturing company's information systems, contribute to strengthening DT and increasing competitiveness. Now regarding the statistically significant role that DT has in the relationship between TC and BP (H4), therefore, a partial mediated effect is confirmed. These results align with the study by Sánchez et al. (2024), who ratify the significant association between technological capability and company performance through the mediation of DT; such technological capability includes: infrastructure investment (database architecture, network communication, IT operations and facilities), and a proactive IT posture (adoption, updating, and continuous improvement of IT use). Likewise, the study by Sharabati et al. (2024) highlights that investment in IT (cloud computing, big data analytics, AI of things) drives the BP of companies through DT. In conclusion, the proven empirical evidence of these influences can be ratified, which addresses the deficiencies identified in the scientific literature.

To conclude, the evidence from this research demonstrates that OP has a significantly greater impact on DT (H_{1d}); however, its direct effect on BP (H_{5a}) is less significant. This evidence coincides with the study by Alshibani et al. (2024), who conclude that, in manufacturing companies, data security acts as a main element, since during technological implementation it strengthens DT and improves data transfer, making it more secure. In a complementary manner, Talluri (2025) explains that data governance, computerized monitoring systems, and data management programming are important, as they affect the success of DT processes, improving competitiveness in an increasingly digital environment. In turn, the study by Schumacher et al. (2016) proposes and validates a six-dimension model with 62 items, which they classify into three elements: processes, governance, and technology as drivers of DT in companies. On the other hand, DT acts as a mediator in the relationship between OP and BP (H5); therefore, a mediating effect is confirmed. This result aligns with (Bindeeba et al., 2025), who show positive effects on BP through the management of IoT, big data analytics, AI technologies, smart factories, process and product digitization (production design), and data governance, highlighting DT as a facilitator. Likewise, the study by (Almeida & Okon, 2025) demonstrates that IoT acts as a mediating mechanism with positive effects in the association between DT and BP, given that devices aligned with the network allow receiving and sending data and information (data governance), and are frequently used to sell items, as they automate operational processes and allow interaction with customers. In conclusion, the results presented reinforce the assumptions that OP and DT play an important role in driving BP in Peruvian manufacturing companies.

Finally, and the most relevant finding of the research, reveals that DT considerably impacts the BP of companies in the manufacturing sector in Peru (H_6). These findings align with the study by (Kim & Jin, 2024), who highlight a statistically direct and indirect impact of digital capabilities on BP through opportunity capacity and entrepreneurial leadership as mediating and moderating variables, which significantly improve BP performance. The research by (Guo & Xu, 2021) also shows that DT has substantial inferences on business performance, showing positive impacts on operational performance in both high-tech and low-tech companies, as well as effects on financial performance in Chinese high-tech manufacturing companies. Likewise, the study by the (Ministerio de la Producción del Perú, 2023), in its findings, determines six dimensions that show a positive level for implementing and using IT in formal micro, small, and medium-sized enterprises (MSMEs): through culture, strategy, people, organization, technologies, processes, and customer experience. In summary, the different results explain how DT, through its indicators, statistically influences the BP of companies in the manufacturing sector.

7. Theoretical and Practical Contributions

7.1 Theoretical Contributions

This study makes several contributions by providing important insights into the emerging literature on critical success factors and DT in the context of manufacturing firms. A considerable body of research on DT has focused primarily on specific sectors and large organizations in developed economies (P. Guo et al., 2025; Popescu & Zbieta Sobczak, 2025; Z. Zhang & Chen, 2025). However, quantitative studies examining critical success factors and DT in the context of emerging economies remain scarce. This study is pioneering in proposing a novel theoretical framework developed through a critical analysis of the existing literature. Specifically, the proposed framework explains how critical success factors, including AW, RD, TC, and OP, influence DT, which is conceptualized as a mediating variable affecting BP. In this regard, the study also offers a fresh perspective that helps address the shortcomings identified in the existing literature.

This study seeks to deepen the theoretical understanding of the critical success factors that drive DT development through the identification of the variables AW, RD, TC, and OP. Although prior studies have identified success factors primarily through qualitative approaches, our research proposes a new model based on a quantitative approach. This helps fill a gap in the literature concerning the cumulative impact of organizational and technological resources on DT efforts. The findings demonstrate how critical success factors shape DT. Previous studies in this field have largely focused on developed countries; therefore, digitalization scholars, such as (Vial, 2019), have emphasized that such findings do not allow for generalizable conclusions and that additional studies in different contexts are needed. Consequently, this study represents one of the first investigations of its kind conducted outside Western European countries, specifically in Peru, in order to respond to this need.

7.2 Practical Contributions

Although this study was conducted in the context of Peruvian manufacturing firms, its results and implications may provide meaningful insights for the practices of many manufacturing firms in developing countries. Our findings have several practical implications. By understanding AW, RD, TC, and OP as critical and strategic factors, this study offers guidance to managers of manufacturing firms on how they should direct their resources and efforts in order to improve operational performance. For example, this research highlights the need to prioritize the development of the Awareness dimension, as these factors collectively influence the decisions of managers and stakeholders to embark on the path toward DT. Likewise, strengthening the Operations dimension is recommended, since the mere selection and use of technologies within firms is not sufficient; it is also essential to focus on their execution and management in order to successfully achieve DT within the organization. Finally, given that decision-making depends largely on the managers of manufacturing firms, we recommend that firms seeking to succeed in their DT process focus specifically on these critical factors.

8. Conclusion and future research

This article provides new evidence on the identification of critical factors that favor the successful implementation of DT and its effect on BP in the context of an emerging country such as Peru, based on formal companies in the manufacturing sector. The study reveals that the main critical factors (AW, RD, TC, and OP) develop a higher probability of success for the implementation of DT; furthermore, how critical factors impact BP through the mediating role of DT was thoroughly analyzed. In light of the above, the need arises to develop a new model oriented toward evaluating and understanding in a more comprehensive manner, but grounded in the RBV, DCT, and the ARTO model. In contrast with previous research, which generally limits itself to proposing new DT success factors based on literature reviews, or from a quantitative scope study that propose new DT measurement models, that analyze DT and its impact on the organization, and that examine the impacts of DT on the performance of manufacturing companies. Thus, this research deepens the unraveling of underlying mechanisms, with the purpose of studying the critical success factors (AW, RD, TC, and OP) that affect DT, and in turn, BP. However, this research has limitations that open avenues for future research. First, the study employed a cross-sectional design to examine the impact of both critical factors and DT on the BP of manufacturing companies; given that the information was collected at a single point in time, BP may not have been captured in its full magnitude, considering that economic and labor results tend to change constantly. Therefore, it is suggested for future research to integrate a longitudinal design in order to evaluate the evolution of BP and obtain a more reliable understanding of DT implementation in manufacturing companies, specifically in a business environment characterized by continuous changes due to technological advances and AI. Also, future research could expand the study population by including informal companies. This is relevant for emerging countries, where informality tends to represent a significant proportion within the business fabric. Including informal companies will allow for a more panoramic vision of the manufacturing sector and generate useful information for the design of public policies focused on accelerating business digitalization. As a consequence, such policies could favor the development of productivity and national competitiveness, with positive results on economic growth.

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Appendix A1

Variable		Indicators	Affirmations	Reference
Awareness (AW)	AW01	External support	The company receives external support.	(Chirumalla et al., 2025; Wagire et al., 2021; Santos & Martinho, 2020)
	AW02	Organizational culture	The company promotes a culture that is open to change.	
	AW03	Organizational structure	The company facilitates the use of new technologies.	
	AW04	Organizational strategies	The company anticipates which technologies it should adopt.	
	AW05	Organizational competence	Staff have the knowledge and skills to use technologies.	
	AW_	General awareness	The company needs to modernize technologically.	
Readiness (RD)	RD01	Organizational structure	The company's work organization allows the installation of new machines.	(Chirumalla et al., 2025; Wagire et al., 2021; Santos & Martinho, 2020; Schumacher et al., 2019)
	RD02	Organizational culture	Staff adapt to new, modern machines.	
	RD03	Organizational leadership	Leaders support the use of digital technologies.	
	RD04	Organizational strategies	The company has a phased plan to implement technology.	
	RD05	Organizational competence	Staff are ready to learn new technologies.	
	RD06	Infrastructure investment	The company has space and internet access to modernize equipment.	
	RD_	General readiness	The company has the funds and personnel to begin technological modernization.	
Technology (TC)	TC01	Digital technology characteristics	Current machines/software are easy to use.	(Temel & Ayaz, 2019; Chirumalla et al., 2025; Temel & Ayaz, 2019; Buer et al., 2021)
	TC02	Digital technology selection	Before investing, the company assesses whether the technology improves work.	
	TC03	Digital technology integration	Digital tools fit the way we work.	
	TC04	Infrastructure investment	Resources are allocated to upgrade and repair equipment/systems.	
	TC_	General technology	Current equipment is sufficient for the company's work.	
Operations (OP)	OP01	Data security	The company protects its information to prevent losses.	(Santos & Martinho, 2020; Temel & Ayaz, 2019; Chirumalla et al., 2025)
	OP02	Data governance	Customer and sales information is well organized and can be retrieved quickly.	
	OP03	Production system design	The workshop/production is organized to leverage technology.	
	OP_	General operations	Technology makes workshop operations faster and more organized.	
Digital Transformation (DT)	DT01	People	Staff use digital tools and software effectively.	(Almajali et al., 2025; Canetta et al., 2018)
	DT02	Technology	Digital technology has improved day-to-day activities.	
	DT03	Processes	Tasks are performed with fewer steps and greater automation.	
	DT04	Customer	Digitalization enables faster responses to customers.	
	DT05	Strategy and investments	The company invests and acts strategically to advance digitalization.	
Business Performance (BP)	BP01	Revenue performance	Revenues have increased due to the use of digital tools.	(J. Kim & Jin, 2024)
	BP02		Technology has increased profits by reducing costs and waste.	
	BP03	Labor performance	Staff productivity has improved through the use of technology.	
	BP04		Technology has improved work coordination and control.	

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