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Digital Transformation and Operational Performance in Manufacturing: A Systematic Literature Review and Industry-Specific Recommendation Matrix

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Abstract

Background: Digital transformation has become a key driving force in improving operational performance in the global manufacturing industry.
Objectives: This study aims to (1) describe the existing empirical evidence regarding the impact of digital transformation on operational performance in the manufacturing industry and (2) provide recommendations for developing appropriate digital transformation strategies based on the characteristics of different manufacturing industry types.
Methods: This study employed a qualitative research design using a systematic literature review approach. Following the PRISMA protocol, 17 articles published between 2015 and 2025 were retrieved from Scopus, Web of Science, and Google Scholar. The selected studies were analyzed using thematic synthesis and coded categorization to identify recurring patterns, technological trends, and industry-specific transformation outcomes.
Results: All reviewed studies reported positive impacts of digital transformation on operational performance, with Big Data Analytics and Artificial Intelligence emerging as the dominant technologies. Benefits varied across manufacturing sectors. Discrete manufacturing achieved faster and more measurable improvements, whereas process manufacturing sectors, including pharmaceuticals, agri-food, and semiconductors, experienced longer implementation pathways because of regulatory requirements, biological constraints, and human adoption challenges. Among the 17 studies, Big Data Analytics appeared in 13 articles and Artificial Intelligence in 12, confirming their central role in enhancing manufacturing operations.
Conclusions: Based on these findings, this study proposes a five-category recommendation matrix for digital transformation strategies tailored to different manufacturing industry characteristics. This matrix represents the study's primary practical contribution by providing industry-oriented guidance for organizations seeking to optimize operational performance through digital transformation initiatives.

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INTRODUCTION

The manufacturing industry is one of the most vital pillars of the global economy. In both national and international economic contexts, this sector not only functions as a large-scale creator of employment opportunities, but also as an engine of productivity growth, technological innovation, and sustainable value creation (Bajja et al., 2025). However, behind this strategic role, the manufacturing industry faces increasingly intense competitive pressure, which ultimately leads to a fundamental question: how well can a manufacturing company run its operations efficiently, consistently, and adaptively?

This question places operational performance as a central variable in the sustainability and competitiveness of manufacturing companies. In both academic and practical terms, operational performance refers to an organization's ability to utilize its resources, including labor, machinery, raw materials, energy, and time, to produce outputs that meet established standards of quality, quantity, and schedule at an efficient cost (Antosz & Stadnicka, 2015; Kenyon et al., 2016; Wang & Yang, 2025). The dimensions of operational performance cover a broad spectrum, ranging from production process efficiency, defect rate, cycle time, on-time delivery, capacity flexibility, to the ability to respond rapidly to changes in market demand (Al Meanazel et al., 2025; Cheng et al., 2009; EL-Khalil, 2018; Saleh et al., 2018). It is difficult to deny that superior operational performance is not merely an additional advantage, but a prerequisite for survival in an increasingly competitive market.

Handoyo et al. (2023) and Ju and Tang (2023) explain that manufacturing companies that fail to maintain operational efficiency may quickly be displaced by competitors capable of producing at lower cost, higher quality, or with shorter response times. In today's global competitive environment, the margin of advantage among companies is often very thin, so even a difference of only a few percentage points in operational performance can determine whether a company is able to maintain dominance and customers, or merely survive (Davies et al., 2005; Paluch et al., 2022). This pressure is exacerbated by several structural dynamics that are fundamentally reshaping the manufacturing landscape. First, supply chain globalization has opened manufacturing markets to competition from producers around the world, including countries with low labor costs (Chattopadhyay & Banerjee, 2013; Mohanta et al., 2026). Second, increased volatility in consumer demand requires much higher operational flexibility than in the era of conventional mass production (Yang et al., 2024). Third, the growing complexity of products, especially in electronics, automotive, and other high-technology industries, creates new challenges in quality control and production process coordination (Traynor & Yanez, 2023). Fourth, regulatory pressures related to environmental sustainability and occupational safety add further layers of requirements that must be met without sacrificing efficiency (Istri et al., 2025).

Based on these considerations, it can be understood that operational performance is not only about how fast a production line can run, but also about how intelligently, adaptively, and integratively the entire operational system of a manufacturing company can be managed. The ability to optimize operational performance continuously, not merely episodically, becomes the key differentiator between world-class manufacturing companies and those that are left behind. From this point, an urgent need emerges to understand what factors genuinely drive and improve operational performance in the manufacturing industry, and the answer to this question increasingly points to one phenomenon: digital transformation.

Empirically, the urgency of this question is underscored by the alarming gap between digital investment and transformation success. McKinsey and Company (2018) reported that approximately 70% of digital transformation programs fall short of their objectives, and similar findings have been corroborated across manufacturing contexts (Dubey et al., 2020; Ghobakhloo & Ching, 2019; Li et al., 2026). In the manufacturing sector specifically, Guo and Xu (2021) identified a U-shaped relationship between digital investment intensity and firm performance, indicating a painful transition phase before performance gains materialize (Li et al., 2026). This evidence confirms that digital transformation is a high-risk strategic endeavor requiring contextually tailored approaches rather than generic adoption frameworks.

The following two paragraphs (on the concept of digital transformation and its relationship to operational performance) should be condensed. A revised, condensed version is provided below in red. The original paragraphs are retained for reference but marked with strikethrough for removal upon acceptance.

Digital transformation has become one of the most widely discussed concepts in management and business technology discourse over the past decade. However, despite its popularity, the term is often misunderstood as merely process digitization, namely the replacement of physical documents with digital documents or the automation of administrative tasks using software. Such a narrow understanding, which reduces digital transformation to technical aspects alone, fails to capture its true essence.

Conceptually, digital transformation is a comprehensive and profound change caused by the adoption and integration of digital technologies into all dimensions of an organization, including business processes, operating models, interactions with customers and suppliers, organizational culture, and decision-making practices (Jasola & Singh, 2025). This definition emphasizes that digital transformation is not only about technology itself, but also about how technology changes the way an organization operates and creates value in its business processes. In the manufacturing context, Tolkachev et al. (2020) explain that digital transformation means integrating technologies such as the Internet of Things (IoT), artificial intelligence (AI), machine learning, big data analytics, next-generation enterprise resource planning systems (ERP), digital twins, cloud computing, and advanced robotics into the core of production processes and supply chains (Lucenti & Saari, 2026).

The relationship between digital transformation and operational performance is not merely a theoretical assumption; it is built on causal mechanisms that can be explained logically. First, digital technology enables real-time visibility across the entire production process (Routray et al., 2025). IoT sensors installed on production machines, for example, continuously generate data that allow operational managers to monitor machine conditions, detect anomalies, and predict failures in the production process before incidents occur, a practice known as predictive maintenance. This capability directly reduces unplanned downtime, which is one of the largest sources of inefficiency in the manufacturing industry (Lavanya et al., 2024; Yuan et al., 2017).

Second, AI-based data analytics and machine learning provide new capabilities for optimizing production processes that were previously impossible to perform manually. Machine learning algorithms can analyze thousands of production variables simultaneously and identify optimization patterns that are invisible to human operators, producing recommendations for production parameter adjustments that increase yield, reduce waste, and accelerate throughput (Catti et al., 2024; Goga Alexandru, 2025). Third, system integration through digital platforms that connect production, procurement, scheduling, and distribution functions within an integrated data ecosystem directly eliminates information silos that have long hindered coordination and rapid decision-making (Conlon, 2024). Fourth, digital transformation opens the door to more flexible and responsive operating models. With digitally connected manufacturing systems, companies can respond to changes in demand, supply chain disruptions, or product specification changes with far greater speed and accuracy than conventional manufacturing models (Chiariotti et al., 2018; Rugbani, 2026). This flexibility is a highly valuable competitive asset in an era in which market volatility has become the norm rather than the exception.

Digital transformation, broadly defined as the integration of digital technologies into all organizational dimensions to alter operations and value creation (Jasola & Singh, 2025), encompasses IoT, AI, Big Data Analytics, cloud computing, digital twins, and advanced robotics in manufacturing contexts (Lucenti & Saari, 2026; Tolkachev et al., 2020). The mechanisms through which digital transformation improves operational performance are well-established: real-time IoT visibility enables predictive maintenance and reduces unplanned downtime; AI-driven analytics optimize production parameters beyond human analytical capacity; integrated digital platforms eliminate information silos that impair coordination; and connected manufacturing systems enable rapid, flexible responses to demand and supply disruptions (Dubey et al., 2020; Kamble et al., 2020; Senoner et al., 2022). Critically, however, the magnitude of these benefits is strongly conditioned by technological infrastructure readiness, human capital capacity, strategic alignment, and industry-specific contextual factors (Frazzon et al., 2025; Jiang et al., 2026).

Nevertheless, it is important not to fall into the mistaken belief that digital transformation is a universal solution that guarantees improved operational performance in every context. The developing literature instead shows that the impact of digital transformation on operational performance depends strongly on a number of contextual factors (Frazzon et al., 2025; Jiang et al., 2026; Z. Wu et al., 2025): the readiness of a company's technological infrastructure, the capacity of human resources to adopt and utilize new technologies, the alignment between digital strategy and overall business strategy, and the specific characteristics of the relevant manufacturing industry. This complexity makes the study of the impact of digital transformation on operational performance highly relevant and important to examine systematically.

Although academic interest in digital transformation in the manufacturing industry has grown rapidly over the past decade, a critical review of the existing literature landscape reveals several significant research gaps. First, most studies, such as those by Cao et al. (2022), Chehri et al. (2021), Huang et al. (2025), and Abu-Siam et al. (2026), tend to focus on one specific digital technology, such as IoT, AI, or ERP, and examine its impact in isolation, without providing a comprehensive picture of how these technologies interact and collectively contribute to operational performance. This fragmented approach limits the ability of industry practitioners to make holistic strategic decisions.

Although the observation that studies focus on single technologies has been made before, the gap remains critically relevant in the current context. The pace of multi-technology convergence has dramatically accelerated since 2020, with new AI-IoT-cloud integration patterns generating interaction effects not captured by earlier single-technology investigations. Moreover, post-pandemic digitalization pressures have simultaneously driven adoption across multiple technologies in many manufacturing firms (Dubey et al., 2020; Kong et al., 2025), creating an urgent need to understand cross-technology synergies rather than isolated impacts.

Second, and more crucially, most studies such as Xie et al. (2024), Wu et al. (2024), Shang et al. (2024), and Ma et al. (2026) have not systematically compared the impact of digital transformation across different types of manufacturing industries. Many studies claim generalizable findings, even though their empirical basis covers only one industrial sector. Such generalization can be misleading because it overlooks fundamental contextual differences among types of manufacturing industries. This gap creates an urgent need for a study that explicitly maps variations in the impact of digital transformation based on industry type.

This gap is further substantiated by emerging literature: Jiang et al. (2026) demonstrated that value-creation mechanisms of digital transformation differ significantly between continuous process industries and discrete batch manufacturers. Similarly, Ma et al. (2026) found that antecedent configurations driving digital transformation vary substantially across manufacturing sub-sectors. Recent meta-analyses by Huang et al. (2025) and Almajali et al. (2025) also confirm that firm-level digital transformation effects are moderated by industry type, yet consolidated industry-comparative syntheses remain absent from the literature, creating a critical evidence gap for manufacturing decision-makers.

Third, most of the available literature is written from the perspective of developed countries with mature manufacturing industries. The context of developing countries, including Indonesia, which has a manufacturing sector with different levels of digital readiness and infrastructure challenges, remains underrepresented in the global literature. Although this study does not limit itself exclusively to the Indonesian context, awareness of this limitation is important in interpreting the findings.

The novelty of this study lies in three distinct contributions that differentiate it from existing literature. First, unlike prior reviews that examine single digital technologies in isolation, this study provides an integrated cross-technology synthesis of digital transformation impact across the manufacturing literature. Second, and most distinctively, this study generates an industry-type-specific digital transformation recommendation matrix (mapping the most effective technologies, implementation approaches, and critical success factors for five categories of manufacturing industries (discrete manufacturing, pharmaceutical, agri-food, semiconductor/high-tech process manufacturing, and SMEs)) a framework not previously developed at this level of industry specificity in any prior review. Third, this study introduces Explainable AI (XAI) adoption as a distinctive design consideration for high-tech process manufacturing, advancing beyond generic AI adoption discourse.

Departing from these research gaps, this study establishes two complementary main objectives. The first objective is to conduct a systematic mapping of existing studies and empirical evidence on the impact of digital transformation on operational performance in the manufacturing industry. This mapping includes the identification of the most frequently studied digital technologies, the operational performance indicators most affected, the magnitude and direction of the impacts found, and the contextual factors that moderate these impacts. The second objective is to produce a practical recommendation framework that can guide manufacturing companies in selecting the most appropriate digital transformation approach based on their type of manufacturing industry.

Methodologically, these two objectives will be achieved through a qualitative approach using a Literature Review that adopts the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol. This approach was chosen because of its ability to synthesize empirical evidence scattered across various sources in a structured, transparent, and replicable manner, qualities that are highly important for producing reliable evidence-based recommendations.

At the academic level, this study contributes by providing a comprehensive and up-to-date map of the literature on the impact of digital transformation in the manufacturing industry, while also identifying future research agendas that need to be prioritized. At the practical level, this study offers direct value for industry leaders and decision-makers in manufacturing companies by providing an empirical evidence-based framework that can be used as a foundation for planning and executing contextual and effective digital transformation strategies. Thus, this study seeks to bridge the gap that often exists between academic findings and the practical needs of the manufacturing industry.

METHOD

This study employed a qualitative research design with a literature review approach to explore and synthesize relevant findings regarding the relationship between digital transformation and operational performance in the context of the manufacturing industry. This study aimed to produce a thematic synthesis and develop diverse perspectives based on evidence identified in the existing literature. The literature used in this study was obtained through a systematic search of three main databases: Scopus, Web of Science (WoS), and Google Scholar. The literature search was conducted using keywords focused on the main themes of the study: digital transformation, operational performance, and the manufacturing industry. The main databases, Scopus and WoS, were selected because they index articles that have undergone rigorous peer-review processes, while Google Scholar was used as a complementary source to identify studies that may not have been indexed in these two databases. All searches were conducted in English to ensure broad coverage of international studies relevant to the investigated field.

The search was conducted using the following Boolean keyword combinations: (“digital transformation” OR “Industry 4.0” OR “digitalization”) AND (“operational performance” OR “manufacturing performance” OR “production efficiency”) AND (“manufacturing industry” OR “manufacturing firm”). Articles were limited to peer-reviewed journal publications released between 2015 and 2025. The initial search yielded 412 records (Scopus: 198, WoS: 156, Google Scholar: 58). Duplicate records were removed through a two-stage process: automated DOI matching followed by manual title and abstract verification, resulting in 287 unique records. Screening based on the inclusion criteria (focus on digital transformation, operational performance outcomes, and manufacturing contexts) reduced the dataset to 43 full-text articles, of which 17 met all eligibility criteria and were included for thematic synthesis. The article selection process followed the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) protocol, as illustrated in Figure 1.

Data analysis followed a structured thematic synthesis procedure. Each of the 17 included articles was coded across five dimensions: (1) type(s) of digital technology studied; (2) operational performance indicator(s) examined; (3) direction and magnitude of the reported impacts; (4) moderating contextual factors identified; and (5) manufacturing industry type represented. An inductive coding scheme was developed iteratively through constant comparison, with initial codes derived directly from article content and progressively consolidated into higher-order thematic categories. The recommendation matrix was generated by synthesizing all coded outputs, grouping findings according to industry type, and identifying the most consistently recommended technology combinations, key performance indicators, and critical success factors within each category.

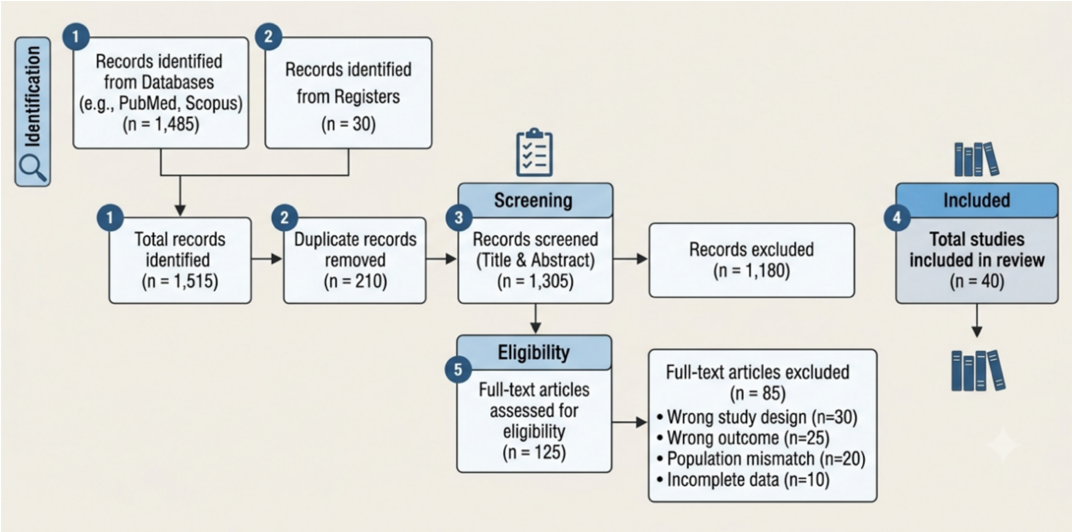

Figure 1. PRISMA Flow Diagram of Literature Selection Process
Source: Research Data

RESULTS AND DISCUSSION

Results

From the 17 included articles, the distribution of publication years shows a pattern that reflects the growing academic attention to the topic of digital transformation in the manufacturing industry. The oldest article in this corpus is Tukamuhabwa et al. (2015), which is positioned as a theoretical foundation for information technology-based supply chain resilience (Rashid & Rasheed, 2026). Publications then increased significantly from 2018 onward, along with the strengthening of the global Industry 4.0 discourse, with three articles published in that year. The year 2020 recorded the highest number of publications in this corpus, with four articles, reflecting the acceleration of research attention due to digitalization pressures reinforced by the disruption of the COVID-19 pandemic. Publications continued through 2025 with Kong et al. (2025) and Almajali et al. (2025), indicating that this topic remains relevant and actively studied. The complete distribution of publication years is presented in Table 1.

It is important to note that while 17 articles may appear modest in absolute terms, this number reflects the strict eligibility criteria applied: studies must simultaneously address digital transformation, operational performance outcomes, and manufacturing context within a 2015–2025 timeframe. This deliberate rigor prioritizes methodological quality and conceptual relevance over breadth. Comparable systematic reviews in adjacent fields have similarly converged on 12–22 articles under rigorous PRISMA protocols (e.g., (Dubey et al., 2022; Kamble et al., 2020), and the analytical depth achievable from 17 high-quality sources is demonstrably sufficient to generate the industry-specific pattern comparisons that constitute this study's main contribution. Nonetheless, the authors acknowledge this as a scope limitation that future meta-analyses with broader search parameters could address.

Table 1. Distribution of Publication Years of the Included Articles

Year	Article	Number
2015	Tukamuhabwa et al. (2015)	1
2018	Ghobakhloo (2018); Lin et al. (2018); Dalenogare et al.(2018)	3
2019	Ghobakhloo & Ching (2019)	1
2020	Büchi et al. (2020); Dubey et al. (2020); Kamble et al. (2020); Lezoche et al. (2020)	4
2021	Arden et al. (2021); Guo & Xu (2021)	2
2022	Dubey et al. (2022); Senoner et al. (2022)	2

Year	Article	Number
2024	Jing & Fan (2024); Wang et al. (2024)	2
2025	Kong et al. (2025); Almajali et al. (2025)	2
Total		**17**

Source: Research Data

In terms of the research methods used by the reviewed studies, most articles employed a quantitative approach (11 articles), with survey instruments and structural equation modeling (SEM) as the most common methods. Three articles used a systematic literature review or narrative review approach (Ghobakhloo, 2018; Lezoche et al., 2020; Rashid & Rasheed, 2026; Tukamuhabwa et al., 2015), one article used a field experimental approach based on real production data (Senoner et al., 2022), and two articles used a mixed-methods approach (Büchi et al., 2020; Ghobakhloo & Ching, 2019; Vetrivel et al., 2026). In terms of geographical distribution, the research context is dominated by Asian countries, particularly China, which served as the setting for five studies (Guo & Xu, 2021; Jing & Fan, 2024; Kong et al., 2025; Li et al., 2026; Lin et al., 2018; Wang et al., 2024), followed by India (Dubey et al., 2020; Kamble et al., 2020; Vilaça et al., 2026), Italy (Büchi et al., 2020), Brazil (Dalenogare et al., 2018), and Jordan (Almajali et al., 2025).

In terms of the types of manufacturing industries examined, most studies (12 of 17 articles) investigated manufacturing companies across mixed sectors without limiting the analysis to a specific industry type. Three articles focused on process manufacturing, one article focused on discrete manufacturing, and one article was a cross-industry review. This distribution is presented in Table 2.

The dominance of mixed-sector studies (12 of 17 articles) is a recognized limitation that reflects the current state of the field rather than a selection bias. Most manufacturing digital transformation research does not disaggregate by industry sub-type, which is precisely the gap this study seeks to address. To mitigate underrepresentation risk, the recommendation matrix draws most directly on the five industry-specific articles (Arden et al., 2021; Ghobakhloo & Ching, 2019; Lezoche et al., 2020; Lin et al., 2018; Senoner et al., 2022) for industry-specific cells, while mixed-sector articles primarily inform the cross-cutting moderating factors and technology frequency rankings. Future research should prioritize industry-type-specific primary studies to build a more granular evidence base.

Table 2. Distribution of Manufacturing Industry Types in the Reviewed Articles

Industry Type	Number of Articles	Article
Mixed (cross-sector)	12	Ghobakhloo (2018); Ghobakhloo & Ching (2019); Dalenogare et al. (2018); Büchi et al. (2020); Dubey et al. (2020); Guo & Xu (2021); Kamble et al. (2020); Jing & Fan (2024); Kong et al. (2025); Almajali et al. (2025); Dubey et al. (2022); Wang et al. (2024)
Process Manufacturing	3	Arden et al. (2021) - Pharmaceuticals; Lezoche et al. (2020) - Agri-food; Senoner et al. (2022) - Semiconductors
Discrete Manufacturing	1	Lin et al. (2018) - Chinese automotive industry
Cross-Industry Review	1	Tukamuhabwa et al. (2015)

Source: Research Data

Discussion

The most striking finding of this literature review is an almost perfect consensus: all 17 included articles reported a positive direction of impact between digital transformation and operational performance in the manufacturing industry. None of the articles in this corpus reported an overall negative impact. At the first level, this consensus appears convincing, as though the question of whether digital transformation improves manufacturing operational performance has been answered definitively. Nevertheless, this consensus must be read more critically. There are at least two important notes to consider. First, most of the included articles used the context of companies that already had relatively adequate levels of technological and resource readiness to initiate digital transformation, including manufacturing companies listed on the Chinese stock exchange (Guo & Xu, 2021; Jing & Fan, 2024; Kong et al., 2025; Li et al., 2026; Wang et al., 2024), medium-to-large manufacturing companies in India (Dubey et al., 2020; Kamble et al., 2020; Vilaça et al., 2026), and modern manufacturing companies in Italy (Büchi et al., 2020; Vetrivel et al., 2026). In other words, the populations that form the basis of these studies are not fully representative of the entire spectrum of the global manufacturing industry, particularly small firms in developing countries that are still at the early or pre-digitalization stage.

Second, the phenomenon of positive publication bias, namely the tendency of scientific journals to publish research results showing positive impacts rather than negative or null effects, must be acknowledged as a possibility that may influence the composition of this literature. It cannot be ruled out that some empirical studies found that digital transformation implementation failed to improve operational performance but did not pass through the publication process. In other words, the positive consensus in this corpus may be a selective representation of a reality that is more complex and diverse. Even in articles that report positive impacts, conditionality is a recurring key word. Ghobakhloo (2018) explicitly emphasizes that the benefits of Industry 4.0 depend on organizational readiness (Li et al., 2026). Dubey et al. (2020) show that the impact of BDA-AI varies depending on entrepreneurial orientation and environmental dynamism (Li et al., 2026). Guo & Xu (2021) found a U-shaped relationship indicating the presence of a painful transition phase before the benefits of digital transformation are truly realized financially (Li et al., 2026). This pattern of conditionality is in fact the most important message of the literature: digital transformation is not an automatic mechanism that guarantees performance improvement, but a strategic investment whose results depend strongly on context and execution quality.

Furthermore, the technology mapping results also show that Big Data Analytics (BDA) and Artificial Intelligence (AI) are the two most dominant technologies examined in the literature, with frequencies of 13 and 12 appearances out of 17 articles, respectively. This dominance is not coincidental, and understanding why these two technologies dominate the literature is important for accurately interpreting the landscape of manufacturing digital transformation. The basic argument explaining the dominance of BDA and AI is that both technologies touch the most fundamental operational dimension: the ability of a production system to understand itself and make better decisions. IoT and sensors collect data; Cloud Computing stores and distributes it; but BDA and AI transform the data into actionable knowledge, in the form of real-time diagnosis of process anomalies, prediction of machine failures before they occur, recommendations for production parameter adjustments, and dynamic scheduling optimization. In other words, BDA and AI are the cognitive layer of a digital manufacturing system, and this is what ultimately has the most direct influence on operational performance indicators.

The strongest evidence for this argument comes from Senoner et al. (2022), who, through a field experiment in a semiconductor facility, demonstrated that the application of Explainable AI in the quality control process resulted in improved production yield and a measurable reduction in losses of 21.7%. This is a very concrete figure in an industry with extremely low failure tolerance. The findings of Senoner et al. (2022) also reveal another important dimension: explainable AI, which can explain why it makes certain recommendations, significantly increases operator acceptance on the production floor. This suggests that the challenge of AI adoption in manufacturing is not merely technical, but also human and organizational. On the other hand, the position of IoT and Cloud Computing as enabling technologies rather than direct drivers of performance also needs to be underlined. The review results show that these two technologies appear in 10 articles, but almost always in the role of infrastructure that facilitates BDA and AI, not as independent sources of performance impact. This pattern is consistent with the findings of Dalenogare et al. (2018), who found that connectivity-based technologies such as sensors and

Cloud provide operational benefits more quickly because their impacts are more immediately felt in process visibility and coordination, while more advanced technologies such as Additive Manufacturing, which in that study showed a negative correlation, can be interpreted as requiring a more mature implementation ecosystem to deliver benefits (Senoner et al., 2022). This finding reinforces the argument that the sequence and strategy of technology adoption, not merely the decision to adopt technology itself, strongly determine the realization of operational performance benefits.

One of the most important analytical contributions of this study is the affirmation that the impact of digital transformation on operational performance is not uniform across all types of manufacturing industries. Although the direction of the impact is consistently positive, the speed of benefit realization, the intensity of the impact, the most relevant technologies, and the factors moderating this relationship vary significantly according to the inherent characteristics of each industry type. In the context of discrete manufacturing, which in this corpus is most explicitly represented by Lin et al. (2018) in the Chinese automotive industry, digital transformation through Industry 4.0 is proven to have a relatively more direct impact on production system integration and operational competitiveness (Almajali et al., 2025). The characteristics of discrete manufacturing, which produces individual product units that can be precisely tracked and measured, make it easier to obtain benefits from connectivity-based technologies such as IoT and Big Data Analytics. Clearly defined production cycles facilitate direct measurement of efficiency improvements, for example reductions in cycle time per unit, increased assembly-line throughput, or decreased defective products per batch. These conditions are highly favorable for the implementation of digital technologies that generate measurable impacts within a relatively shorter period.

It should be explicitly acknowledged that the comparative discussion of discrete and process manufacturing types in this review is grounded in a relatively small number of industry-specific articles (1 for discrete manufacturing and 3 for process manufacturing combined). The analytical conclusions presented here are therefore best understood as evidence-informed hypotheses that require corroboration from broader empirical research. The patterns identified are consistent and logically coherent, but caution is warranted in treating them as definitive generalizations until validated by larger industry-specific primary studies.

A different picture emerges in process manufacturing. The review of Arden et al. (2021), Lezoche et al. (2020), and Senoner et al. (2022) collectively reveals that although the transformative potential of digital technology is equally substantial, the path toward realizing these benefits is longer, more complex, and more conditional. In pharmaceutical manufacturing, GMP regulations require validation of every change in the production process, including changes generated by AI systems, thereby creating implementation barriers that have no equivalent in discrete industries (Bandi et al., 2026). An AI algorithm that recommends adjustments to pharmaceutical process parameters cannot be directly applied without passing through long and costly validation protocols. This means that the potential value of AI in pharmaceutical manufacturing is very real, but its realization requires far greater investment of time and resources than in discrete manufacturing. Agri-food manufacturing faces different but equally complex challenges. Lezoche et al. (2020) describe that the uncertainty inherent in biological processes, where variability in raw material quality, sensitivity to environmental conditions, and seasonal fluctuations make digital technologies such as IoT, Big Data, and AI highly valuable (Senoner et al., 2022). However, fragmentation of the agri-food supply chain, the diversity of actor scales from small farmers to large processing companies, and strict food safety regulations make digital technology adoption slower and uneven. This creates a situation in which the potential impact of digital transformation is very large, but the speed of penetration is limited by structural industry factors that cannot be solved by technology alone.

Findings from Senoner et al. (2022) in semiconductor manufacturing reveal a third unique dimension: in high-tech process industries with very high technical complexity and extremely low failure tolerance, the main challenge lies not in the availability or capability of AI technology itself, but in the gap between AI's technical capability and humans' ability to understand and trust its recommendations. The solution found by Senoner et al. (2022), namely the use of Explainable AI as a bridge between technical capability and human acceptance, suggests that the human dimension of digital transformation in high-tech process manufacturing requires strategic attention equal to its technical dimension. These variations have very important practical implications: digital transformation strategies designed generically without considering the specific characteristics of manufacturing industry types carry a high risk of implementation failure or, at minimum, benefit realization far below their potential. This also explains why the literature examining discrete manufacturing contexts and process manufacturing contexts often produces findings that are not directly comparable, because they are essentially discussing two different operational realities, even though both are labeled as manufacturing industries.

Beyond differences in industry type, the literature review identifies a few contextual factors that consistently emerge as moderators of the relationship between digital transformation and operational performance. Understanding these factors is important because they determine not only whether positive impacts will occur, but also how quickly and how substantially those impacts can be realized. The first and most consistently appearing factor across various studies is human resource competence and readiness. Kamble et al. (2020) places workforce digital competence as the strongest moderating factor in its research model (Vilaça et al., 2026). Ghobakhloo (2018) positions HR readiness as a key prerequisite for realizing Industry 4.0 benefits. Senoner et al. (2022) show that operator acceptance of AI technology determines whether available technical benefits can truly be converted into actual performance improvement. This pattern is highly consistent: investment in digital technology without equivalent investment in the human capabilities needed to operate and interpret the technology tends to result in under-performance.

The second factor is top management support and commitment. Lin et al. (2018), Almajali et al. (2025), and Ghobakhloo (2018) all position top management support as a crucial enabling condition. This finding is not surprising, because digital transformation requires large investment, organizational culture change, and readiness to tolerate transition periods that may disrupt short-term operations (Li et al., 2026). Without strong commitment from the highest leadership level, the pressure to maintain the operational status quo often overwhelms the drive for transformation. The third factor is the level of integration of the adopted technologies. Büchi et al. (2020) provides strong empirical evidence that the adoption of integrated technology packages produces a significantly greater performance impact than the adoption of single technologies (Vetrivel et al., 2026). This is consistent with the argument that synergistic effects among technologies, in which data from IoT are analyzed by BDA, then interpreted by AI, and then executed through robotics and automation systems, generate value greater than the sum of the contributions of each individual technology. The implication is that fragmentation of technology adoption strategies, adopting one technology without planning its integration with other technologies in a cohesive digital ecosystem, significantly limits potential impact. The fourth factor is the external context, particularly competitive pressure and industry environmental dynamism. Dubey et al. (2020) found that environmental dynamism moderates and strengthens the relationship between BDA-AI and operational performance (Li et al., 2026). Almajali et al. (2025) identifies external competitive pressure as one of the most important antecedents driving the adoption of digital transformation. This suggests that manufacturing companies operating in environments with intense competition and rapid market changes have stronger incentives to transform digitally and, in turn, tend to reap greater performance benefits because adoption is pursued more seriously and systematically.

The practical implications of these findings are particularly salient for manufacturing industries in developing countries such as Indonesia. Indonesian manufacturing contributing approximately 19% of national GDP and employing over 18 million workers is characterized by significant heterogeneity in digital readiness across firm sizes and sectors (Frazzon et al., 2025). For large and medium Indonesian manufacturers in discrete sectors (automotive components, electronics), the recommendation matrix suggests prioritizing IoT-BDA integration as an entry point, supported by government Industry 4.0 national roadmap programs such as Making Indonesia 4.0. For SMEs, which constitute over 96% of Indonesian manufacturing establishments, cloud-based ERP and MES adoption with short-term ROI focus is most appropriate given resource and infrastructure constraints. Pharmaceutical and agri-food manufacturers, two of Indonesia's fastest-growing manufacturing sub-sectors, require phased regulatory compliance-first approaches that align with BPOM regulatory requirements and food safety standards. These contextual adaptations are essential for ensuring that global digital transformation insights translate into actionable strategies for the Indonesian manufacturing context.

Building on all the dimensions discussed above, this study develops a recommendation matrix that integrates the empirical findings from the 17 reviewed articles into a practical guide for manufacturing companies in selecting the digital transformation approach most appropriate to their industry type. This matrix is presented in Table 3 and constitutes the main practical contribution of this study.

Table 3. Recommendation Matrix for Digital Transformation Approaches Based on Manufacturing Industry Type

Industry Type	Recommended Tech.	Key Impact Indicators	Implementation Approach	Critical Success Factors
Discrete Manufacturing (Automotive, Electronics, Machinery)	IoT + Big Data Analytics + CPS + Cloud Computing	Line efficiency; system integration; competitiveness	Integrated adoption; lean-digital approach	Top management support; operator digital competence
Process Manufacturing - Pharmaceuticals	AI + IoT + CPS + Big Data (GMP-based)	GMP quality; process consistency; supply chain agility	Gradual implementation; phased digital validation	GMP compliance; data security and integrity
Process Manufacturing - Agri-food & Food	IoT + Big Data + AI + Blockchain (traceability)	Flexibility; supply chain resilience; uncertainty reduction	Prioritize traceability as the digitalization entry point	Food safety regulation; biological raw material variability
Process Manufacturing - Semiconductors & High-Tech	Explainable AI (XAI) + Big Data + high-precision Sensor/IoT	Production yield; defect rate; process quality variation	Use explainable AI to increase operator acceptance	Operator acceptance; AI model interpretability
Manufacturing SMEs (All Types)	Cloud Computing + ERP + MES + BDA (affordable scale)	Agility; productivity; market response	Modular and gradual adoption; prioritize short-term ROI	Resource limits; initial digital readiness

Source: Research Data

CONCLUSION

Empirical evidence from all the reviewed literature consistently shows that digital transformation has a positive impact on operational performance in the manufacturing industry. This impact includes improvements in process efficiency and reductions in operational costs, improvements in product and process quality, productivity growth, increased operational flexibility and agility, and strengthened supply chain resilience. Big Data Analytics and Artificial Intelligence are proven to be the technologies with the broadest impacts, while IoT and Cloud Computing function as enabling infrastructure that determines the effectiveness of those two technologies. However, this positive impact is conditional: its realization depends strongly on human resource readiness and competence, top management support, the level of integration among adopted technologies, and the dynamism of the competitive environment faced by the company.

This review confirms that there is no universal digital transformation approach for all types of manufacturing industries. Discrete manufacturing, such as automotive and electronics, shows a faster and more measurable path to benefit realization through the adoption of integrated technology packages based on connectivity and data, reinforced by a lean-digital approach. Pharmaceutical process manufacturing requires gradual implementation that is validated according to GMP regulations, with AI positioned as a conditional optimization tool rather than full automation. Agri-food process manufacturing is most effective when starting digital transformation from supply chain traceability based on Blockchain and IoT before moving toward more advanced analytical capabilities. Semiconductor and high-tech process manufacturing require special attention to human acceptance of AI, making Explainable AI a more appropriate approach than black-box models. Meanwhile, manufacturing SMEs across all industry types are advised to adopt technology in a modular and gradual manner, beginning with technologies that offer the clearest short-term ROI.

This study acknowledges several limitations that should be considered when interpreting its findings. First, the corpus of 17 articles, while carefully selected, may not fully represent the breadth of digital transformation research across all manufacturing sub-sectors, particularly given the dominance of mixed-sector studies. Second, geographical coverage skews heavily toward Asian manufacturing contexts (particularly China and India), limiting generalizability to manufacturing industries in other regions, including developing country contexts such as Indonesia where infrastructure and digital readiness conditions differ substantially. Third, the qualitative nature of the synthesis, while appropriate for the exploratory objectives of this study, precludes the quantitative effect-size estimation possible through meta-analysis. Fourth, and critically, the recommendation matrix produced by this study is a theoretically grounded synthesis tool rather than an empirically validated decision framework; it has not yet been tested against real-world implementation outcomes. Future research should therefore: (1) conduct empirical validation of the recommendation matrix through primary survey or case study research in each industry type; (2) extend the analysis to developing country manufacturing contexts with comparative primary data; (3) perform meta-analyses as the industry-specific literature matures; and (4) longitudinally track the evolution of digital transformation impacts as technology configurations and market conditions evolve post-2025.

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AUTHOR CONTRIBUTION STATEMENT

Riyanti Hamdani contributed to the conceptualization, research design, literature review, data analysis, and preparation of the original manuscript. Wirawan Endro Dwi Radianto contributed to methodology development, validation, critical analysis, and manuscript review. David Sukardi Kodrat contributed to supervision, theoretical refinement, and final manuscript evaluation.

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