Digital Twin Technology Adoption and Sustainable Manufacturing Performance in Emerging Economies: A Literature Review

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Abstract

The review investigates the adoption of digital twins and how the technology affects sustainable manufacturing performance in developing countries. In particular, it analyses the scope and application of digital twins, impact of the technology on manufacturing performance, including resource efficiency, efficiency of energy usage, efficiency of production, efficiency of material usage, and environmental sustainability, and highlights the key factors that drive the adoption of digital twins, inhibit it, and pose implementation challenges. A structured literature review was carried out based on journal articles, conference papers, book chapters, reviews, simulation, frameworks, and empirical studies on digital twins published between 2019 and 2026. According to the literature, the application of digital twins has evolved from virtual representation and workshop modeling to real-time monitoring, prediction, self-maintenance, artificial intelligence-based management, adaptive production planning and scheduling, coordination within the supply chain, circular economy applications, and resilience. Digital twins help to improve manufacturing decision-making through enhancing process visibility, conducting tests under different scenarios, failure prediction, ensuring quality, and optimization of energy and materials usage. However, evidence of environmental and economic benefits of digital twins is still scarce since many studies rely on simulation, prototype implementation, laboratory experiments, and individual cases instead of enterprise-wide implementations throughout several years. Implementation barriers include high investment cost, uncertainty about the payback period, weak infrastructure, lack of necessary skills, low data quality, cybersecurity concerns, inability of the legacy systems to work with the new system, change aversion, and poor interoperability. Barriers are especially significant for small and medium-sized companies operating in developing countries. The results of the research show that implementation of digital twins can help to achieve sustainable

manufacturing performance if it is facilitated by reliable infrastructure, necessary skills, organizational readiness, adequate governance, and sustainability metrics.

Keywords: *Digital twin technology, emerging economies, sustainable manufacturing, operational efficiency, environmental sustainability, technology adoption.*

1.1 Introduction

Digital manufacturing requires the integration of various aspects of cyber-physical systems, IIoT devices, artificial intelligence, cloud/edge computing and real-time analysis. Under this context, digital twin technology appears to become a crucial way of associating physical manufacturing components with virtual models, which can be queried, analyzed and updated based on their performance characteristics. The initial research within the manufacturing domain was centered around such aspects as representation, modelling, workshop control, and information exchange based on service-oriented architecture (Bao et al., 2019; Longo et al., 2019; Zheng et al., 2019). Further literature reviews have provided an expanded vision, where data from sensors, bidirectional communication, analytics and feedback allow keeping the virtual object updated in comparison to the physical one (He & Bai, 2021; Iliuţă et al., 2024; Melesse et al., 2020). This change is significant since a twin is no longer just an electronic version of a machine but can be used as a decision support layer covering design, operation, maintenance and reconfiguration of manufacturing assets.

Similarly, there is a widening ambition with regard to the timeline of the literature. The publications in the years between 2019 and 2021 created frameworks for the application, models for manufacturing, production management procedures, and sustainability-oriented architectures (Bao et al., 2019; Ma et al., 2020; Park et al., 2020; Zheng et al., 2019). The publications in the years between 2022 and 2024 began making links between digital twins and concepts such as Industry 4.0, IIoT, flexible manufacturing, operations intelligence, and decision making (Attaran et al., 2023; Attaran et al., 2024; Santos et al., 2024; Stavropoulos & Mourtzis, 2022). From 2025 and 2026 on, researchers turned their attention to topics like AI-enabled closed-loop control, explainable anomaly detection, adaptive planning, circularity, resilience, human-centric Industry 5.0, and integrated supply chain applications (Barata & Kayser, 2024; Fani et al., 2026; Li et al., 2026; Qian et al., 2026). It should be noted that the progression does not mean that all manufacturing companies have reached an advanced level of twin architectures but reflects the growing field of research where the theoretical capabilities often develop faster than the actual deployment by enterprises.

Sustainable manufacturing performance goes beyond just increased output. Economically speaking, sustainable performance relates to productivity, quality, throughput, cost, equipment availability, and responsiveness. Environmentally speaking, it relates to energy/material efficiency, waste/emission reductions, clean(er) production, and life cycle assessment. Thirdly, sustainability relates to resilience – an ability of a system to foresee disruptions, adjust schedules, ensure continuity, and recover without significant resource losses. The contribution of digital twins to these results can include visualization of invisible process states, experimentation with alternatives before the physical implementation, anomaly detection, predictions about asset degradation and coordination across different lifecycle phases (He & Bai, 2021; Resman et al., 2025). However, the improvements in terms of operational performance do not necessarily lead to environmental improvements. Increased throughput can reduce energy intensity per unit but also increase the amount of overall energy consumption if production increases. Sustainable manufacturing performance should thus involve clear indicators.

The distinction is especially important for emerging economies. The term covers diverse industrial regimes: some cases demonstrate advanced capabilities for the development of electronics, automotive, energy, and platforms, and some are characterized by SME-led manufacturing, uneven level of automation, unstable connectivity, use of foreign equipment, and limited access to long-term financing. For example, evidence on China's industry shows greater potential for the integration of digital twins adoption and innovation and green finance (Liu et al., 2026). The Nigerian construction evidence, on the other hand, focuses on institutional, capability, and implementation conditions for circular-economy adoption (Awodele et al., 2025). Evidence on Saudi Arabia's industry connects digital twins with maintenance and smart manufacturing, but also points out the importance of organizational mechanisms that make technology affect performance (Elgebaly et al., 2025). These situations should not be reduced to one deficit paradigm: they show distinct combinations of industrial depth, finance, infrastructure, and support from the side of policy.

The main issue is that there is an uneven research base in terms of geography and methods of investigation. A good number of papers are done in developed or technology-intensive countries, and many studies apply simulation, lab experiments, prototyping, case study analysis, reviews, and concept frameworks. The work of such kind is important for the assessment of technical possibility, but it cannot prove adoption, benefits, and transferability of environmental impact by itself. Old machines may be not equipped with the sensors or interface, data may be insufficient and not compatible, companies may lack the skills in artificial intelligence and modeling, and the business case may be uncertain in the case of old asset or small production volumes (Bean et al., 2026; Kumar et al., 2026; Mohanraj & Balaji, 2026). These limitations may be more common in emerging economies, although they depend on the country, sector, firm size, and supply chain position.

There is thus a research gap on the conditions of sustainable effects of digital twins adoption, rather than its possibilities for improvement of manufacturing process. Existing reviews cover architectures and applications, but fewer studies establish the relationships between maturity of adoption, capability, institutional setting, and sustainable performance. This paper seeks to fill this gap with critical structured review of literature. The main objective of the paper is to analyze the digital-twin adoption and its consequences for the sustainable performance in emerging economies. Specifically, it seeks to:

(1) Examine the extent, patterns, and major applications of adoption

(2) Assess influence on operational efficiency, resource utilization, energy efficiency, productivity, and environmental sustainability

(3) Identify the main drivers, barriers, and implementation challenges.

2.0 Literature Review

2.1 Conceptual Review

2.1.1 Concept of Digital Twin Technology

The connection between a physical asset or process and its digital twin is created through the means of data transfer, synchronization, simulation, analysis, and, in some cases, feedback. Digital twin has evolved from the static model into the architecture of information and decision-support, combining physical systems, models, services, and data (Bao et al., 2019; Longo et al., 2019; Zheng et al., 2019). Components of this architecture include sensors, Industrial IoT devices, behavioral or geometrical models, communication infrastructure, analytical tools, among other options (Attaran et al., 2023; Iliuţă et al., 2024; Melesse et al., 2020; Mohanraj & Balaji, 2026).

Thus, artificial intelligence is not a required component of a digital twin. However, in combination with a digital twin, AI can improve the ability to detect anomalies, predict the

future performance, optimize the process, and make adaptive decisions (Jethi et al., 2026; Li et al., 2026; Qian et al., 2026; Yue et al., 2026). However, these abilities create certain challenges in terms of the explainability, cybersecurity, model drift, and accountability. In this regard, a simulation on its own will be called a digital twin only if it is still connected to a physical system via recent data and feedback, if necessary (Guo et al., 2021; Pérez et al., 2020). Thus, digital twin technology means a data-synchronized virtual representation of a specific physical asset or system utilizing modeling and analysis for decision-making purposes.

2.1.2 Digital Twin Technology Adoption

Digital twin adoption involves more than purchasing software or completing a pilot. It is a socio-technical process through which firms develop, integrate, govern and scale twin capabilities. Successful adoption depends on technological readiness, including sensors, connectivity, cybersecurity and interoperable data; organisational readiness, such as leadership, employee skills and process ownership; and environmental factors, including finance, regulation, infrastructure and vendor support.

Pilot projects usually address a specific problem, whereas enterprise deployment connects several assets, functions and lifecycle stages. Scaling therefore requires reliable data governance, compatible architecture, change management and sustained funding (Fantozzi et al., 2025). It also requires a clear business case showing that expected benefits justify implementation and maintenance costs (Banyai & Kovacs, 2023; Bean et al., 2026; Korepin et al., 2025). In emerging economies, firms may need to improve their data systems, connectivity and workforce capabilities before adopting advanced twins. Financial limitations, weak infrastructure and vendor dependence can further restrict implementation, particularly among SMEs (Awodele et al., 2025). Because these barriers are interconnected, adoption should be understood as a gradual maturity pathway rather than a simple adopted-or-not-adopted decision (Kumar et al., 2026).

2.1.3 Concept of Sustainable Manufacturing Performance

Sustainable performance in manufacturing is multi-dimensional and involves economic, environmental and resilience aspects. The economic and operational performance includes productivity, process flow rate, quality, unit costs, lead time, machine availability and maintenance performance. Digital twins might improve these aspects through observing production processes, predicting failures, simulation of production schedules and faster decision-making. However, the extent to which these advantages can be achieved will depend on the technology design and evaluation (Longo et al., 2019; Resman et al., 2025).

The environmental performance involves energy consumption, materials consumption, generation of waste and emissions, and life cycle efficiency. Digital twins might reveal ways of reducing energy consumption, enable cleaner production, and manage the trade-off between quality and energy consumption (Ba et al., 2025; Ogorodnyk et al., 2026; Piron et al., 2025). The actual gains will be conditional on the production scale, energy sources used, and implementation of the suggestions. The resilience performance includes predictions, continuity, adaptability, responsiveness and risk management. Digital twins can help in increasing resilience of factories and supply chains. However, this might involve additional redundancies and higher requirements for computing which will affect environment adversely (Fani et al., 2026; Srivastava & Bag, 2026; Stadtfeld et al., 2025). Therefore, sustainable performance must be estimated using balanced indicators, clear system boundaries, and proper time horizon.

2.2 Theoretical Framework

2.2.1 Technology–Organization–Environment Framework

Technology–Organization–Environment (TOE) approach, usually associated with the research of Tornatzky and Fleischer (1990), describes the process of organization adoption through interactions of three different contexts. Technological context includes the available technologies and existing ones, such as relative advantage, compatibility, complexity, cybersecurity, and infrastructure. When considering the implementation of digital twins, it includes sensor coverage, model fidelity, data quality, IoT integration, interoperability, AI capabilities, and compatibility with legacy systems. Even an application of a technically attractive technology can fail in case of too much integration risk and insufficient possibility to get required information for the reasonable price.

Organizational context includes the size of the company, its resources, structure, leadership, skills, culture, and readiness. Implementation of digital twins requires sponsorship from the top management since it implies cross-cutting consequences for operations technology, information technology, engineering, maintenance, and sustainability functions. Skills of employees define if the models will be properly maintained and predictions trusted. Environmental context includes the industry standards, competition, suppliers, regulation, finance, infrastructure, and public policy. In emerging economies, unreliability of connectivity, lack of specialists' ecosystem, or insufficient funding can block the implementation even of willing companies, while green finance and industrial modernization can support it (Liu et al., 2026). The reason why TOE is suitable in our case is the existence of interdependencies between barriers. For example, Kumar et al. (2026) study the relations between supply-chain twin barriers, while Bean et al. (2026) prove the dependence of legacy system adoption from technical feasibility and business case. In general, TOE does not reduce problems of adoption to technology acceptance of end-users. The limitation of this model is its better explanation of adoption conditions than the value creation after adoption. It can also become a simple checklist.

2.2.2 Resource-Based View

The Resource-Based View (RBV) was mainly introduced by Wernerfelt (1984) and further elaborated by Barney (1991). In other words, the RBV, related to Barney's strategic-resource approach, explains the sources of performance variations based on valuable, rare, inimitable, and non-substitutable resources and capabilities. A single digital twin platform will hardly meet such criteria because there is an opportunity to purchase comparable software. The competitive advantage is achieved by using the digital twin along with unique firm's process knowledge, quality data, IoT technology, competencies, analytics, management decision-making and learning processes. The presence of these complementary resources makes a difference between the implementation of digital twin outputs in operations.

In the context of RBV, implementation brings about potential resources, whereas integration produces capabilities. Thus, one can state that the company that continuously improves model accuracy, connects predictions with maintenance plans and learns from discrepancies develops a dynamic capability to adapt. On the contrary, even if the company possesses sensors and visualization tools but does not have enough reliable data and does not change its decision-making pattern, it receives little benefit from implementation. Researches conducted by Resman et al. (2025), Li et al. (2026), and Fani et al. (2026) prove the general statement that integrated capabilities, not artefact, connect digital twins with efficiency, sustainability and resilience. Both theories complement each other. TOE framework explains what conditions lead to the adoption and why it occurs. RBV explains how twin-related resources are used and embedded to achieve performance. In combination, they predict a moderated capability process

in which institutional conditions and readiness of companies are the factors that allow or restrict adoption, while complementary resources mediate transition of adoption into results. The proposed combination of frameworks is better for emerging economies than technological determinism because it considers both external constraints and internal variations.

3.0 Methodology

A critical literature review approach was used for this research. This source database includes articles published around 2019-2026 and includes journal articles, conference papers, reviews, book chapters, simulations, applications, framework models, and empirical research related to digital twins, manufacturing, operations, supply chains, sustainability, resilience, and emerging economies. Source relevance was evaluated based on each source's ability to contribute to at least one of the four analytical areas: evolution/conceptual architecture, manufacturing/supply chain applications, performance outcomes related to sustainability, and conditions for adoption. Sources could be designated as emerging economies-related only based on the geographical context of the source. Articles related to advanced economies or without geographical context could be included into the database if they contributed to overall technical/conceptual knowledge of digital twins, but their transferability was considered doubtful. Analysis was conducted using thematic classification. Sources were divided into ten main categories, including: (1) digital twin evolution and architecture; (2) manufacturing applications; (3) operational efficiency; (4) resource/energy efficiency; (5) predictive maintenance; (6) sustainability and circular economy; (7) resilience; (8) supply chain applications; (9) adoption factors; and (10) emerging economies. Comparison criteria included publication year, industry, geographical context, application, methodological approach, performance outcome, contribution to sustainability, and implementation challenge.

Five evidential categories were revealed during synthesis. The first is realized benefit which was witnessed in a described prototype, laboratory or case study context. The second category of simulated benefits came from model scenarios. Anticipated benefits were inferred from architectural reasoning or from previous studies. Conceptual benefits were claimed in theoretical frameworks or reviews. The last category included empirically validated outcomes which have been verified by field evidence as well as by an analytical design which can analyze connections. These categories do not make up a quality score but they help to avoid confounding technical feasibility with widespread industry success. Then, the review presented findings with respect to the three objectives and interpreted them using the TOE and RBV frameworks. Two limitations come from the methodology. Firstly, the provided corpus may not include all relevant literature, thus the conclusions apply to the patterns found there. Secondly, the heterogeneity in industries, units of analysis and methods prevents statistical summarization. The strength of structured literature review is transparency of conceptual separation and comparative analysis. For this reason, no fabricated search numbers, effect sizes or geographic classifications are reported in this paper.

4.0 Literature Synthesis and Findings

4.1 Extent, Patterns, and Applications of Digital Twin Adoption in Emerging Economies

The first goal relates to the extent, patterns, and key applications of the digital twin. As per the review of the literature, the extent is increasing and the depth is uneven. The early research provided the grammatical framework of twin creation in manufacturing. Zheng et al. (2019) provided an application framework and case study, Bao et al. (2019) discussed modelling and operations, and Longo et al. (2019) studied a service-oriented twin as a factory knowledge source. The contribution of these researchers lies in considering the twin as the link between

physical manufacturing and enterprise-level decision making. Their importance is foundational but does not amount to sector-wide diffusion.

From 2020 to 2021, applications gained further specialization. Ma et al. (2020) enhanced the management of production at the workshop level based on twins, Zhang et al. (2020) analyzed the control of synchronized production, Park et al. (2020) described operations at work centers in the context of sustainable and smart manufacturing, Polini and Corrado (2020) created a model of composite assembly, Pérez et al. (2020) utilized the twins for VR and multi-robot cell commissioning, and Guo et al. (2021) optimized the workshop layout based on a digital twin. For all these applications, a trend could be observed, and that was the fact that the application was limited only to a particular cell, workshop, line, or process.

Between 2022 and 2024, the body of knowledge started consolidating the architecture and expanded the unit of analysis. Bhandal et al. (2022) noted the expansion into operations and supply chain management. Attaran et al. (2023) related digital twins to intelligent manufacturing, and Attaran et al. (2024) focused on the IIoT-enabled operational intelligence. Cimino et al. (2023) used the twin-based approach to the design of production lines, while Daraba et al. (2024) applied the real-time CNC monitoring. Ullah and Younas (2024) paid attention to flexible manufacturing control, and Vinci-Carlavan et al. (2024) addressed engineering-to-order operations. This research is characterized by a move from representation to operational orchestration, although not all approaches are mature in terms of bidirectional control. The recent applications are technologically more sophisticated. The AI-based twins facilitate closed-loop manufacturing, reinforcement-learning control in sugar production, adaptive planning, explainable anomaly diagnosis, and contrastive learning tool wear monitoring (Besigomwe, 2025; Jethi et al., 2026; Li et al., 2026; Qian et al., 2026; Yue et al., 2026). There have been developed equipment-level twins for industrial robots, while modeling concerns wire arc additive manufacturing and battery systems (Denkena et al., 2026; Hu et al., 2026; Madani et al., 2026). Sectorial reviews involve chemical manufacturing and turbomachinery (Ali et al., 2026; Mane et al., 2024).

Parallel trends of interest include the expansion into energy and supply networks. Ba et al. (2025) examine energy efficiency applications; Kavousi-Fard et al. (2025) create a deep learning twin for wind farm wake effects; and Ogorodnyk et al. (2026) explore the connection between demand response, quality, and energy optimization. In supply chains, twins have been considered with respect to viability, humanitarian resilience, food systems, biopharmaceuticals adoption, logistics circularity, and autonomous agri-food transportation (Charoenwut et al., 2026; Huang et al., 2026; Shoaib et al., 2026; Srivastava & Bag, 2026; Stadtfeld et al., 2025; Suvarna & Awasthi, 2026). Such a broadening increases the strategic importance of this approach, but also raises the problem of data ownership and interoperability since not one company owns the whole physical system.

The second group comprises circular economy and sustainability applications. He and Bai (2021) created an early synthesis based on the sustainable development theme. Piron et al. (2025) explore soft sensing, life-cycle assessment, and cleaner production in relation. Ali et al. (2026) analyze sustainability in semiconductor packaging; Awodele et al. (2025) explore circular economy transition in Nigerian construction; Liu et al. (2026) link adoption with green finance and innovation in China; and Shoaib et al. (2026) introduce circular economy criteria to logistics. Sources mentioned above go beyond the mere productivity but the scope of evidential support includes empirical relationships, theoretical frameworks, and proceedings. Claims related to environmental performance have to be analyzed correspondingly.

Industrial maturity differs. The fields of machining, production planning, robotics, and equipment maintenance enjoy measurable state description, developed sensing technology, and known operating baseline. In order to implement twin technology in the semiconductor

industry, batteries, chemicals, or turbomachines, high-fidelity domain models and expert knowledge are required. In construction and supply chains, temporary nature of configuration, multiple organizations, and fragmented data make it hard to synchronize continuously. Enterprises of any size can utilize collaborative design or simulation tools without having their own enterprise twin (Tonelli et al., 2026).

There are no examples of mature real-world adoption in the literature within the context of emerging economies. The literature shows an increasing number of applications as well as relatively few empirical works or case studies. A considerable proportion of the literature involves either a review, simulation, framework, laboratory test, or just one application. For instance, Yeung et al. (2026) refer to a laboratory test in the context of construction; Suvarna and Awasthi (2026) provide a simulation framework, while Huang et al. (2026) use system dynamics. Such types of studies help test different mechanisms, but they do not prove performance in reality. Therefore, the most appropriate conclusion concerning Objective One is that adoption is transitioning from asset-based modeling to AI-enabled networked sustainability-focused applications.

4.2 Digital Twins and Sustainable Manufacturing Performance in Emerging Economies

4.2.1 Operational Efficiency

The most robust evidence of improvement via digital twins is that of operational efficiency. The integration of production state, equipment state, and simulated alternative solutions leads to better visibility, planning, and coordination (Cimino et al., 2023; Daraba et al., 2024; Longo et al., 2019; Ma et al., 2020; Vinci-Carlavan et al., 2024; Zhang et al., 2020). This results in faster troubleshooting and enables decisions to be tested without interfering with production.

Moreover, digital twins provide the means for predictive maintenance through identifying worn out tools, malfunctioning equipment, and anomalies (Elgebaly et al., 2025; Hu et al., 2026; Qian et al., 2026; Yue et al., 2026). Nonetheless, accurate predictions alone do not mean decreased downtime. The success of digital twins depends on maintenance capabilities, presence of spare parts, decision-making authority, and coordination with production. Digital twins have different worth in various contexts. Digital twins are most beneficial in high-mix, mixed-model, and engineering-to-order systems which require frequent reconfiguration and complex scheduling (Fani et al., 2026; Vinci-Carlavan et al., 2024; Wang et al., 2026). In simple or low-value processes, the cost of implementing digital twins exceeds their worth. Therefore, digital twins can improve operational decision-making.

4.2.2 Resource Utilization

Resource use involves the use of equipment, labor, materials, capacity, and information. Digital twins are able to locate bottlenecks, perform simulations and distribute tasks before changes in the system, which can decrease idle time and work in process (Cimino et al., 2023; Guo et al., 2021; Ma et al., 2020; Park et al., 2020). However, savings are often noted in specific examples only. Digital twins may increase lifecycle efficiency through improvement of tests, maintenance, reuse, and end-of-life strategies (Piron et al., 2025; Waqar & Shafiq, 2026). Increased knowledge about the state of assets and materials may facilitate repair, remanufacturing, and recovery, but most of the evidence on that issue is theoretical or based on models (Awodele et al., 2025; Liu et al., 2026). The above-mentioned benefits must be compared to resources needed for the operation of the twin – sensors, storage, computing facilities, and specialist knowledge. Thus, evaluation should compare total benefits and costs relative to the baseline.

4.2.3 Energy Efficiency

The digital twin supports energy efficiency by means of monitoring, prediction, simulation, and optimization. It helps in the detection of abnormal energy use, energy demand forecasting, as well as trying out other schedules or parameters without shutting down operations. Moreover, it helps in aligning the energy use with quality and quantity of products (Ba et al., 2025; Ogorodnyk et al., 2026).

Some of the applications include wind farms, thermal systems, and batteries (Chaudhari et al., 2025; Kavousi-Fard et al., 2025; Madani et al., 2026). However, the potential energy savings predicted with the help of models do not necessarily occur at plants. This depends on the implementation quality, state of the equipment, and response of the operators.

4.2.4 Productivity and Quality

Digital twins can improve productivity and quality with predictive analytics, detection of anomalies, process optimization, and combination with Lean. Lean is responsible for waste elimination and process standardization, whereas digital twins provide real-time data and scenario modeling (Mojumder, 2025; Roquini et al., 2026). However, increased complexity of digital systems can lead to yet another type of waste.

In terms of machinery, the use of digital twins can provide tool wear monitoring, explainable anomaly detection, and adaptive manufacturing planning (Jethi et al., 2026; Li et al., 2026; Qian et al., 2026; Yue et al., 2026). Such features require thorough validation, especially in manufacturing facilities that lack enough data. Productivity evaluation also needs to consider expenses on model development, training, false detections, integration, and maintenance. Generally, the evidence is better when it comes to detection and planning, not productivity.

4.2.5 Environmental Sustainability and Circular Economy

Sustainable practices demand an evaluation process. Digital twins can track materials and energy streams, conduct lifecycle analysis, predict waste generation, and analyze cleaner production processes (He & Bai, 2021; Piron et al., 2025). Digital twins can help balance conflicting needs of materials, energy, and quality, as seen in semiconductors packaging (Ali et al., 2026). The use of digital twins in the circular economy is possible in building, industry, and logistics sectors (Awodele et al., 2025; Liu et al., 2026; Shoaib et al., 2026). Nevertheless, better information systems cannot guarantee recovery markets, reverse logistics, repair practices, and financing schemes. In general, the strongest evidence comes from improvements in productivity, machinery efficiency, and quality control. Potential energy and resource savings seem to be encouraging, although most evidence is provided by simulations and case studies. Environmental gains and circular economy practices deserve further evidence.

4.3 Drivers of Digital Twin Adoption

The concept of Industry 4.0 fosters the adoption of digital twins due to combining physical processes with data, modeling, and decision making. Increased maturity of IIoT decreases data collection costs, whereas artificial intelligence increases monitoring and forecasting (Attaran et al., 2024). The adoption becomes attractive for organizations which have expensive equipment failures, product changes, commissioning risks, or production interruptions.

Cost saving and competitive needs foster adoption as well. In such a way, digital twins allow for conducting virtual experiments in order to decrease the number of physical tests, delays, and prototyping costs. This feature is especially valuable in high-mix and engineering-to-order production (Vinci-Carlavan et al., 2024; Wang et al., 2026). Investment becomes possible when expected savings can be traced to specific assets and decisions (Banyai & Kovacs, 2023).

Sustainability goals can also motivate adoption. Digital twins facilitate energy optimization, life-cycle assessment, and circular production (Ba et al., 2025; Piron et al., 2025). Green finance can reduce investment barriers (Liu et al., 2026). They increase visibility and resilience of supply chains through shortage, delay, and demand change simulation (Srivastava & Bag, 2026; Stadtfeld et al., 2025). The priorities in adoption are different in emerging economies depending on local features. At the beginning, organizations might focus on the basics like monitoring, maintenance, or energy consumption. Adoption is related to the importance of solving a business problem through digital twin capabilities and practical feasibility of implementation considering finance, competencies, infrastructure, and institutions.

4.4 Barriers and Implementation Challenges in Emerging Economies

Technical barriers arise from limited sensor coverage, insufficient data quality, and the inability to integrate existing devices with enterprise software, cloud-based services, and suppliers (Bean et al., 2026; Mohanraj & Balaji, 2026). An increase in data volume does not solve the problem because sensors can be faulty, signals can drift, and different departments may define variables inconsistently (Attaran et al., 2023; Iliuţă et al., 2024; Mohanraj & Balaji, 2026). Hence, the accuracy of digital twins depends on good data, knowledge of physical laws, correct modelling, and verification (Ali et al., 2026; Bao et al., 2019; Chaudhari et al., 2025). AI-based twins face problems such as biased training sets, model drift, and lack of explainability (Besigomwe, 2025; Mohanraj & Balaji, 2026; Qian et al., 2026).

Cybersecurity issues are exacerbated as operational processes become more connected through sensors, IIoT platforms, and digital twins. Stolen data or models may produce false readings, reveal proprietary information, or affect automation decisions (Attaran et al., 2024; Daraba et al., 2024; Ullah & Younas, 2024). Supply chain twins create extra concerns related to data ownership, access, confidentiality, accountability, and liability in case of damages (Bhandal et al., 2022; Charoenwut et al., 2026; Kumar et al., 2026).

Organizational barriers include skills shortage, low management ability, change resistance, and poor fit to current processes (Attaran et al., 2023; Awodele et al., 2025; Kumar et al., 2026). The success of digital twins requires the collaboration between engineering, operations, IT, maintenance, sustainability, and finance (Bao et al., 2019; Bhandal et al., 2022; Fantozzi et al., 2025). Poorly defined roles can impede the transition of insights into managerial decisions (Attaran et al., 2024; Bean et al., 2026). Moreover, workers can perceive digital monitoring as surveillance or job threats (Barata & Kayser, 2024; Kumar et al., 2026). More information available for people does not necessarily improve decision quality but increases their workload (Torrecilla-García et al., 2026). Financial barriers include the expenses associated with the implementation of sensors, connectivity, models, integrations, licenses, cloud computing services, cybersecurity and specialized labor (Banyai & Kovacs, 2023; Bean et al., 2026; Kumar et al., 2026). They are especially pronounced for SMEs where an unsuccessful pilot can leave limited capital depleted (Tonelli et al., 2026). Therefore, adoption requires affordability, modularity and convincing demonstration of returns (Banyai & Kovacs, 2023; Fantozzi et al., 2025). Lack of reliable power supply, poor access to the Internet, absence of local experts and reliance on foreign technologies add to challenges in developing economies (Awodele et al., 2025). Absence of standards adds to the problems of interoperability and exchange of data between organizations (Attaran et al., 2024; Bhandal et al., 2022; Charoenwut et al., 2026). It can be concluded that existing evidence shows that investments in infrastructural development and institutional coordination are more justified than any regulation (Awodele et al., 2025; Barata & Kayser, 2024). Such barriers reinforce each other: limited finances reduce the number of sensors, low-quality data reduce the quality of models, unreliable output reduces the justification of business case and low return makes it less supported by management (Banyai

& Kovacs, 2023; Bean et al., 2026; Kumar et al., 2026). Therefore, firms require integrated investments in technological, human resources, data governance and managerial issues rather than isolated spending on software (Attaran et al., 2023; Fantozzi et al., 2025; Resman et al., 2025). Specific priorities will vary by the country. Green finance could support circularity in China (Liu et al., 2026), Nigerian construction industry will face different institutional challenges (Awodele et al., 2025), and maintenance policies will define the effectiveness of IoT solutions in Saudi industry (Elgebaly et al., 2025). For developing economies, phased development of capabilities around a specific use case is a more realistic goal than immediate implementation across the enterprise.

5.0 Critical Discussion

Literature shows that digital twins can support manufacturing planning, monitoring, and decision-making (Attaran et al., 2023; Bao et al., 2019; Longo et al., 2019; Ma et al., 2020). However, evidence proving their consistent economic, ecological, and resilient impacts is more uncertain (Ba et al., 2025; He & Bai, 2021; Resman et al., 2025). Studies show the capability of the technology to model, monitor, predict, and optimize certain processes (Chaudhari et al., 2025; Daraba et al., 2024; Guo et al., 2021; Yue et al., 2026). Moreover, review papers highlight the potential sustainability paths (Attaran et al., 2023; Iliuţă et al., 2024; Melesse et al., 2020). However, few works measure mature systems against clear baselines over time. This way, the literature is better at identifying the potential of digital twins than their impacts (Bean et al., 2026; Bhandal et al., 2022).

Overestimating the potential due to technological optimism is especially relevant when efficiency and sustainability are not clearly distinguished in the context of system boundaries and possible trade-offs (Fantozzi et al., 2025; He & Bai, 2021). The reduction in downtime may lead to reduced resource consumption on a per unit basis but increased overall production and consumption. While predictive maintenance increases the lifespan of assets, sensors and computing infrastructure have ecological costs (Ali et al., 2026; Elgebaly et al., 2025). Thus, a more thorough assessment should include the combination of operation and lifecycle analysis and evaluation of both quality and energy consumption (Ogorodnyk et al., 2026; Piron et al., 2025). While adoption may be exaggerated, simulations, prototypes, and implementations should be carefully differentiated. In this way, lab demonstrations and simulations only prove feasibility but do not imply adoption (Huang et al., 2026; Suvarna & Awasthi, 2026; Yeung et al., 2026). Case studies may show support for an activity without proving adoption (Chaudhari et al., 2025; Cimino et al., 2023; Vinci-Carlavan et al., 2024). The measures of adoption, therefore, need to include connectivity, real-time synchronization, analytical capabilities, feedback, organizational application, and scale of implementation (Attaran et al., 2023; Iliuţă et al., 2024; Roquini et al., 2026).

Geographical evidence is still lacking. Geographical studies carried out in Nigeria, China, and Saudi Arabia provide useful knowledge (Awodele et al., 2025; Elgebaly et al., 2025; Liu et al., 2026); however, manufacturing in Africa is under-represented. Technologies invented in rich countries could require different designs where connectivity, financing, skills, power generation, and automation are limited (Attaran et al., 2024; Awodele et al., 2025; Kumar et al., 2026). Small and medium enterprises face conditions different from large businesses. They have fewer resources, less expertise and capability to experiment with technologies over long periods of time (Bean et al., 2026; Tonelli et al., 2026). Yet certain careful and bound applications could be feasible (Tonelli et al., 2026). Modular platforms and testbeds might decrease expenses but create risks of interoperability, dependence on vendors, and loss of data (Bhandal et al., 2022; Charoenwut et al., 2026; Kumar et al., 2026). In the case of SMEs, the

adoption of digital twins should be done in proportion to the level of capability and high-value decisions (Banyai & Kovacs, 2023; Bean et al., 2026; Tonelli et al., 2026).

The outcome of digital twin adoption is contingent upon the presence of complementary capabilities. IIoT makes data available; computing infrastructure helps analyze the data; artificial intelligence discovers patterns; governance ensures quality of data and analysis; and the workforce makes conclusions. The evidence from adaptive planning, resilience, and operational efficiency studies supports the view (Fani et al., 2026; Li et al., 2026; Resman et al., 2025). Industry 5.0 implies that there should be human-centered, resilient, and sustainable systems (Barata & Kayser, 2024). Moreover, the area of cognitive ergonomics focuses on the effects of digital twins on workload and quality of decisions made by people (Torrecilla-García et al., 2026). Society 5.0 perspectives stress the need of openness and socially-based decisions (i Casas & i Palomes, 2026). The main evidentiary gap is the evidence chain that starts with capability, goes through adoption maturity, organizational usage, investments, and ends with multiple dimensions of performance over time. Until there is more evidence on this subject, the most defendable conclusion is that digital twins can support sustainable manufacturing but sustainability depends on the way of implementation, governance, and support.

6.0 Research Gaps

6.1 Geographic Gap

The literature related to digital twins in developing countries, especially those in Africa, is still scarce. Most of the literature is generated from technologically advanced countries where digital infrastructure and manufacturing systems are more developed (Attaran et al., 2023; Bhandal et al., 2022; Iliuţă et al., 2024). In Nigeria, studies mostly concentrate on construction and shift to the circular economy (Awodele et al., 2025), and in China and Saudi Arabia, studies focus on industrial sustainability and smart maintenance (Elgebaly et al., 2025; Liu et al., 2026). However, the presence of financial, infrastructural, institutional, and skill gaps among others restricts generalization. Thus, future cross-country research needs to examine the factors influencing adoption and not just adoption rates.

6.2 Empirical Gap

Research continues to be highly reliant on review papers, simulation exercises, prototyping, and single-case studies (Ba et al., 2025; Bhandal et al., 2022; Melesse et al., 2020). This body of research highlights the potential of digital twins in manufacturing systems planning, energy management systems, supply chain management, and construction; however, there is little evidence concerning their adoption within organizations and their performance (Cimino et al., 2023; Huang et al., 2026; Suvarna & Awasthi, 2026; Yeung et al., 2026). Field research should be conducted in order to understand how digital twins become part of daily activities and why certain initiatives are successful whereas others stay in the pilot stage (Bean et al., 2026; Kumar et al., 2026).

6.3 Methodological Gap

Longitudinal, multi-organization, cross-national, and comparative studies are few and far between in the digital twin literature. In fact, much of what is published in this field uses review, theoretical modeling, simulations, and single organization case studies, thus limiting any causality or generalizability from such studies (Bao et al., 2019; Melesse et al., 2020; Chaudhari et al., 2025). The mere correlation from cross-sectional data does not provide an understanding of whether the adoption of digital twins improves organizational performance or whether organizations that are more economically and technologically sound have a better

capability of adopting such technology. Future research will need to use quasi-experimental design, matching comparisons, repetitive measures, and mixed method evaluation studies.

6.4 Sustainability Measurement Gap

Efficiency is assessed more systematically compared to sustainability, whereby the focus of most research is on production, machinery monitoring, maintenance, optimization of processes, and energy utilization (Daraba et al., 2024; Elgebaly et al., 2025; Fantozzi et al., 2025). Sustainability is often an assumed aspect from improvements in efficiency rather than a direct measure (Ba et al., 2025; He & Bai, 2021). In future research, the energy utilization, emission of greenhouse gases, generation of waste, water utilization, material yields, asset lifetime, and recyclability need to be assessed within clear boundaries of the system. The digital overheads and the rebound effect should also be taken into account.

6.5 Adoption–Performance Gap

No research identifies the association between the maturity level of digital twins and certain organizational benefits. Static digital twins, connected digital shadows, predictive twins, and autonomous systems require different skills and cannot be seen as identical entities (Attaran et al., 2023; Besigomwe, 2025; Iliuță et al., 2024). Current implementations include production tracking, layout optimization, AI-driven automation, and dynamic planning (Daraba et al., 2024; Guo et al., 2021; Li et al., 2026). Nevertheless, there is no evidence regarding the interconnection of maturity level, costs, and efficiency. Validated scales for measuring maturity can show which capabilities ensure certain benefits and how much such a process costs (Banyai & Kovacs, 2023; Bean et al., 2026).

7.0 Implications

7.1 Theoretical Implications

This review extends TOE by showing the interaction of technological, organizational, and environmental factors and their variation with adoption maturity. RBV also indicates that performance is dependent on integration of the digital twin technology with process knowledge, accurate data, competences, and learning. Therefore, the digital transformation process needs to make a distinction between technology adoption and capability development. If Industry 4.0 emphasizes connectivity and automation, Industry 5.0 stresses human orientation, resilience, and sustainability.

7.2 Managerial Implications

In the case of manufacturing managers, one must begin with something tangible rather than some general platform objective. The pilot project should identify what is being managed, baselines, data needs, expected actions, and KPIs. It should also factor in expenses related to hardware, integration, cybersecurity, training, computing power, and maintenance. Scaling should only be attempted after demonstrating that the pilot has added value in terms of decision-making. Sustainability in adoption requires cross-functionality, reliability of data governance, training of employees, and compatibility with old systems. Evaluations for sustainability should include both business-related factors and direct environment-related measures. Engaging employees may increase the accuracy of models, while explanations and escalation procedures grow increasingly important as AI takes on more independence.

7.3 Policy Implications

Emerging markets are recommended by the analysis to engage in efforts regarding reliable digital and energy infrastructure, industry technology policies, modernization of production,

support of small and medium-sized businesses, and skills. These conclusions emerge from the analysis, but there is no evidence of a single optimal strategy. Test beds, research-industry collaboration, interoperability, and selective financing might lower the cost of experimentation. Financial assistance must be provided based on realistic applications and outcome metrics to ensure that no funds go to purchasing technologies without building capabilities. Policy research in Africa also needs to focus on local vendor ecosystems, retrofit options, data management, and SME clusters.

8.0 Conclusion

This review examines the adoption of digital twins and sustainable manufacturing performance in developing nations through three research questions. In regard to the first research question, it is shown that there is clear progress going from virtual representation, shop floor modeling and layout design to equipment monitoring and reaching real time, AI-based, closed loop, supply chain, circular economy, resilience and Industry 5.0 applications. Adoption is growing in machining, robotics, additive manufacturing, batteries, energy, semiconductor packaging, chemical processes, sugar manufacturing, construction, logistics, and food systems. Nonetheless, the evidence remains largely of prototypes, simulations, reviews, frameworks, laboratories, or case studies. The use of digital twins at enterprise level and especially in Africa is yet to be proven. In regard to the second research question, digital twins may contribute to efficiency via better visibility, scenario evaluation, predictive maintenance, adaptive planning, and anomaly detection. It is possible to support resource and energy decisions via integration of measurement with simulation and optimization. Applications of productivity and quality are highly advanced and circular economy and life cycle applications are increasing. However, the evidence is stronger for decision capability and operationally bounded performance than for directly measured and long-term environmental performance. Efficiency should not be used as an unconditional proxy for sustainability and simulated improvements should not be presented as industrial performance gains. In regard to the third research question, adoption is facilitated by Industry 4.0 and IIoT maturity, AI availability, need for real-time monitoring, predictive maintenance, costs and quality pressure, sustainability goals, resilience and competitiveness. Technical obstacles include sensorization, data quality, interoperability, model fidelity, integration with legacy systems, and cybersecurity. Organizational obstacles involve leadership, skills, cross-functional collaboration, resistance, and poor decision-making processes. Economic and institutional obstacles include high capital requirements, uncertainty of ROI, problems for SMEs, infrastructure, standards, and ecosystem development.

11.0 Recommendations for Future Research

1. Conduct longitudinal research on twin projects from baseline all the way to pilot, integration, scale, and model sustainment, including failed attempts.
2. Create multination comparisons for emerging economies in Africa, Asia, Middle East, and Latin America using identical constructs but giving context-sensitive rationales.
3. Generate a body of evidence on African industry without depending mostly on construction and without applying lessons learned from advanced economies.
4. Look at architectures relevant for small and medium-size enterprises, testbeds in common use, retrofit approaches, vendor dependence, and minimum viable cases for business.
5. Carry out full-fledged cost-benefit and return on investment analysis that covers data preparation, integration, cybersecurity, competencies, subscription services, model degradation, and decommissioning.

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