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Digital Twins as Engines of Industrial Digital Transformation: Enabling Technologies, Applications, and Adoption Challenges

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ABSTRACT

The digital twin, a virtual representation of a physical asset or process kept synchronized with its counterpart through a live flow of data, has moved in little more than a decade from a conceptual curiosity to one of the central enabling technologies of industrial digital transformation. This review synthesizes the state of the field for an automation and digital-transformation audience. We first clarify the concept and the widely used taxonomy that distinguishes a digital model, a digital shadow, and a full digital twin by the degree to which data flow between physical and virtual is automated. We then examine the technologies that make twins possible, the Internet of Things, cloud and edge computing, simulation and physics-based modelling, big data, connectivity, and above all machine learning, and we map the principal application domains, from manufacturing and predictive maintenance to smart cities, healthcare, energy, and supply chains. Across these domains the recurring value proposition is the same: a twin turns data into foresight, allowing operators to monitor, predict, and optimize rather than merely react. We give particular attention to predictive maintenance, where the integration of machine learning with digital twins has produced the clearest returns, and to the human-centric turn of Industry 5.0, in which twins increasingly model people and their interaction with machines. Finally, we analyse the barriers that keep adoption uneven, especially among smaller enterprises: data quality and interoperability, the absence of shared standards, model fidelity, cost, a scarcity of skills, and cybersecurity and privacy risk. We argue that the technical foundations are now mature enough that the frontier of value has shifted from feasibility to disciplined implementation, standardisation, and organisational readiness. The review is narrative rather than exhaustive and is weighted toward manufacturing, where the literature is deepest.

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1. Introduction

Digital transformation has become the defining strategic project of the modern enterprise, a process in which digital technologies disrupt established ways of creating value and force organizations to reconfigure their operations, their business models, and sometimes their identities (Vial, 2019). Much of the scholarship on that transformation has been concerned with strategy, culture, and organizational change; less of it has examined, in technical depth, the specific technologies through which transformation is actually enacted on the factory floor and in the field. Among those technologies few are as consequential, or as emblematic of what digital transformation means in an industrial setting, as the digital twin.

A digital twin is, at its simplest, a virtual representation of a physical entity, an object, a process, or a whole system, that is kept in step with its physical counterpart through a continuous exchange of data (Tao, Zhang, Liu, & Nee, 2019). The idea is older than the term's current popularity, but two developments have made it practical at scale: the proliferation of low-cost sensors and connectivity that lets a physical asset stream its state in real time, and the maturation of computing and machine learning that lets a virtual model absorb that stream and reason over it. Where earlier engineering relied on static models built once and consulted occasionally, the digital twin is a living model, updated continuously, that can be used not only to understand an asset but to predict its behaviour and to optimize it. This is why the digital twin is frequently described as a key enabler of Industry 4.0 and, increasingly, of the more human-centric Industry 5.0 (Fuller, Fan, Day, & Barlow, 2020).

The purpose of this review is to give an integrated account of the digital twin as an engine of industrial digital transformation, aimed at readers concerned with automation and digital change rather than with any single engineering sub-discipline. We pursue four questions. What, precisely, is a digital twin, and how does it differ from related but weaker constructs? What technologies make it work? Where is it delivering value, and how much? And what keeps its adoption uneven, particularly for the small and medium-sized enterprises that make up the bulk of most economies? In answering, we connect the technical literature on digital twins to the broader research on digital transformation, and we note the growing regional engagement with these questions, including in the Gulf, where organizations are actively studying the adoption of data-driven and digital-transformation technologies and their effect on performance (Rihawi, 2025; Hyder, 2025).

2. Scope and Method

This is a narrative review supported by a structured search of the engineering, information-systems, and management literature. We drew on foundational and highly cited syntheses of the digital twin, on recent domain-specific reviews, and on the digital-transformation literature that situates the technology in its organizational context, identified through academic databases and citation searching. Our aim is to represent the principal concepts, technologies, applications, and challenges rather than to enumerate every study, and the review is deliberately weighted toward manufacturing, where the digital-twin literature is deepest and where the concept was first operationalized. We organize the synthesis conceptually: from definitions and taxonomy, through enabling technologies and applications, to adoption challenges, so that each layer builds on the last.

3. Concept and Taxonomy

The idea behind the digital twin is older than the phrase now attached to it. Its intellectual origins are usually traced to product-lifecycle-management thinking in the early 2000s, in which a physical product was paired with a virtual counterpart carrying its information across its life, and its practical ancestry reaches back further still, to the paired physical models that engineers maintained to reason about remote systems they could not directly inspect. What changed in the last decade was not the concept but its feasibility: sensing became cheap, connectivity ubiquitous, and computation abundant, so that the virtual counterpart could at last be fed continuously rather than assembled once and left to age. The digital twin as understood today is therefore best read as an old engineering intuition, that it helps to reason on a faithful model before acting on the real thing, made continuous and automatic by the technologies of the fourth industrial revolution (Tao et al., 2019; Fuller et al., 2020).

A persistent obstacle to clear thinking about digital twins is that the term is used loosely, applied to everything from a static CAD drawing to a fully synchronized live replica. The most useful discipline the field has imposed on itself is a taxonomy that classifies representations by the degree to which the flow of data between the physical and virtual entities is automated (Kritzinger, Karner, Traar, Henjes, & Sihn, 2018). In a digital model, both directions of data flow are manual: a virtual model exists, but changes in the physical asset do not automatically update it, nor do changes in the model automatically affect the asset. In a digital shadow, the physical-to-virtual flow is automated, so the model updates itself from live data, but the reverse flow remains manual. Only when both directions are automated, when the virtual entity updates from the physical in real time and can in turn act back upon it, does one have a true digital twin. Figure 2 illustrates this progression, which matters because much of what industry calls a digital twin is, on this definition, a shadow or a model.

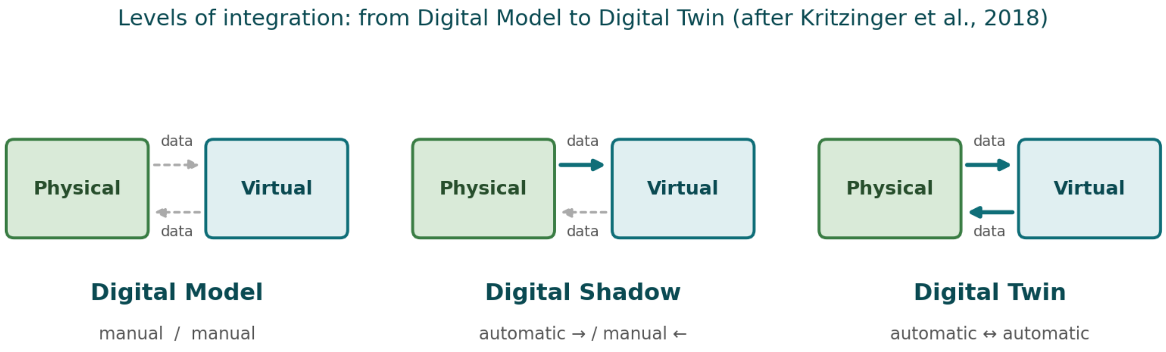

Figure 2. Levels of integration distinguished by the automation of data flow, after Kritzinger et al. (2018).

Systematic reviews that have sought to consolidate the concept converge on a small set of essential characteristics: a physical entity, a virtual entity, and the data connections that bind them, together with the state, fidelity, and synchronization that make the binding meaningful (Jones, Snider, Nassehi, Yon, & Hicks, 2020). Two of these deserve emphasis because they are what a shadow or model lacks. The first is synchronization: a genuine twin tracks its physical counterpart closely enough in time that decisions taken on the model are valid for the asset as it is now, not as it was. The second is bidirectionality: the twin is not merely observed but can inform, and in automated settings directly effect, action on the physical system. Figure 1 depicts this closed loop, the architecture that distinguishes a digital twin from an ordinary simulation.

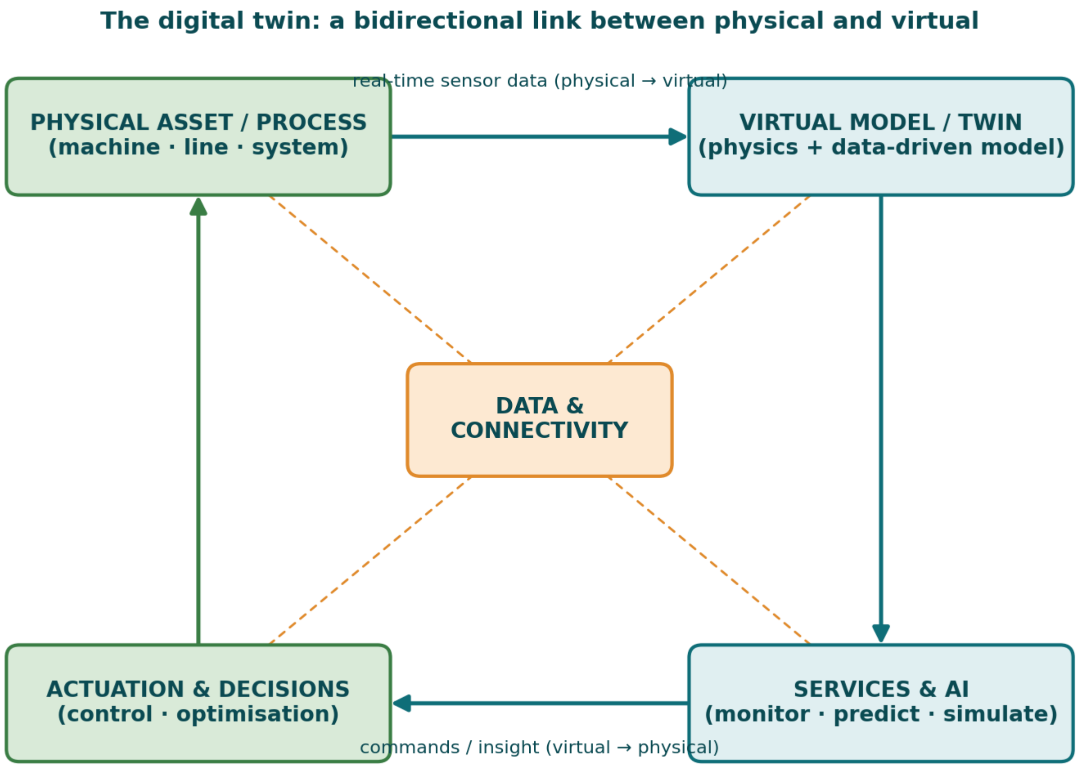

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Figure 1. Reference architecture of a digital twin: a bidirectional loop linking a physical asset to a virtual model through data, analytics, and actuation.

It is useful to make the notion of synchronization precise, because it is the property on which a twin's value ultimately rests. If $x_p(t)$ denotes the state of the physical asset at time t and $x_v(t)$ the state of its virtual counterpart, the fidelity of the twin can be characterized by the synchronization error

$$e(t) = \| x_p(t) - x_v(t) \| ,$$

which a well-designed twin drives toward zero and keeps there as conditions change. The rate at which the model is refreshed from the physical stream, sometimes called the twinning rate, determines how small e(t) can be held; a low twinning rate yields a laggard model that is, in effect, only a shadow of recent history. This simple formalism clarifies why connectivity and data quality, treated below, are not peripheral concerns but the very things that determine whether a twin is worthy of the name.

4. Enabling Technologies

A digital twin is less a single technology than an orchestration of several, each supplying one element of the loop in Figure 1. The Internet of Things provides the sensing and connectivity that let a physical asset report its state continuously, and it is the precondition for automating the physical-to-virtual flow that defines a true twin (Fuller et al., 2020). Cloud and, increasingly, edge computing supply the elastic processing and storage that a live model demands, with edge deployment reducing the latency that would otherwise inflate the synchronization error for time-critical control. Simulation and physics-based modelling contribute the virtual entity itself, the executable representation whose behaviour can be compared with, and projected beyond, the physical asset's. Big-data infrastructure manages the volume and velocity of the resulting streams, and connectivity standards knit the parts together.

Above all, machine learning has become the analytical engine that turns a twin from a mirror into an oracle. Where physics-based models struggle with complexity or incomplete knowledge, data-driven models learn patterns directly from the asset's history, enabling the twin to detect anomalies, classify faults, and forecast future states (Chen, Fu, Zheng, Tao, & Liu, 2023). The most powerful contemporary architectures are hybrid, combining physics-based and machine-learning models so that each compensates for the other's weaknesses. Table 1 summarizes the enabling technologies and the role each plays in the loop.

Two further ingredients deserve mention because they are easy to overlook yet decisive in practice. The first is connectivity of sufficient bandwidth and reliability, increasingly furnished by industrial wireless and 5G, which governs the twinning rate and therefore the smallest synchronization error a twin can sustain; a model that cannot receive data quickly enough is condemned to lag its asset. The second is the digital thread, the connected flow of data and models across an asset's whole life cycle, from design through operation to retirement, which lets a twin draw on engineering provenance rather than only on live telemetry. Where the digital thread is intact, a twin can reason about why an asset behaves as it does and not merely that it does; where it is broken, the twin is confined to the present. Both ingredients underline a theme that runs through this review: the value of a twin is set less by the sophistication of any single component than by the integrity of the connections among them.

Table 1. Core technologies enabling the digital twin and their function in the physical–virtual loop.

Technology	Function in the twin	Notes
Internet of Things (IoT)	Senses physical state; automates the physical-to-virtual data flow.	Precondition for a true (not shadow) twin.
Cloud & edge computing	Elastic processing and storage; low-latency control at the edge.	Edge reduces synchronization lag.
Simulation & physics modelling	Provides the executable virtual entity.	Basis for prediction beyond observed data.
Machine learning / AI	Detects anomalies, classifies faults, forecasts states.	Turns the twin from mirror to predictor.
Big data & connectivity	Handles volume/velocity; binds components.	Data quality governs fidelity.

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Extended reality (AR/VR)	Human interface to the virtual entity.	Supports the Industry 5.0 human-centric turn.

5. Applications and Value

The digital twin has diffused across sectors, but the underlying value proposition is remarkably constant: by maintaining a live, queryable model of a physical system, a twin lets operators shift from reacting to events to anticipating and shaping them. Reviews of digital-twin applications toward Industry 4.0 catalogue uses spanning product design, production planning, quality control, and asset management, with manufacturing the most mature domain (Javaid, Haleem, & Suman, 2023). Beyond the factory, twins have been applied to smart cities, where they model infrastructure and traffic; to healthcare, where they represent organs or patients; and to energy and supply-chain systems, where they optimize flows across distributed networks (Fuller et al., 2020).

5.1 Predictive maintenance: the clearest return

If any single application has demonstrated the digital twin's value most convincingly, it is predictive maintenance. By coupling a live twin of a machine with machine-learning models trained on its history, operators can recognize the signature of an incipient fault and intervene before failure, shifting maintenance from reactive or fixed-schedule regimes to a condition-based one that minimizes both downtime and unnecessary servicing (Chen et al., 2023). Recent reviews of digital-twin and machine-learning integration report gains in reliability, real-time analytics, and cost across manufacturing, healthcare, and smart-city settings (Torba et al., 2025), and domain-specific syntheses, for instance in mining, document the increasing adoption of deep learning and twins for anomaly detection and asset management (Rojas et al., 2025). The economic logic is direct: unplanned downtime is expensive, and a twin that converts even a fraction of unplanned into planned maintenance pays for itself.

The value can be framed compactly. If unplanned failures occur with probability p_f over a period and each carries an expected cost C_f, while a predictive regime detects a fraction δ of those failures in advance at a reduced intervention cost, the expected saving relative to reactive maintenance is approximately

$$\Delta C \approx \delta \cdot p_f \cdot (C_f - C_p) - C_{twin} ,$$

where C_p is the cost of a planned intervention and C_{twin} the amortized cost of building and running the twin. The expression makes explicit why predictive maintenance is most attractive where failures are frequent or catastrophic and where the twin's running cost is modest: the benefit scales with the failures avoided and the gap between the cost of a surprise and the cost of a scheduled fix. It also connects to the standard manufacturing metric of overall equipment effectiveness, OEE = Availability × Performance × Quality, since reducing unplanned downtime raises availability and, through it, OEE.

5.2 From Industry 4.0 to the human-centric twin

As industrial thinking has shifted from the efficiency focus of Industry 4.0 toward the human-centric, sustainable emphasis of Industry 5.0, the digital twin has followed. A newer strand of work models not only machines but people and their interaction with machines, giving rise to human digital twins and human-centred frameworks that place the worker inside the twin's loop rather than outside it (Modoni & Sacco, 2023). The concept is still consolidating, and a recent systematic review has had to disambiguate human digital models, shadows, and twins much as the earlier literature did for machines, while flagging the distinctive ethical questions, around sensing personal data, privacy, and consent, that arise when the twinned entity is a person (Gaffinet et al., 2025). This human-centric turn matters for digital transformation because it reframes the twin from a tool that optimizes assets to one that can also support, augment, and protect the people who work with them.

5.3 Beyond the factory: cities, health, and supply chains

Although manufacturing remains the twin's heartland, some of the most ambitious applications now lie beyond it. Urban digital twins model the built environment, traffic, and utility networks of whole cities, letting planners simulate the effect of an intervention, a new junction, a change in transit, before committing to it in concrete; the appeal is precisely that a city is too costly and too consequential to experiment on directly, so a faithful twin becomes the safe place to try (Fuller et al., 2020). In healthcare, twins of organs or of whole patients promise personalized simulation of how a given body will respond to a given therapy, moving medicine toward a model-guided practice, though the fidelity and data-governance demands here are especially severe. In energy and supply-chain systems, twins of distributed networks optimize flows that no single operator can see in full, coordinating assets across organizational boundaries (Javaid et al., 2023).

What these varied domains share is instructive. In each, the twin's advantage comes from making a complex, distributed, and expensive-to-experiment-on system

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observable and testable in software before action is taken in the world. This is the same logic that drives predictive maintenance, generalized: the twin lowers the cost of foresight. It is also why the barriers examined later, data quality, interoperability, and trust in the model, recur identically across domains, for they are properties of the twinning relationship itself rather than of any one application.

5.4 Emerging frontiers: generative AI and the industrial metaverse

The field's leading edge is now being reshaped by two further currents. The first is the arrival of generative artificial intelligence, which promises to lower the effort of building and interrogating twins, by helping to generate models, synthesize training data where real data are scarce, and let engineers query a twin in natural language, though it also imports fresh questions of reliability and governance that the field is only beginning to address. The second is the industrial metaverse, in which twins are situated in shared, immersive virtual environments where stakeholders across a value chain, factories, customers, and suppliers, can interact with the same living models; recent work has begun to prototype exactly such platforms for small manufacturers using open-source tooling (Kiangala & Wang, 2025). Both currents point in the same direction, toward twins that are cheaper to build, easier to use, and more widely shared, which is precisely what is needed if the technology's benefits are to reach beyond the large and well-resourced firms that have led its adoption so far.

Table 2. Principal application domains of the digital twin, with representative value and evidence.

Domain	Representative value	Evidence
Manufacturing	Design, production planning, quality, asset management.	Tao et al. (2019); Javaid et al. (2023)
Predictive maintenance	Condition-based servicing; reduced downtime and cost.	Chen et al. (2023); Torba et al. (2025)
Smart cities & infrastructure	Modelling of traffic, utilities, and the built environment.	Fuller et al. (2020)
Healthcare	Patient- and organ-level modelling and monitoring.	Fuller et al. (2020)
Energy & supply chain	Optimization of distributed flows and networks.	Javaid et al. (2023)
Human-centric (Industry 5.0)	Modelling workers and human–machine interaction.	Modoni & Sacco (2023); Gaffinet et al. (2025)

6. Adoption Challenges

If the digital twin's value is now well evidenced, its adoption remains strikingly uneven, and the reasons are more organizational and infrastructural than they are conceptual. Six barriers recur across the literature. The first is data quality and availability: a twin is only as good as the data that feed it, and gaps, noise, or low sampling rates inflate the synchronization error and undermine every downstream inference. The second is interoperability and the absence of shared standards: industrial environments are heterogeneous, and connecting legacy equipment, proprietary systems, and modern platforms into a coherent twin is a substantial integration challenge (Jones et al., 2020). The third is model fidelity: building a virtual entity faithful enough to be trusted for decisions is difficult, and an over-simplified model can mislead as easily as an accurate one informs.

The remaining barriers are as much about organizations as about engineering. Cost and complexity put full twins out of easy reach for many firms, and the burden falls hardest on the small and medium-sized enterprises that dominate most economies; recent work has therefore focused on lightweight, affordable twin frameworks built with open-source tools specifically to lower the barrier for SMEs (DeMarchi et al., 2024; Kiangala & Wang, 2025). A skills gap compounds the cost problem, since twins demand scarce competencies spanning data engineering, modelling, and domain expertise. And cybersecurity and privacy rise in importance precisely because a twin's bidirectional link means that a compromised virtual entity can become a vector for harm to the physical asset, a concern that intensifies as twins begin to model people. Table 3 summarizes the barriers and the directions in which the field is responding.

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The small and medium-sized enterprise deserves separate emphasis, because it is where the gap between the technology's promise and its realisation is widest. SMEs account for the great majority of firms and a large share of employment in most economies, yet they are frequently siloed from the full benefits of Industry 4.0 by financial constraints, thin technical staffing, and a simple absence of guidance, and the same constraints apply with added force to a technology as integrative as the digital twin (DeMarchi et al., 2024). The response emerging in the literature is not to shrink the ambition but to change the delivery: lightweight twins assembled from open-source components, low-code and no-code tooling, cloud-hosted platforms that externalise the infrastructure burden, and stepwise adoption that begins with a modest shadow rather than a full twin (Kiangala & Wang, 2025). Whether these approaches succeed in democratising the technology is one of the more consequential open questions in the field, because it will determine whether digital twins narrow or widen the gap between large and small firms.

A further barrier is easy to miss because it is not technical at all: the organisational change that adoption demands. A digital twin alters how decisions are made, moving authority from experience and intuition toward model-based inference, and it requires new roles, new workflows, and a degree of trust in software that established operators may be slow to extend. The digital-transformation literature is emphatic that technology adoption succeeds or fails on these organisational factors as much as on the technology itself, and that firms which treat a twin as a purely technical project, rather than as a change in how work is done, tend to under-realise its value (Vial, 2019; Verhoef et al., 2021). Managing that change, aligning incentives, building trust in the model, and reskilling the workforce, is therefore inseparable from the engineering, and it is where much of the practical difficulty of adoption actually resides.

Table 3. Barriers to digital-twin adoption and emerging responses.

Barrier	Why it matters	Emerging response
Data quality & availability	Poor data inflate synchronization error.	Better sensing, data governance, edge processing.
Interoperability & standards	Heterogeneous, legacy systems resist integration.	Open standards; reference architectures.
Model fidelity	Inaccurate models mislead decisions.	Hybrid physics + machine-learning models.
Cost & complexity	Full twins are costly, hard for SMEs.	Lightweight, open-source twin frameworks.
Skills gap	Scarce data, modelling, and domain skills.	Training; low-code tools; vendor platforms.
Cybersecurity & privacy	Bidirectional link and human data raise risk.	Security-by-design; privacy and consent frameworks.

7. Discussion

Read as a whole, the literature supports a clear thesis: the digital twin has crossed the threshold from research concept to practical enabler of industrial digital transformation, and the centre of gravity of the field has moved accordingly. The foundational questions, what a twin is, what technologies it requires, and whether it delivers value, are substantially settled; the pressing questions now are ones of implementation, standardisation, and reach. This maturation is itself a marker of digital transformation's broader pattern, in which the decisive challenge shifts, over time, from whether a technology works to whether an organization can absorb it, a shift the digital-transformation literature has documented across many technologies (Vial, 2019; Verhoef et al., 2021).

Three implications follow for practitioners and policymakers. First, because value is now demonstrable, especially in predictive maintenance, the case for adoption is increasingly economic rather than speculative, and organizations can reason about twins using the kind of cost logic sketched above rather than as an act of faith. Second, because the binding constraints are data, standards, skills, and security rather than core feasibility, the highest-leverage investments are often in the unglamorous foundations, data governance, interoperability, and workforce capability, rather than in the twin itself. Third, because cost and complexity fall

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hardest on smaller firms, the diffusion of affordable, standardized, and human-centric twins is where much of the remaining social and economic value lies, and it is an area where regional research and policy attention, including studies of digital-transformation adoption and its organizational effects in the Gulf and elsewhere, can make a practical difference (Rihawi, 2025; Hyder, 2025).

Table 4. Priority actions for organisations adopting digital twins, by readiness dimension.

Dimension	Near-term action	Longer-term action
Data foundations	Instrument key assets; establish data governance and quality checks.	Build the digital thread across the asset life cycle.
Architecture & standards	Adopt open, interoperable platforms; avoid lock-in.	Align on reference architectures and industry standards.
Analytics & fidelity	Start with a digital shadow for monitoring; validate models.	Progress to hybrid physics + ML twins with bidirectional control.
People & skills	Upskill staff; use low-code tools to widen participation.	Build cross-disciplinary teams spanning data and domain expertise.
Security & trust	Apply security-by-design; segment physical–virtual links.	Adopt privacy and consent frameworks, especially for human twins.

There is also a strategic lesson in the trajectory of the technology. The organisations that have gained most from digital twins are, on the whole, not those that pursued the most elaborate twin but those that matched the twin's level of integration to a concrete decision they needed to make better. A digital shadow that reliably warns of an impending failure can be worth more than a technically superior full twin that answers a question no one is asking. This argues for an incremental adoption path, beginning with monitoring and prediction on the assets where the cost of surprise is highest, demonstrating value, and only then extending toward the closed-loop control and enterprise-wide integration that a mature twin allows. Framed this way, the digital twin is less a destination to be reached in a single leap than a capability to be grown, and the discipline of growing it deliberately is what separates the organisations that realise its promise from those that acquire the technology without the returns.

8. Limitations

Several limitations bound this review. As a narrative synthesis it represents the principal themes and most influential works rather than an exhaustive census, and its selection, though structured, reflects judgement. The evidence base is weighted toward manufacturing and toward higher-income industrial settings, so conclusions transfer less securely to other sectors and to resource-constrained environments. Much of the quantified value evidence, particularly for predictive maintenance, comes from case studies and vendor reports whose generalizability is uncertain, and the cost expressions we present are illustrative rather than validated models. Finally, the field is moving quickly, especially at the intersections of digital twins with generative AI and with human-centric Industry 5.0 applications, so some conclusions are necessarily provisional.

9. Conclusion

The digital twin has become one of the clearest instances of what industrial digital transformation means in practice: a live, data-fed virtual model that lets organizations monitor, predict, and optimize the physical systems on which they depend. Its concept is now well defined, its enabling technologies, the Internet of Things, cloud and edge computing, simulation, and above all machine learning, are mature, and its value is demonstrated most convincingly in predictive maintenance and increasingly in the human-centric applications of Industry 5.0. What remains is not principally a problem of invention but of implementation: of data quality, interoperability and standards, model fidelity, cost, skills, and security, and of extending the technology's reach to the smaller firms that stand to gain from it. For the enterprise navigating digital transformation, the digital twin is therefore best understood not as a futuristic aspiration but as an available and increasingly indispensable engine, whose returns now depend less on the technology itself than on the discipline and readiness with which it is adopted.

References

Chen, C., Fu, H., Zheng, Y., Tao, F., & Liu, Y. (2023). The advance of digital twin for predictive

ISSN: 2791-2957 - https://doi.org/10.54878/zqaw9j97

maintenance: The role and function of machine learning. Journal of Manufacturing Systems, 71, 581–594. https://doi.org/10.1016/j.jmsy.2023.10.010

DeMarchi, M., Gallala, A., Anwar, A., Plapper, P., & others. (2024). A digital twin for SMEs in the context of Industry 5.0. Procedia CIRP, 130, 1–6. https://doi.org/10.1016/j.procir.2024.10.001

Fuller, A., Fan, Z., Day, C., & Barlow, C. (2020). Digital twin: Enabling technologies, challenges and open research. IEEE Access, 8, 108952–108971. https://doi.org/10.1109/ACCESS.2020.2998358

Gaffinet, B., Panetto, H., Weichhart, G., & Loures, E. (2025). Human digital twins: A systematic literature review and concept disambiguation for Industry 5.0. Computers in Industry, 165, 104217. https://doi.org/10.1016/j.compind.2024.104217

Hyder, S. S. (2025). Adoption of data analysis technology and its impact on decision-making efficiency and research output in the UAE higher education system. International Journal of Automation and Digital Transformation, 4(1).

Javaid, M., Haleem, A., & Suman, R. (2023). Digital twin applications toward Industry 4.0: A review. Cognitive Robotics, 3, 71–92. https://doi.org/10.1016/j.cogr.2023.04.003

Jones, D., Snider, C., Nassehi, A., Yon, J., & Hicks, B. (2020). Characterising the digital twin: A systematic literature review. CIRP Journal of Manufacturing Science and Technology, 29, 36–52. https://doi.org/10.1016/j.cirpj.2020.02.002

Kiangala, K. S., & Wang, Z. (2025). An inceptive approach for designing simple digital twins and industrial metaverse process frameworks for small manufacturing I5.0 environments using Node-RED. The International Journal of Advanced Manufacturing Technology. Advance online publication. https://doi.org/10.1007/s00170-025-15111-y

Kritzinger, W., Karner, M., Traar, G., Henjes, J., & Sihn, W. (2018). Digital twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, 51(11), 1016–1022. https://doi.org/10.1016/j.ifacol.2018.08.474

Modoni, G. E., & Sacco, M. (2023). A human digital-twin-based framework driving human centricity towards Industry 5.0. Sensors, 23(13), 6054. https://doi.org/10.3390/s23136054

Rihawi, B. (2025). Digital transformation and its impact on quality management in logistics companies. International Journal of Automation and Digital Transformation, 4(1).

Rojas, L., Peña, Á., & García, J. (2025). AI-driven predictive maintenance in mining: A systematic literature review on fault detection, digital twins, and intelligent asset management. Applied Sciences, 15(6), 3337. https://doi.org/10.3390/app15063337

Tao, F., Zhang, H., Liu, A., & Nee, A. Y. C. (2019). Digital twin in industry: State-of-the-art. IEEE Transactions on Industrial Informatics, 15(4), 2405–2415. https://doi.org/10.1109/TII.2018.2873186

Torba, E., et al. (2025). Integrating digital twins and machine learning for enhanced predictive maintenance, real-time analytics, and cost savings: A review. 2025 20th Annual System of Systems Engineering Conference (SoSE), IEEE.

Verhoef, P. C., Broekhuizen, T., Bart, Y., Bhattacharya, A., Qi Dong, J., Fabian, N., & Haenlein, M. (2021). Digital transformation: A multidisciplinary reflection and research agenda. Journal of Business Research, 122, 889–901. https://doi.org/10.1016/j.jbusres.2019.09.022

Vial, G. (2019). Understanding digital transformation: A review and a research agenda. The Journal of Strategic Information Systems, 28(2), 118–144. https://doi.org/10.1016/j.jsis.2019.01.003

ISSN: 2791-2957 - https://doi.org/10.54878/zqaw9j97