Vol. 16 (2026): Proceedings of the 2026 International Conference on AI and Technological Innovation Applications (AITIA 2026)
E-ISSN: 3105-0522 P-ISSN: 3105-0514
DOI: https://doi.org/10.70267/aitia.2026326335

From Monitoring to Supervised Control: A Capability-Maturity Perspective on Digital Twins in Smart Manufacturing

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Abstract

Manufacturing digital twins are increasingly promoted as a route from shop-floor visibility to data-driven operational improvement. In practice, however, many implementations remain descriptive dashboards and do not demonstrate measurable gains in quality, throughput, maintenance, or energy performance. Existing reviews also tend to classify studies by algorithm family rather than by the manufacturing capability delivered. This paper develops a capability-maturity lens for AI-enabled manufacturing digital twins by aligning the NIST progression from descriptive to intelligent capabilities with the ISO 23247 reference architecture and the digital thread. Based on PRISMA-guided screening of 34 studies published between 2018 and 2026, the review shows that current literature is concentrated in descriptive monitoring and predictive analytics, while prescriptive decision support and supervised intelligent control remain comparatively limited. More importantly, many studies do not report standard-compliant integration pathways or KPI-validated shop-floor outcomes. The paper therefore synthesises scenario-level evidence, identifies transition barriers between maturity bands, and proposes an engineering agenda for trustworthy progression toward supervised, auditable control.

Keywords

digital twin, smart manufacturing, ISO 23247, capability maturity, physics-informed modelling, digital thread

1. Introduction

Digital twins (DTs) have become a central concept in smart manufacturing, yet their practical value remains uneven. Many manufacturing programmes use DTs to visualise machine status, collect sensor data, or display alarms, but far fewer demonstrate closed-loop improvement in quality, throughput, maintenance scheduling, or energy consumption. For practitioners, the key question is therefore not simply whether a DT uses artificial intelligence (AI), but what level of manufacturing capability it enables. A twin that reports tool wear, a twin that predicts remaining useful life, and a twin that recommends or executes a production adjustment represent substantially different levels of operational maturity.

This distinction is often blurred in the existing literature. Algorithm-centred reviews commonly group studies by model type, such as convolutional neural networks, recurrent networks, reinforcement learning, or multi-agent systems. Such taxonomies are useful for understanding technical trends, but they do not always clarify whether a study delivers auditable prediction, traceable prescription, or governed execution in a real manufacturing environment. A reinforcement-learning scheduler trained only in simulation, for example, should not be treated as equivalent to a standard-integrated shop-floor control system. Similarly, a highly accurate prediction model may still offer limited manufacturing value if it is disconnected from maintenance planning, quality inspection, or production scheduling.

The need for a capability-oriented vocabulary is reinforced by emerging standards and industrial architectures. NIST distinguishes descriptive, diagnostic, predictive, prescriptive, and intelligent capabilities, while ISO 23247 defines a manufacturing DT through a reference architecture connecting observable manufacturing elements, device communication, twin analytics, and user applications [1, 2]. Interoperability standards such as MTConnect, OPC UA, STEP, and the Quality Information Framework (QIF) further determine whether twin outputs can be synchronised with production systems rather than remaining isolated demonstrations. In parallel, physics-informed data-driven (PIDD) modelling has become increasingly important because purely data-driven models may extrapolate poorly outside the training regime and may be difficult for operators to trust in safety-critical manufacturing decisions.

This paper addresses the gap between algorithmic sophistication and manufacturing maturity. It proposes a capability-maturity lens that classifies AI-enabled manufacturing DTs into four main bands: descriptive monitoring, predictive analytics, prescriptive decision support, and supervised intelligent control. Diagnostic reasoning is treated as a cross-cutting bridge because explanation and root-cause traceability are required before predictions can credibly support action. Using this lens, the review synthesises 34 studies published between 2018 and 2026 across predictive maintenance, quality assurance, scheduling, human–robot collaboration, and energy optimisation. The emphasis is deliberately engineering-oriented: the paper does not propose a new algorithm, but offers a structured way to judge whether reported DT capabilities are supported by standards, integration evidence, and shop-floor KPIs.

The review finds a clear imbalance. Most studies remain concentrated around descriptive monitoring and predictive analytics, while relatively few provide convincing evidence of prescriptive decision support or supervised intelligent control. Only a minority of papers explicitly report numerical shop-floor KPIs, and explicit references to ISO 23247, OPC UA, MTConnect, QIF, or human-in-the-loop governance are also limited. This suggests that the principal bottleneck is not simply the absence of advanced AI methods, but the lack of evidence connecting those methods to standard-aware integration and measurable manufacturing outcomes. The remainder of the paper first defines the capability-maturity framework, then evaluates application scenarios, and finally discusses transition barriers and future research directions.

2. Capability-Maturity Lens and Standards Grounding

ISO 23247 defines a manufacturing DT as a fit-for-purpose and synchronised digital representation of an observable manufacturing element, such as a machine, tool, production line, product, or process [1, 2]. This definition is important because related terms are often used interchangeably. A *digital model* may support offline simulation without continuous synchronisation. A *digital shadow* may mirror production states without bidirectional control intent. A *cyber-physical production system* describes the broader connected environment in which one or more twins operate. These distinctions matter when assessing capability maturity: descriptive monitoring may be achieved with a unidirectional digital shadow, whereas prescriptive or intelligent twins require stronger synchronisation, traceability, and governance.

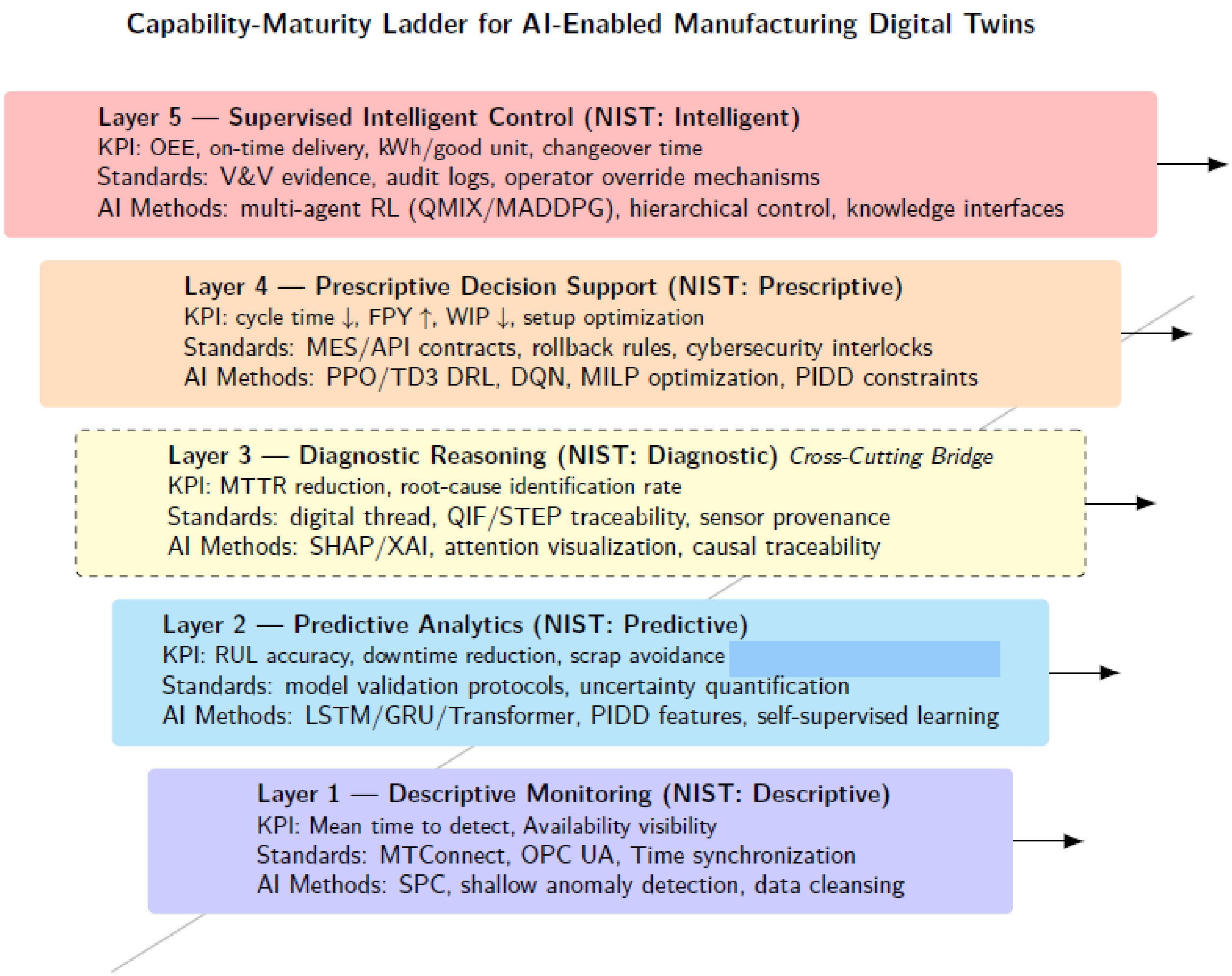
The digital thread provides the data continuity needed for higher-maturity twins. It links design, planning, fabrication, inspection, maintenance, and service data so that decisions are tied to specific material lots, fixtures, tools, process plans, and inspection records. Without this continuity, a prescriptive setpoint may lack the context required for safe or compliant deployment. Standards such as STEP and QIF help reduce manual data re-entry, while MTConnect and OPC UA support machine and device communication. Industry 5.0 adds further requirements of human-centricity, resilience, and sustainability, particularly in collaborative or assembly-intensive environments where operators must understand, approve, and override AI recommendations [3, 4].

Against this background, the review uses four capability bands plus a cross-cutting diagnostic layer. Table 1 summarises the manufacturing intent of each band, and Figure 1 visualises the corresponding progression from monitoring to supervised control.

Table 1: Capability-maturity lens mapped to manufacturing intent (NIST-aligned).

Band	NIST class	Manufacturing intent	Enablers / KPI hooks
Descriptive monitoring	Descriptive	See, alert, trend	MTConnect, OPC UA; availability
Predictive analytics	Predictive	Forecast wear, quality drift	ML/DL, PIDD features; RUL, scrap risk
Diagnostic reasoning	Diagnostic	Explain root cause	Digital thread, XAI; MTTR
Prescriptive decision support	Prescriptive	Recommend setpoints, schedules	RL, optimisation; cycle time, FPY
Supervised intelligent control	Intelligent	Governed multi-asset coordination	Multi-agent control; OEE, OTD

Figure 1: Capability-Maturity Ladder for AI-Enabled Manufacturing Digital Twins. Five capability bands span from descriptive monitoring to supervised intelligent control, with diagnostic reasoning acting as a cross-cutting bridge connecting predictive analytics and prescriptive decision-making through end-to-end digital thread continuity



Descriptive monitoring mirrors the current state of a manufacturing asset and raises alarms, but it does not change production parameters. At this stage, MTConnect and OPC UA adapters standardise data acquisition, while NTP or PTP time synchronisation supports consistent historian integration. Statistical process control and lightweight anomaly detection can operate at the edge, with recent tool-condition monitoring deployments reporting low-latency performance [5]. Reusable monitoring architectures can further reduce bespoke integration overhead across machines [6].

Predictive analytics extends monitoring by forecasting degradation, quality drift, or process instability. Time-series models, including LSTMs, GRUs, and Transformers, are widely used for remaining-useful-life estimation, while PIDD hybrids incorporate process constraints to improve extrapolation beyond the training data [5, 7]. Edge-deployed wear models [8] and scalable cyber-twin prediction frameworks [9] show technical progress, whereas enterprise-level econometric studies [10] strengthen the business case for predictive maintenance but often provide less evidence of synchronised twin architectures.

Diagnostic reasoning connects accurate prediction with trustworthy action. Explainable AI techniques such as SHAP, Grad-CAM, and attention-weighted visualisation can translate model outputs into physically interpretable signals for operators, as shown in cobot error-compensation and weld-defect detection cases [11, 12]. Digital-thread continuity strengthens this layer by allowing anomalies to be traced not only to abstract feature shifts, but also to specific tools, material lots, fixture versions, inspection records, or operator interventions.

Prescriptive decision support is the critical transition from prediction to action. A prescriptive twin should answer three questions: what action is recommended, what evidence validates the recommendation, and how the recommendation enters production under human approval and safety constraints. Recommended actions may include injection-moulding parameters, maintenance windows, dispatching rules, or CNC chip-removal settings. Validation may rely on simulation, uncertainty bounds, PIDD constraints, or historical KPI comparisons. Production release should be governed by operator approval, rollback rules, and safety interlocks [13-16]. Khdoudi et al. [13] optimise injection-moulding quality through reinforcement learning on an OPC-linked shadow, while Xia et al. [14] train scheduling policies in a virtual-commissioning twin before MES release. Without governed release, prescriptive analytics may remain an offline benchmark rather than a manufacturing capability.

Supervised intelligent control denotes coordinated policies across machines, cells, or production lines within explicit safety envelopes. It should not be confused with unrestricted autonomy. In this band, multi-agent reinforcement learning protocols such as QMIX and MADDPG may support distributed dispatching, but deterministic failover, audit logging, and operator override remain essential. Heik et al. [17] compare single-agent and multi-agent reinforcement-learning formulations for flexible job-shop scheduling and report stronger performance than heuristic dispatching under high variability. Huang et al. [18] extend coordinated optimisation to production lines involving human–robot collaboration constraints. Nevertheless, operator–product–process integration remains a recurring weakness: product-quality twins, process-parameter twins, and operator-facing twins must be synchronised before plant-level KPI gains can be attributed to DT-enabled control [19].

This capability-band framing helps avoid a common overstatement in DT literature. Model complexity alone does not establish maturity. A sophisticated AI model trained offline may still belong to the predictive band if it does not influence production decisions through a governed interface. Conversely, a simpler model connected to standardised data flows and validated against shop-floor KPIs may represent a more mature manufacturing system. The proposed lens therefore classifies studies by operational impact, integration evidence, and governance rather than by algorithm family alone.

3. Application Scenarios and Evidence of Maturity

This section organises the reviewed studies by manufacturing scenario. The aim is not to provide an exhaustive catalogue, but to evaluate where capability progression is most evident and where the reported evidence remains weak.

4. Predictive Maintenance

Predictive maintenance remains concentrated at the descriptive-to-predictive boundary. Edge-deployed tool-wear and tool-condition monitoring models demonstrate the value of low-latency data processing and reduce dependence on cloud-based analytics [5, 8]. Scalable cyber-twin frameworks further address reuse across assets [9, 20]. However, many predictive-maintenance studies stop before the prescriptive step. They may forecast failure risk or remaining useful life, but they do not always connect those predictions to production schedules, spare-part availability, or maintenance-window optimisation. Nagy et al. [10] provide credible business-case evidence, but enterprise-level predictions are often less explicit about synchronised twin architectures. Overall, the strongest shop-floor KPI evidence in this scenario appears in machining-monitoring cases rather than in broader enterprise studies.

5. Quality Assurance

Quality assurance is the most mature scenario for PIDD-driven capability progression. Welding and machining studies combine process physics, production data, simulation, and inspection feedback to support movement from monitoring toward prescriptive decision support [7, 21-23]. Explainable cobot correction and weld-defect detection also show how diagnostic reasoning can make AI outputs more acceptable to operators [11, 12]. Reinforcement-learning-based injection-moulding optimisation demonstrates the potential of prescriptive quality control when models remain constrained by process limits [13]. This scenario offers the clearest route toward supervised closed-loop quality control because quality outcomes are directly linked to controllable process parameters. Even so, explicit QIF or ISO 23247 framing remains uncommon, and many papers still read as technique demonstrations rather than auditable quality loops.

6. Scheduling

Scheduling is the scenario closest to supervised intelligent control. Digital twins can serve as reinforcement-learning training environments that encode routings, buffers, machine availability, and stochastic disruptions before policies are released to an MES [14, 17]. This creates a relatively clear pathway from simulation to dispatch decisions and makes scheduling a strong candidate for early supervised-control deployment. However, the evidence remains incomplete. Many studies report improved makespan, utilisation, or tardiness in simulation, but fewer document rollback mechanisms, standard MES interfaces, or operator governance. Multidimensional job-shop models clarify zero-defect manufacturing scheduling concepts [24, 25], but shop-floor KPI tables and deployment evidence are still limited.

7. Human–Robot Collaboration

Human–robot collaboration (HRC) is shaped by Industry 5.0 concerns such as safety, ergonomics, explainability, and human oversight [3, 15, 26]. Current HRC twins are mostly located in descriptive monitoring and early prescriptive decision support. Vision- and AR-assisted task allocation systems extend twin functionality in collaborative cells [27, 28], but links between HRC safety twins and line-level OEE reporting remain weak. Progression to higher maturity will require operator-facing interfaces, override mechanisms, and ISO 23247-aligned integration to be designed together rather than added after model development. Multi-agent line-level studies [18] suggest a possible route forward, but they still rarely provide detailed standardisation evidence.

8. Energy and Resource Optimisation

Energy and resource optimisation is the least developed of the five scenarios. The difficulty lies not only in energy metering, but also in attributing savings to a specific twin capability in multi-process manufacturing environments. Most work remains descriptive or predictive, with fewer studies reaching prescriptive control. Resman et al. [4] show that discrete-event twins integrated with quality inspection systems can increase good-piece rate from 71% to 93% and reduce waste through inspection-placement decisions. This indicates that sustainability benefits may arise indirectly from quality and inspection optimisation rather than from energy analytics alone. Vatankhah Barenji et al. [29] provide one of the clearer examples of prescriptive energy control in a robotic cell, but factory-wide or multi-machine demonstrations remain rare. Higher maturity in this scenario will require tighter coupling between high-frequency energy models, process controllers, and standardised KPIs aligned with energy-management practices.

Across scenarios, the most convincing studies combine three forms of evidence: a defined capability band, standard-aware data integration, and numerical KPI movement. Simulation-validated scheduling and sustainability studies [4, 17] and OPC-linked machining twins [5] provide relatively strong engineering evidence. By contrast, prescriptive reinforcement-learning studies often demonstrate algorithmic promise but omit sufficient detail on standard interfaces, governed release, or plant-level KPI validation [13, 14].

9. Challenges and Future Directions

The transition from descriptive monitoring to predictive analytics is constrained by heterogeneous legacy equipment, sparse failure labels, inconsistent sensor quality, and unsynchronised timestamps. MTConnect adapters, edge preprocessing, and active-learning strategies can mitigate these problems, but only when maintenance and quality workflows are prepared to act on model outputs. Otherwise, improved prediction accuracy does not translate into operational change.

The transition from prediction to prescription is more difficult because it requires trust, governance, and process validity. Offline accuracy is insufficient if operators cannot understand the recommendation or if the model extrapolates beyond safe process limits. PIDD constraints, recalibration routines, diagnostic explanations, and uncertainty bounds can reduce this risk. For example, a prescriptive system should distinguish bearing vibration, tool-offset wear, fixture misalignment, and material-lot variation before recommending a parameter change. Black-box reinforcement-learning policies therefore face adoption barriers even when they perform well in simulation [13, 14].

The transition from decision support to supervised intelligent control introduces additional IT/OT challenges. Low-latency communication, deterministic failover, cybersecurity, version control, audit logs, and operator override must be designed as core system requirements. Verification and validation methods for prescriptive twins remain less mature than established machinery functional-safety practices. Certification, liability, and rollback procedures must be defined before unattended execution can be justified. Multi-DT orchestration also requires clear semantics for resource allocation when different cells report conflicting bottleneck states [17, 18].

Several cross-cutting priorities follow from these barriers. First, digital-thread continuity across PLM, MES, QMS, and service systems should be treated as a prerequisite for higher maturity, not as a documentation exercise. Second, workforce training should develop in parallel with analytics maturity so that operators can interpret, challenge, and improve twin recommendations. Third, SMEs need staged adoption paths: OEE visibility first, targeted predictive maintenance on bottleneck assets second, single-operation prescriptive pilots third, and plant-level coordination only after governance and ROI evidence are established.

Contextual adaptation is also necessary. Discrete manufacturing often emphasises takt time, routing, setup, and tool wear, whereas process industries may prioritise batch traceability, recipe control, and continuous quality drift. The capability bands remain applicable in both settings, but the relevant KPIs and control risks differ. Concept drift and non-stationary production mixes further complicate deployment [30]. Tool wear changes with material batches, ambient conditions affect welding distributions, and operator interventions alter system dynamics. Continuous model validation and retraining pipelines, integrated through the digital thread, are therefore required for sustained maturity across all bands.

Large language models and foundation models offer an emerging opportunity, especially for diagnostic reasoning and early prescriptive decision support. Recent systematic reviews identify three promising pathways: natural-language operator interfaces for querying twin data, automated extraction of FMEA and setup-sheet knowledge from unstructured documents, and LLM-augmented diagnostic reasoning that combines sensor data with process documentation [31]. These functions may be especially useful for SMEs because they lower the cost of custom dashboard development and make prescriptive analytics more accessible. However, LLM-enabled twins should remain recommendation-first unless outputs are constrained by validated process knowledge, audit trails, and human approval.

Future research should prioritise ISO 23247-aligned interface profiles for each capability band [1, 2], convergence with MTConnect and QIF, reusable monitoring architectures across machines [6], human-in-the-loop governance for collaborative cells [3, 15], and KPI-transparent validation protocols published through ASME and NIST channels [32-34]. The central principle should be progressive deployment: advanced AI should first support monitoring, diagnosis, and recommendation before being allowed to influence closed-loop execution.

10. Conclusion

Manufacturing digital twins should be evaluated by the capability they enable and the KPIs they improve, not by algorithmic novelty alone. This review shows that current AI-enabled DT research is concentrated in descriptive monitoring and predictive analytics, while prescriptive decision support and supervised intelligent control are still supported by thinner evidence. It also shows that standard-aware integration and KPI reporting remain inconsistent, even in technically advanced studies.

The proposed capability-maturity lens offers a practical roadmap for moving from shop-floor visibility toward supervised, auditable control. Descriptive monitoring establishes synchronised data visibility; predictive analytics forecasts degradation and quality drift; diagnostic reasoning explains causes and builds operator trust; prescriptive decision support recommends governed actions; and supervised intelligent control coordinates production within explicit safety envelopes. Future progress will depend less on adding more complex models in isolation and more on connecting AI outputs to digital-thread continuity, interoperability standards, human oversight, and measurable manufacturing outcomes.

This review is limited to English-language publications from 2018 to 2026 and includes both journal articles and conference proceedings. It may therefore exclude earlier foundational work, non-English industrial studies, and very recent empirical demonstrations that have not yet undergone peer review. Even with these limitations, the evidence indicates a clear direction for the field: DT maturity should be claimed only when technical capability, integration evidence, governance, and KPI validation are reported together.

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Funding

This research received no external funding.

Conflicts of Interest

The authors declare no conflict of interest.

Acknowledgment

This paper is an output of the science project.