

AI-Driven Digital Twin Frameworks for Predictive Maintenance and Closed-Loop Remote Control in Smart Factories: A Structured Review

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Abstract

The increasing connectivity of industrial machines has changed maintenance from a largely schedule-driven activity into a continuous, data-driven process. Digital Twin (DT) technology supports this transition by providing a dynamic virtual representation of a physical asset that is continually updated using operational data. When artificial intelligence (AI) is embedded within the twin, the resulting system can move beyond visualization to support fault identification, anomaly detection, degradation assessment, Remaining Useful Life (RUL) estimation, and maintenance decision-making. This paper presents a structured review of AI-enabled digital twin approaches for predictive maintenance in smart manufacturing, examined end-to-end across physical sensing, data acquisition, communication, twin synchronization, intelligent analytics, maintenance decision-making, and remote corrective control. Machine learning, deep learning, unsupervised anomaly detection, hybrid and physics-informed models, edge intelligence, federated learning, and generative AI (GenAI) are discussed with respect to their industrial suitability and their bearing on the accessibility of digital-twin maintenance for resource-constrained manufacturers. Particular attention is given to a limitation that remains evident throughout the literature: most reported systems detect or predict abnormal behavior but stop short of converting those predictions into safe, closed-loop actions. The review classifies systems by their progression from monitoring and diagnosis to prediction, prescription, and autonomous control, and introduces a GenAI-Augmented Digital Twin Maturity Evaluation (GADT-ME) framework that scores a system jointly on functional maturity and generative-AI capability. Challenges relating to scarce failure data, latency, cybersecurity, synchronization, explainability, interoperability, computational cost, and deployment cost for small and medium enterprises (SMEs) are also examined. The review concludes that future research should prioritize hybrid edge-cloud intelligence, secure actuation, multi-sensor fusion, interpretable and generative AI, federated learning, and self-healing, accessible industrial systems. **Keywords:** Artificial Intelligence; Digital Twins; Predictive Maintenance; Smart Manufacturing; Closed-Loop Control.

1 INTRODUCTION

Manufacturing systems are progressively becoming more connected, observable, and software-controlled.

Modern production environments integrate sensors, programmable controllers, industrial networks, edge devices, cloud platforms, robotics, and data-analytics services, together forming the technological foundation of

Industry 4.0 and, increasingly, the human-centric and resilience-oriented goals of Industry 5.0 [1], [2].

Maintenance remains one of the most consequential industrial functions because equipment degradation directly affects production continuity, safety, product quality, energy consumption, and operating cost. An unexpected failure in a motor, bearing, conveyor, compressor, robotic arm, or turbine can interrupt an entire production line.

Maintenance strategy has therefore evolved from reactive practice toward preventive, condition-based, predictive, and prescriptive approaches. Reactive maintenance is initiated only after failure and can cause long, unplanned downtime; preventive maintenance reduces this risk through fixed servicing intervals but may service

equipment that is still healthy; and predictive maintenance instead estimates equipment condition from measured

operating data, allowing degradation to be identified before a functional failure occurs [1].

Digital Twin technology extends this idea by maintaining a virtual representation that stays continuously synchronized with its physical counterpart through data exchange. Measurements such as vibration, temperature,

current, rotational speed, pressure, load, acoustic emission, and energy consumption update the virtual

representation in near real time [2], [5]. Artificial intelligence adds a further layer of functionality: machine-learning algorithms recognize fault patterns, estimate equipment health, and forecast degradation, while deep

neural networks can learn temporal or spectral characteristics directly from raw sensor data. Most recently, generative AI (GenAI) — including large language models, diffusion models, and generative adversarial networks

— has begun to augment this pipeline by synthesizing rare-failure data, producing natural-language explanations

of twin state, and drafting maintenance recommendations, a direction discussed in detail in Section VII-A [26]—

[31].

1.1 The Research Gap

Despite this progress, the maturity of digital-twin-based maintenance systems remains uneven. Monitoring, diagnosis, and prediction have received substantial research attention, whereas closed-loop response is demonstrated far less often. Predicting that a bearing, motor, or production asset is approaching an unsafe state is useful, but prediction alone cannot prevent failure. A practical maintenance system must also determine what action should follow, how quickly that action must be executed, whether it can be performed safely, and — increasingly — whether an operator without deep AI expertise can trust and act on the twin's output. Three specific gaps motivate this review:

- Prediction-to-action gap: reported systems overwhelmingly stop at alarms or dashboards; validated end-

to-end pipelines that carry a prediction through decision-making to safe remote actuation are comparatively rare (Section XIII-A).

- Evaluation gap: existing maturity taxonomies classify digital twins by functional level (monitoring through

autonomous control) but do not yet account for the rapidly growing role of generative AI within each level, making it difficult to compare a GenAI-assisted diagnostic twin against a conventional one on common terms.

- Accessibility gap: the literature on AI-enabled digital twins is dominated by large-enterprise deployments

with substantial sensor, cloud, and engineering budgets; comparatively little synthesis connects predictive-maintenance capability with the low-cost, low-expertise constraints faced by small and medium manufacturing enterprises (SMEs) [32]–[34].

The distinguishing perspective of this review is therefore to treat predictive maintenance as an end-to-end cyber-physical feedback process — not solely as a machine-learning problem — and to evaluate that process jointly on

functional maturity, generative-AI contribution, and practical accessibility.

1.2 Contributions

The major contributions of this revised review are:

- A structured classification of AI-enabled digital twin maintenance systems according to sensing modality,

AI technique, deployment architecture, digital-twin capability, and control level.

- A comparative discussion of machine learning, deep learning, unsupervised anomaly detection, hybrid AI,

physics-informed approaches, edge intelligence, and generative AI.

- A functional maturity taxonomy separating monitoring, diagnostic, predictive, prescriptive, and

autonomous digital twins.

- A new GenAI-Augmented Digital Twin Maturity Evaluation (GADT-ME) framework that scores systems

jointly on functional maturity and generative-AI capability (Section XV).

- An examination of the transition from fault prediction to remote corrective action and closed-loop

maintenance, including its practical implications for plant operators (Section XVI).

- Identification of major technical barriers, including limited industrial failure data, latency, cybersecurity,

explainability, synchronization, interoperability, computational demand, and deployment cost for SMEs.

- A synthesis of emerging research directions involving edge-cloud intelligence, federated learning,

explainable and generative AI, multi-sensor fusion, secure control, and self-healing, accessible systems.

2 EVOLUTION OF INDUSTRIAL MAINTENANCE

Industrial maintenance strategies can be viewed as a progression from failure response toward intelligent intervention.

2.1 Reactive Maintenance

Reactive, or breakdown, maintenance is performed only after a component has failed. It requires little initial monitoring infrastructure but can produce unpredictable repair costs and prolonged equipment downtime.

2.2 Preventive Maintenance

Preventive maintenance schedules inspection or replacement according to time, operating cycles, or manufacturer recommendations. It reduces the probability of sudden breakdown but may also result in premature servicing of components that remain healthy.

3 Condition-Based Maintenance

Condition-based maintenance continuously observes equipment variables and triggers maintenance when measurements indicate deterioration. This approach depends strongly on sensor quality and on appropriate threshold selection.

3.1 Predictive Maintenance

Predictive maintenance estimates future machine condition from historical and real-time observations. Statistical analysis, machine learning, signal processing, and deep learning can each be used to estimate fault probability or remaining useful life.

Table 1: Comparison of Industrial Maintenance Strategies

Strategy	Operating Principle	Primary Limitation
Reactive	Repair after equipment failure	High downtime and unpredictable repair cost
Preventive	Maintenance at predetermined intervals	Healthy components may be serviced unnecessarily
Condition-based	Maintenance based on monitored condition	Requires reliable sensing and threshold selection
Predictive	Future degradation estimated using data models	Requires representative historical or operational data
Prescriptive	System recommends a corrective maintenance action	Decision quality and explainability become critical
Autonomous	Corrective response may be automatically executed	Requires trustworthy AI and secure closed-loop control

3.2 Prescriptive and Autonomous Maintenance

Prescriptive maintenance extends prediction by recommending a specific response. Autonomous maintenance closes the feedback loop further still by executing an approved corrective action without requiring continuous human intervention.

4 DIGITAL TWIN TECHNOLOGY

Digital Twin (DT) technology provides a continuously updated virtual representation of a physical asset, process, or system. In smart manufacturing, measurements such as vibration, temperature, current, rotational speed, pressure, load, acoustic emission, and energy consumption can be transferred from the physical environment to the virtual representation. The resulting twin can support condition monitoring, fault identification, degradation assessment, predictive maintenance, and maintenance decision-making [2], [5]. The level of representation may range from an individual component to a complete manufacturing system.

4.1 Component or Product Twin

A component or product twin represents an individual physical asset, component, or manufactured product. Typical examples include bearings, motors, gears, pumps, robotic arms, conveyor components, and turbine elements. The twin is updated using measurements from sensors attached to the corresponding physical object. For example, vibration, temperature, rotational speed, and load measurements from a motor bearing can be used to estimate its current health state and identify changes that may indicate degradation. In predictive maintenance, the component twin therefore provides an asset-level view of condition and supports early fault detection and remaining-useful-life estimation.

4.2 Process Twin

A process twin represents a manufacturing process or a sequence of operations rather than a single physical component. It can describe relationships among processing stages and monitor variables such as production rate, temperature, pressure, energy consumption, machine utilization, processing time, and product quality. A process twin can therefore help identify how changes in one stage affect subsequent stages. For predictive maintenance, combining process information with equipment measurements can provide additional context when an abnormal operating condition is detected.

4.3 System Twin

A system twin represents an interconnected manufacturing system, production line, or group of cooperating machines. It can integrate information from machines, robots, conveyors, controllers, sensors, and other industrial assets. This system-level representation is important because degradation in one asset can influence downstream or upstream operations. For example, deterioration of a conveyor motor may change material flow and subsequently affect the operation of downstream equipment. A system twin can represent these dependencies and support system-level diagnosis, prediction, and maintenance planning.

5 INDUSTRIAL IOT AND SENSOR INFRASTRUCTURE

Industrial Internet of Things (IIoT) infrastructure provides the sensing and communication foundation required to keep a Digital Twin synchronized with the physical environment. Sensors continuously collect operational measurements, while industrial communication networks transfer these observations to edge, local, or cloud processing resources. Typical measurements include vibration for rotating-component condition, temperature for thermal abnormalities, current for motor and load behavior, pressure for pumps and compressors, rotational speed for operating-state changes, acoustic emissions for mechanical damage, and energy consumption for efficiency and equipment-state analysis.

The resulting data flow can be represented as: *physical machine* → *sensors* → *data acquisition* → *communication network* → *Digital Twin* → *AI analytics*. Reliable sensing, synchronization, communication, and data quality are therefore prerequisites for trustworthy AI-driven maintenance. Noise, missing observations, sensor drift, communication delay, and sensor failure can propagate uncertainty into the twin and subsequently affect maintenance decisions.

6 ARTIFICIAL INTELLIGENCE FOR PREDICTIVE MAINTENANCE

Artificial Intelligence (AI) adds analytical capability to the Digital Twin by learning patterns from historical and real-time operational data. Depending on the objective

and available data, AI can be used for anomaly detection, fault diagnosis, equipment-health assessment, degradation forecasting, Remaining Useful Life (RUL) estimation, and maintenance decision support. The principal approaches considered in this review are traditional machine learning, deep learning, unsupervised anomaly detection, and hybrid or physics-informed models. Generative AI is discussed separately as an emerging augmentation layer for explanation, data generation, and maintenance assistance.

6.1 Traditional Machine Learning

Traditional machine-learning methods generally operate on structured or engineered features extracted from sensor measurements. Decision trees, random forests, support vector machines, and regression models can be used for fault classification, health-state classification, and predictive modelling. A typical pipeline converts measurements such as vibration, temperature, current, rotational speed, and load into features that are supplied to a trained model. The model then produces an estimated equipment state or fault class.

These methods can be comparatively interpretable and can perform effectively with moderate-sized structured datasets. Random forests can provide nonlinear modelling and feature-importance information, while support vector machines can be effective for classification with appropriately selected feature sets. However, performance may depend strongly on feature engineering, data quality, and operating-condition coverage. The AI-method comparison in Table 2 summarizes these characteristics.

6.2 Deep Learning

Deep-learning models use multiple neural-network layers to learn complex representations from sensor and time-series data. Convolutional Neural Networks (CNNs) can process vibration signals or transformed representations such as spectrograms, while Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) networks are suited to sequential degradation patterns. Autoencoders can also learn compact representations of normal operating behavior.

For predictive maintenance, deep learning can learn temporal, spectral, or nonlinear relationships that may be difficult to capture through manually engineered features. For example, an LSTM or GRU model can use a sequence of historical measurements to estimate future equipment condition or RUL. The principal limitations are the need for representative training data, computational resources, careful model tuning, and additional techniques when interpretability is required.

6.3 Unsupervised Anomaly Detection

Unsupervised anomaly detection is particularly relevant when labelled failure examples are scarce. Industrial equipment may generate large volumes of normal operating data while actual failures remain relatively rare. Instead of requiring a large set of labelled fault examples, an unsupervised model can learn the characteristics of normal operation and flag observations that deviate substantially from that learned pattern.

Autoencoders and Isolation Forests are examples considered in this review. An autoencoder learns to reconstruct normal sensor patterns; a large reconstruction error can indicate a potential anomaly. Isolation Forests identify observations that are relatively easy to isolate from the majority of the data. This approach can reduce dependence on labelled failure datasets, but the selection and calibration of anomaly thresholds remain important challenges. An anomaly should therefore be interpreted together with operating context rather than treated automatically as a confirmed failure.

6.4 Hybrid and Physics-Informed Models

Hybrid and physics-informed approaches combine data-driven AI with engineering knowledge or physical models. A purely data-driven model learns relationships from observations, whereas a physics-informed approach can incorporate known relationships governing mechanical, thermal, electrical, or degradation behavior. The combination is useful when industrial failure data are limited or when physically meaningful constraints are important.

For example, a bearing-degradation model may combine vibration and temperature observations with engineering knowledge about load, friction, thermal effects, or degradation mechanisms. Such a model can be used for degradation assessment and RUL estimation while constraining predictions toward physically plausible behavior. Hybrid approaches can therefore improve physical consistency and may support better generalization when training data do not cover all operating conditions. Their limitation is that an appropriate physical model or engineering relationship must be available and correctly specified.

6.5 Generative AI

Generative AI (GenAI) is an emerging augmentation layer for Digital Twin maintenance systems. Generative models can support rare-failure data augmentation, natural-language explanation of twin states, maintenance-recommendation drafting, and operator assistance. In this role, GenAI complements rather than automatically replaces the predictive models responsible for detection or forecasting. Because generated outputs may contain errors or unsupported recommendations, guardrails, validation, uncertainty information, and human or control-system oversight are required before generated content is allowed to influence physical actuation [26]–[31].

7 REVIEW METHODOLOGY

This study uses a structured evidence-mapping approach to synthesize research on artificial intelligence (AI)-enabled digital twins (DTs) for predictive maintenance and closed-loop maintenance. The review is organized around predefined research questions, an explicit eligibility framework, thematic evidence mapping, bibliographic verification, and conservative maturity coding. It is intentionally reported as a *structured review* rather than a PRISMA-compliant systematic review because a contemporaneous database-export and screening log was not retained for the present evidence set. Accordingly, no

Table 2: Comparison of AI Methods for Predictive Maintenance

Method	Typical Application	Application	Strength	Limitation
Decision Tree	Fault classification	classification	Simple and interpretable	May overfit noisy training data
Random Forest	Fault health classification	diagnosis, classification	Robust nonlinear modeling, feature importance	Larger ensembles increase computational cost
SVM	Fault classification	classification	Effective with moderate feature sets	Training expensive for large datasets
CNN	Signal/spectrogram analysis		Automatic feature learning	Requires sufficient labelled data
LSTM/GRU	Temporal degradation, RUL prediction		Captures sequential dependencies	Training cost and tuning complexity
Autoencoder	Unsupervised anomaly detection	anomaly detection	No large labelled fault dataset required	Anomaly threshold selection is difficult
Isolation Forest	Tabular anomaly detection	anomaly detection	Computationally efficient	Limited temporal representation
Physics-Informed AI	Degradation and RUL modeling		Combines engineering knowledge and data	Requires an appropriate physical model
Generative AI	Data augmentation, explanation, recommendation drafting		Mitigates data scarcity; improves operator trust and accessibility	Hallucination risk; needs guardrails before acting on output

database retrieval, deduplication, screening, or PRISMA counts are inferred from the final evidence matrix.

7.1 Review Protocol and Reproducibility

To improve methodological transparency, the review protocol specifies the information sources, conceptual search terms, eligibility criteria, evidence categories, bibliographic verification procedure, and maturity-coding rules used in the evidence map. These elements define a reproducible analytical framework without reconstructing unsupported retrieval or screening statistics. The original contemporaneous database-export and screening files were not retained; therefore, the manuscript does not report reconstructed numbers for database retrieval, duplicate removal, title/abstract screening, full-text exclusion, or final inclusion. Such numbers would not be auditable from the available evidence and are consequently not inferred. The reproducibility of the present study should therefore be understood at the level of the documented protocol and coding framework. Another researcher can reproduce the intended search concepts, apply the stated eligibility rules, verify bibliographic records, and repeat the GADT-ME classification procedure. For a future update requiring formal systematic-review reporting, the searches should be re-executed and archived with database-specific search strings, execution dates, exported records, deduplication procedures, screening decisions, exclusion reasons, and the final included-study set. This distinction is maintained throughout the manuscript so that methodological transparency is strengthened without overstating the evidentiary basis of the current review.

7.2 Research Questions

The review is guided by five questions:

- 1. **RQ1:** Which AI and machine-learning techniques are being integrated with digital twins for predictive

maintenance and prognostics?

- 2. **RQ2:** How are digital-twin systems evolving from condition monitoring and fault diagnosis toward prediction, prescription, and autonomous maintenance?
- 3. **RQ3:** Which sensing, communication, digital-twin, analytics, decision, and actuation components are required to support closed-loop predictive maintenance?
- 4. **RQ4:** What technical and operational barriers limit deployment, particularly with respect to data availability, latency, cybersecurity, explainability, interoperability, scalability, and cost?
- 5. **RQ5:** What emerging opportunities, including edge-cloud intelligence, federated learning, physics-informed AI, and generative AI, can strengthen digital-twin-based predictive maintenance and decision support?

7.3 Information Sources and Search Protocol

The review protocol was structured around five bibliographic and scholarly information sources: Scopus, Web of Science Core Collection, IEEE Xplore, ScienceDirect, and SpringerLink. Publisher webpages and DOI/index records were used for bibliographic verification and DOI resolution. The protocol was designed to be reproducible at the level of databases, concepts, eligibility rules, and coding variables. Importantly, the present manuscript does not retrospectively report database retrieval counts, duplicate counts, or screening counts because the contemporaneous database-export and screening log for the evidence set was not retained. No such counts are reconstructed from the final reference list.

The conceptual search was organized into four term blocks:

- 1. **Digital-twin block (A):** “digital twin”, “digital twins”, “virtual twin”, “digital replica”;
- 2. **Maintenance block (B):** “predictive maintenance”, “condition monitoring”, “fault diagnosis”, “prognostics”, “remaining useful life”, “prescriptive maintenance”;
- 3. **AI block (C):** “artificial intelligence”, “machine learning”, “deep learning”, “anomaly detection”, “physics-informed”, “reinforcement learning”, “generative AI”;
- 4. **Control/deployment block (D):** “closed-loop”, “remote control”, “autonomous maintenance”, “edge AI”, “industrial IoT”.

The core conceptual expression was defined as (A) AND (B) AND (C), with block (D) used as an additional refinement when the database supported sufficiently specific control/deployment fields. To support reproducibility, the database adaptations were defined as follows:

- **Scopus:** TITLE-ABS-KEY search across the four conceptual blocks.

- **Web of Science:** Topic (TS) search using the same four blocks with database-specific field syntax.
- **IEEE Xplore:** Metadata/All Metadata search using the same concepts, with phrase searching where supported.
- **ScienceDirect:** Title, abstract, and keyword-oriented search using the same concepts.
- **SpringerLink:** Article metadata/full-text search using the same concepts, followed by relevance screening.

The evidence map covers literature from **2019 through 2026**, reflecting the period represented by the primary-study matrix, and prioritizes peer-reviewed journal articles and conference papers. The intended language criterion is English. Records were eligible when they addressed AI-enabled digital twins in predictive maintenance, prognostics, fault diagnosis, maintenance optimization, or closed-loop maintenance/control, or when they provided a directly relevant enabling architecture or technology. Review and survey papers were retained for contextual synthesis but excluded from the primary-study maturity denominator.

Because the original database execution logs were not retained, the database names, conceptual terms, eligibility rules, and coding protocol above should be interpreted as the *documented review protocol* rather than as a claim that a complete database export and screening sequence was reconstructed. This distinction is maintained throughout the manuscript to avoid introducing unsupported retrieval or screening numbers. If a future revision is required to meet a journal's formal systematic-review reporting standard, the searches should be re-executed using the protocol above, with the exact execution dates, database-specific strings, retrieved records, deduplication, screening decisions, and final included set archived as supplementary material.

7.4 Eligibility and Study Classification

The evidence map prioritizes peer-reviewed journal articles and conference papers directly relevant to AI-enabled digital twins, predictive maintenance, prognostics, fault diagnosis, maintenance optimization, or closed-loop maintenance. Records were retained when the title, bibliographic identity (including DOI or publisher/index record), and topical relevance could be established. Review/context papers were retained for landscape synthesis but were not treated as empirical primary evidence. Framework/architecture papers were retained for conceptual and system-design analysis, while adjacent/technical papers were retained only when they provided an enabling technology materially relevant to the review questions.

Primary studies provide an empirical or implementation-oriented contribution. Framework/architecture studies describe reference architectures or methodologies. Adjacent/technical studies address enabling sensing, process-control, communication, or related infrastructure. Review/context studies synthesize previous literature. Bibliographic identification is kept separate from full-text evidence coding; records whose full-text capability could not be independently established

are not presented as stronger evidence than the available source supports.

7.5 Study Selection and Evidence Coding

Selection was conducted at the evidence-map level using the predefined eligibility categories and bibliographic verification criteria. Each retained record was coded for publication year, title, venue, DOI, AI method, application domain, maintenance task, evidence type, and quality. Primary/implementation records were additionally coded on the GADT-ME maturity dimensions. The DOI verification register records the bibliographic verification status and the evidence basis used for maturity coding.

The evidence-coding workflow followed five stages: (1) identify a candidate record from the defined literature sources or cited literature; (2) verify title, venue, year, and DOI against a publisher or DOI/index record; (3) classify the record as primary/implementation, framework/architecture, adjacent/technical, or review/context; (4) extract the AI method, application domain, maintenance task, and evidence quality; and (5) assign GADT-ME maturity codes only where the available evidence supports the classification. Where full-text evidence could not be independently established, the record was not upgraded beyond what the available publisher/index evidence supports.

The primary evidence matrix and the separate review/survey matrix provide the audit trail for the synthesis. The DOI-Based Reference Verification Register provides a second bibliographic audit layer. These three representations are intentionally separated so that bibliographic completeness, evidence classification, and maturity coding are not conflated.

7.6 Literature Synthesis

The literature was synthesized using qualitative thematic comparison and evidence mapping rather than statistical meta-analysis. Primary studies were compared across AI method, domain, maintenance task, architectural role, and maturity. Review and survey studies were analyzed separately so that secondary evidence did not enter the primary-study maturity calculations. The synthesis compares five functional stages: monitoring, diagnosis, prediction/prognostics, prescription/optimization, and autonomous maintenance/control.

7.7 Maturity Coding Protocol

For the GADT-ME analysis, each primary/implementation record was assigned a functional maturity code and a generative-AI capability code only when the available evidence supported the classification. The functional axis is M1 (monitoring), M2 (diagnostic/anomaly identification), M3 (prediction/prognostics), M4 (prescriptive decision-making or maintenance optimization), and M5 (validated autonomous maintenance/control). The generative-AI axis is G0 (no demonstrated generative-AI capability), G1 (generative-AI augmentation), G2 (generative-AI co-pilot), and G3 (generative-AI-enabled actuation). Records without a demonstrated maturity stage are coded NR and excluded from the maturity denominator.

The coding is conservative: prediction is not upgraded to M4 unless a maintenance recommendation, optimization, or scheduling function is demonstrated; an architecture is not upgraded to M5 unless autonomous corrective action is demonstrated; and conventional neural networks or autoencoders are not treated as GenAI merely because they are generative models in the broad machine-learning sense. The 2025 “Generative and Predictive AI for digital twin systems in manufacturing” study is coded M3/G1 because the published study demonstrates predictive/quality capabilities together with generative-AI augmentation, while agentic autonomous control is described as future work. The “Investigating determinants of digital twins for predictive maintenance” study is coded NR/NR because it evaluates implementation determinants rather than demonstrating a maintenance maturity stage. The 2025 Industry 5.0 ML study is coded M3/G0 because its documented contribution is predictive maintenance using ML without demonstrated GenAI capability.

Of the 35 records in the primary matrix, 34 provide a maturity-stage code and one is NR. The resulting maturity distribution is M1: 2 (5.9%), M2: 6 (17.6%), M3: 23 (67.6%), M4: 3 (8.8%), and M5: 0. The GenAI distribution is G0: 33 (97.1%), G1: 1 (2.9%), G2: 0, and G3: 0. These percentages describe the evidence map and are not meta-analytic effect estimates.

7.8 Generative AI in Digital Twins (2025–2026 developments)

Generative AI (GenAI) is emerging as an augmentation layer for digital-twin systems rather than a replacement for established predictive-maintenance models. Recent work considers large language models and other generative techniques for synthesizing scarce or rare-failure data, explaining equipment condition in natural language, assisting maintenance planning, and supporting operator interaction with complex twin states. In a manufacturing setting, a GenAI component can translate model outputs such as anomaly scores, health indices, or predicted failure probabilities into structured maintenance explanations and recommendations while the underlying numerical prediction remains the responsibility of validated analytical models [26]–[31].

The evidence mapped in this review indicates that GenAI capability is still at an early stage relative to conventional AI-enabled predictive maintenance. Most identified systems remain focused on monitoring, diagnosis, or prediction, while validated GenAI-enabled actuation is not yet demonstrated in the primary evidence set. Accordingly, the GADT-ME framework treats GenAI augmentation, co-pilot functionality, and GenAI-enabled actuation as distinct capability levels. This separation is important because natural-language generation or data synthesis alone should not be interpreted as autonomous industrial control. Safety constraints, human oversight, verification, and secure interfaces remain necessary before generated recommendations can influence physical equipment.

8 TAXONOMY OF AI-ENABLED DIGITAL TWIN SYSTEMS

8.1 Classification by Sensor Modality

AI-enabled digital twins can be classified according to the type and combination of sensor information used to update the virtual representation. Common modalities include vibration, temperature, current, pressure, rotational speed, acoustic emission, energy consumption, and process-quality measurements. Single-modality twins focus on one dominant signal, whereas multi-sensor twins combine complementary observations to obtain a more complete representation of equipment condition.

Multi-sensor integration is particularly useful when different failure mechanisms produce different observable signatures. For example, vibration can reveal mechanical abnormalities while temperature and current provide additional thermal and electrical context. Sensor fusion can therefore improve the robustness of condition assessment, although synchronization, missing values, noise, and sensor reliability must be managed explicitly.

8.2 Classification by Intelligence

Digital-twin systems can also be classified according to the level of intelligence applied to the synchronized data. At the basic level, the twin supports monitoring and visualization. Higher levels introduce anomaly detection and diagnosis, predictive models for degradation and RUL, prescriptive optimization, and eventually autonomous maintenance or control. AI methods may include traditional machine learning, deep learning, unsupervised detection, hybrid models, physics-informed learning, reinforcement learning, and generative AI.

This classification complements the GADT-ME maturity model used in this review. The distinction is important because the presence of an AI algorithm does not by itself indicate that a twin performs predictive or autonomous maintenance. The functional role of the AI within the end-to-end system must be established.

9 Classification by Twin Function

Digital twins can be differentiated by the primary function they perform in the maintenance workflow. A component or product twin focuses on an individual asset; a process twin represents a manufacturing process; and a system twin represents interacting machines and production resources. From a maintenance perspective, the functional role may further progress from monitoring and diagnosis to prediction, prescription, and autonomous control.

This functional classification provides a bridge between the physical scope of the twin and the intelligence applied to it. It also supports comparison of studies that use different manufacturing domains but address similar maintenance functions.

9.1 Classification by Deployment

Deployment architecture describes where sensing, Digital Twin synchronization, AI inference, and decision-making are executed. Cloud-based deployment provides scalable

computing and centralized data management, whereas edge deployment places processing close to the physical equipment to reduce communication delay. Hybrid edge-cloud architectures distribute tasks between local and remote resources.

For closed-loop maintenance, deployment location directly affects latency, connectivity, privacy, and computational constraints. Time-critical anomaly detection or safety-related responses may require local processing, while model training, historical analysis, and large-scale fleet analytics can be performed in cloud infrastructure.

10 REFERENCE ARCHITECTURE FOR AI-DRIVEN PREDICTIVE MAINTENANCE

10.1 Physical Asset Layer

The physical asset layer contains the machines, components, production lines, robots, actuators, and other equipment whose condition is represented by the Digital Twin. This layer is the source of the physical state that the virtual model seeks to represent. Typical assets include motors, bearings, pumps, conveyors, robotic arms, turbines, and manufacturing machines.

Maintenance actions ultimately affect this layer. Consequently, any closed-loop architecture must maintain a clear relationship between predicted equipment state, authorized maintenance decisions, and the physical action applied to the asset.

10.2 Sensing Layer

The sensing layer captures measurements from the physical asset using industrial sensors and data-acquisition devices. Vibration, temperature, current, pressure, speed, load, acoustic emission, and energy measurements provide observations of operating condition. The quality of these observations determines the reliability of subsequent Digital Twin and AI functions.

Sensor calibration, synchronization, redundancy, missing-data handling, and fault detection are therefore essential. A sensor failure or systematic drift can otherwise be interpreted incorrectly as equipment degradation.

11 Communication Layer

The communication layer transfers measurements and control information between physical equipment, edge devices, Digital Twin services, AI models, and actuation systems. Industrial networks and messaging infrastructures provide the connectivity required for continuous synchronization.

Communication latency and packet loss are particularly important in closed-loop predictive maintenance. A technically accurate prediction may still be operationally ineffective if the information arrives too late for the required intervention. Communication security is also essential because unauthorized modification of sensor data or control commands can affect physical equipment.

11.1 Digital Twin Layer

The Digital Twin layer maintains the virtual representation of the physical asset or system and updates it as new observations arrive. It provides the state representation used by downstream analytics and can maintain historical information needed to understand degradation trends.

The twin should preserve synchronization between physical and virtual states while representing relevant operating context. In predictive maintenance, this layer connects raw industrial observations with higher-level asset-health and maintenance information.

11.2 AI Analytics Layer

The AI analytics layer transforms synchronized Digital Twin data into maintenance-related intelligence. Depending on the application, it can perform anomaly detection, fault diagnosis, health estimation, degradation prediction, RUL estimation, or maintenance optimization.

Different models can be combined within this layer. For example, an unsupervised detector may identify an abnormal operating condition, followed by a supervised or deep-learning model that estimates the likely fault or future degradation. Hybrid and physics-informed models can provide additional engineering constraints.

11.3 Decision and Actuation Layer

The decision and actuation layer converts analytical results into maintenance actions. At lower maturity levels, the output may be an alarm or operator notification. At higher levels, the system may recommend inspection, maintenance scheduling, parameter adjustment, or another corrective response. Autonomous operation requires an additional level of validation and secure authorization before commands reach physical equipment.

The distinction between prediction and action is central to this review. A prediction becomes part of a closed-loop system only when its output is connected to a validated decision process and, where appropriate, a controlled physical response.

12 MATHEMATICAL FOUNDATIONS

12.1 Digital Twin State

The Digital Twin state can be represented by a vector of variables describing the current condition and operating context of the physical system. A generic state representation is

$$\mathbf{x}_t = [x_{1,t}, x_{2,t}, \dots, x_{n,t}]^T, \quad (1)$$

where each component may represent a measured or estimated quantity such as temperature, vibration, speed, load, health index, or other relevant state variable at time t . The state is updated as new sensor observations become available.

The quality of this state representation depends on sensor coverage, synchronization, preprocessing, and the ability of the twin to retain relevant temporal information. AI models use the resulting state or a sequence of states as input for diagnosis, prediction, or decision support.

Fig. 1. Closed-loop architecture of an AI-driven digital twin maintenance system

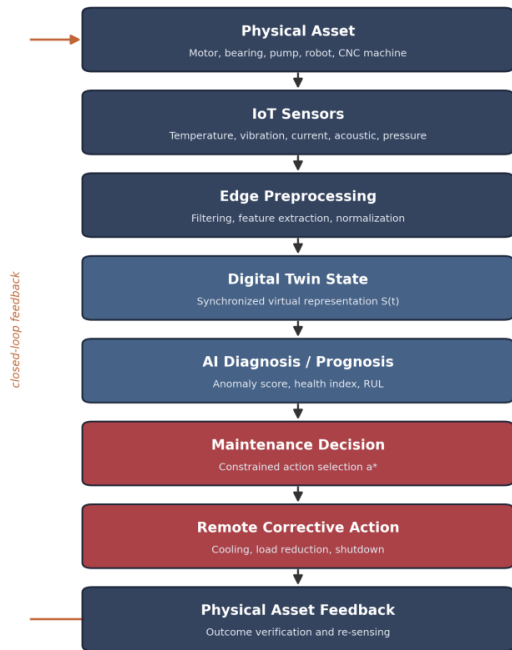


Figure 1: Closed-loop architecture of an AI-driven digital twin maintenance system. Each stage feeds forward into the next; outcome verification closes the loop back to the physical asset.

12.2 Feature Normalization

Sensor variables can have very different numerical ranges and units. Feature normalization reduces scale differences before model training or inference. A common min-max transformation is

$$x' = \frac{x - x_{\min}}{x_{\max} - x_{\min}}, \quad (2)$$

which maps a feature to a defined range when the minimum and maximum values are known. Standardization can alternatively be used when a zero-mean, unit-variance representation is appropriate.

Consistent preprocessing is important because changes in scaling between training and deployment can alter model behavior. Normalization parameters should therefore be derived from the training procedure and applied consistently during operational inference.

13 Health Index

A health index (HI) provides a compact representation of equipment condition derived from one or more sensor variables or model outputs. It can combine vibration, temperature, current, operating load, and other indicators into a value that changes as equipment condition evolves.

The HI is useful for Digital Twin maintenance because it provides a common state variable for visualization, trend analysis, degradation modelling, and RUL estimation. Its interpretation should remain consistent across operating conditions; otherwise changes in load or environment may be mistaken for degradation.

13.1 Remaining Useful Life

Remaining Useful Life (RUL) represents the estimated amount of useful operating time remaining before an asset reaches a defined failure or maintenance threshold. An AI model can estimate RUL from historical degradation trajectories, current operating state, and contextual variables.

RUL estimation is particularly useful for maintenance planning because it connects condition prediction with scheduling decisions. However, the estimate is uncertain and should be interpreted together with confidence information and operating context rather than as an exact failure time.

13.2 Failure Probability

Failure probability represents the estimated likelihood that an asset will enter a defined failure state within a specified prediction horizon. A generic formulation can be written as

$$P(F_{t+h} = 1 \mid \mathbf{x}_{1:t}), \quad (3)$$

where F_{t+h} denotes failure within the future horizon and $\mathbf{x}_{1:t}$ represents observations available up to time t .

This measure supports risk-based maintenance decisions. The prediction horizon and failure definition must be stated clearly because a probability without a time window is difficult to interpret operationally.

13.3 Z-Score Anomaly Detection

The z-score measures how far an observation is from the mean in units of standard deviation. It can be used as a simple statistical anomaly indicator when the monitored variable has a reasonably stable reference distribution.

For an observation x , mean μ , and standard deviation σ , the standardized score is

$$z = \frac{x - \mu}{\sigma}. \quad (4)$$

Large positive or negative values indicate observations that are far from the reference behavior. In industrial applications, the threshold should be calibrated using operating context because normal changes in load or speed can also produce large standardized values.

13.4 Autoencoder Anomaly Score

An autoencoder learns to reconstruct input observations. When trained primarily on normal operating data, it should reconstruct familiar patterns with relatively small error. The reconstruction error can therefore be used as an anomaly score.

For an input vector $\mathbf{x}$ and reconstructed vector $\hat{\mathbf{x}}$, a mean-squared reconstruction score can be expressed as

$$E = \frac{1}{n} \sum_{i=1}^n (x_i - \hat{x}_i)^2. \quad (5)$$

A sufficiently large value of E can trigger an anomaly flag. Threshold calibration and changing operating conditions remain important limitations.

Table 3: Comparative Analysis of Predictive Maintenance Approaches

Approach	Data Need	Interpretability	Real-Time Suitability	Main Limitation
Rule-Based	Low	High	Very High	Cannot learn complex degradation behavior
Traditional ML	Medium	Medium–High	High	Depends strongly on engineered features
Deep Learning	High	Low	Medium	Large datasets and compute required
Unsupervised Detection	Medium	Medium	High	Threshold calibration can be difficult
Cloud AI Digital Twin	High	Medium	Medium	Network latency, connectivity, privacy concerns
Edge AI Digital Twin	Medium	Medium	Very High	Limited edge memory and processing capacity
Hybrid Edge–Cloud Twin	Medium–High	Medium	High	Greater orchestration and synchronization complexity

13.5 Total Closed-Loop Latency

Closed-loop latency is the elapsed time between sensing a relevant physical change and completing the corresponding validated response. It can be considered as the combined delay of sensing, data transfer, Digital Twin synchronization, AI inference, decision-making, communication, and actuation.

A simplified representation is

$$T_{total} = T_{sense} + T_{comm} + T_{twin} + T_{AI} + T_{decision} + T_{actuation} \tag{6}$$

Reducing this latency is particularly important when equipment condition can deteriorate rapidly. Edge or hybrid architectures can reduce communication and inference delays, but they introduce additional resource-management and synchronization requirements.

14 COMPARATIVE ANALYSIS

15 CLOSED-LOOP PREDICTIVE MAINTENANCE

Closed-loop predictive maintenance extends conventional predictive maintenance by connecting prediction to a validated decision and, where authorized, to corrective action. The overall sequence can be represented as physical observation → sensing → Digital Twin synchronization → AI prediction → decision → actuation → outcome verification.

Most predictive-maintenance systems reported in the evidence map stop at monitoring, diagnosis, prediction, or an operator alarm. A closed-loop system must additionally determine what action should follow, verify that the action is safe and appropriate, and observe the resulting equipment state. This prediction-to-action transition is therefore a central research gap identified by the review. Human approval can remain in the loop for maintenance actions that require additional operational or safety authorization.

16 CHALLENGES AND RE-SEARCH GAPS

The evidence map identifies several barriers to dependable AI-driven Digital Twin maintenance. These include limited validation of closed-loop actuation, scarcity of real failure data, domain shift, latency, sensor reliability, cybersecurity, explainability, interoperability, and deployment cost. These challenges affect not only model accuracy but also the ability to move from laboratory demonstrations to reliable industrial operation.

16.1 Limited Closed-Loop Validation

A major gap is the limited number of studies that demonstrate an end-to-end path from fault prediction to safe physical response. Many systems generate an alarm, health estimate, or RUL value without validating the subsequent maintenance action. Future studies should therefore report decision logic, actuation constraints, response latency, safety mechanisms, and outcome verification rather than evaluating prediction accuracy alone.

16.2 Scarcity of Industrial Failure Data

Real industrial failures are relatively rare and may be costly or unsafe to reproduce. Consequently, many datasets contain abundant normal observations but comparatively few labelled failure events. Synthetic data generation, transfer learning, self-supervised learning, federated learning, and carefully validated generative methods can help address this limitation, but synthetic observations should not be assumed to represent real failure mechanisms without validation.

17 Domain Shift

AI models trained under one machine configuration, load profile, environment, or operating regime may perform differently when deployed under another. This domain-shift problem is especially relevant to Digital Twins because the physical system may change over time and because twins can be transferred across machines or production environments. Continual learning, domain adaptation, transfer learning, and explicit operating-context representation can help maintain model reliability.

17.1 Latency

Prediction and intervention are time-sensitive in many industrial processes. Communication delay, cloud round trips, model inference time, and actuation delay can collectively reduce the usefulness of a prediction. Edge AI and hybrid edge–cloud architectures can place time-critical functions closer to the equipment while retaining cloud resources for training and fleet-level analysis.

17.2 Sensor Reliability

Sensor noise, missing values, drift, calibration errors, and sensor failure can degrade Digital Twin synchronization and AI performance. Redundant sensing, sensor-health monitoring, multi-sensor fusion, robust preprocessing, and

uncertainty estimation can reduce the effect of unreliable measurements.

17.3 Cybersecurity

A Digital Twin connected to physical equipment creates security requirements at both the data and control levels. Manipulated sensor measurements can cause incorrect predictions, while unauthorized control commands can directly affect equipment. Authentication, authorization, secure communication, signed commands, monitoring, and intrusion-detection mechanisms are therefore important for closed-loop deployment.

17.4 Explainability

Maintenance personnel may need to understand why an AI system generated an alarm or recommendation before acting on it. Interpretable models, feature-importance methods, confidence estimates, and validated natural-language explanations can improve transparency. Generative explanations should remain grounded in verified model outputs and should not be treated as independent evidence of equipment condition.

17.5 Interoperability

Industrial Digital Twins must exchange information across sensors, controllers, enterprise systems, AI services, and heterogeneous machines. Differences in data models, communication protocols, semantic representations, and vendor interfaces can make integration difficult. Standardized interfaces and semantically consistent data representations are therefore important for scalable deployment.

18 Cost and SME Accessibility

The deployment of AI-enabled Digital Twins can be difficult for small and medium enterprises (SMEs) because the complete solution may require sensors, industrial gateways, networking infrastructure, computing resources, software integration, data engineering, cybersecurity controls, and personnel with specialized expertise. A technically effective predictive-maintenance architecture therefore also needs to be evaluated in terms of acquisition cost, operating cost, maintenance effort, scalability, and required technical skills.

For SMEs, a practical deployment can begin with a limited number of high-value assets and a focused sensor set rather than instrumenting the entire production facility. Edge computing can reduce continuous cloud-transfer requirements, while hybrid edge-cloud architectures can reserve cloud resources for model training, historical analysis, fleet-level learning, and long-term storage. Open interfaces and interoperable data representations can also reduce dependence on a single vendor. The objective is not simply to minimize the initial investment, but to achieve an acceptable balance among predictive-maintenance benefit, computational cost, latency, reliability, and operational complexity.

The accessibility problem is also related to human expertise. Maintenance personnel may need actionable explanations rather than raw model outputs. Carefully

Table 4: Major Research Gaps and Potential Research Directions

Research Gap	Current Problem	Potential Direction
Closed-loop control	Prediction often ends with an alarm	Integrate constrained decision-making and validated remote actuation
Limited labelled failures	Real industrial failure data are scarce	Synthetic/GenAI data, transfer learning, self-supervised and federated learning
Cloud latency	Network communication delays intervention	Edge AI and hybrid edge-cloud architectures
Model generalization	Performance decreases across machines or operating conditions	Domain adaptation and continual learning
Cybersecurity	Manipulated data or commands can affect physical equipment	Secure communication, authentication, signed commands, intrusion detection
Explainability	Operators may not trust opaque predictions	SHAP, LIME, interpretable models, validated GenAI rationales, confidence estimates
Sensor quality	Noise, drift, missing values, sensor failure	Sensor fusion, redundancy, health monitoring, uncertainty estimation

constrained GenAI interfaces may assist with natural-language explanations, maintenance documentation, and operator interaction, but recommendations affecting physical equipment should remain grounded in verified sensor observations, validated model outputs, and appropriate safety controls.

19 FUTURE RESEARCH DIRECTIONS

The reviewed evidence indicates that future Digital Twin research needs to move from isolated prediction models toward deployable, secure, interoperable, and continuously improving cyber-physical systems. The following directions are particularly relevant to predictive maintenance and closed-loop manufacturing.

19.1 Edge AI

Edge AI places selected analytics and inference functions close to the physical equipment. This reduces dependence on continuous cloud connectivity and can shorten the time between sensing, inference, and intervention. Edge deployment is particularly useful for vibration monitoring, anomaly detection, safety-related alarms, and other applications where latency is important. Resource constraints remain a challenge because industrial edge devices may have limited memory, processing capability, and energy budgets. Model compression, lightweight architectures, hardware acceleration, and adaptive workload placement can therefore support practical deployment.

19.2 Hybrid Edge-Cloud Digital Twins

A hybrid edge-cloud Digital Twin can divide computation according to latency, data-volume, privacy, and computational requirements. Time-critical anomaly detection and local control can be performed at the edge, while computationally intensive model training, historical analysis, fleet-level comparison, and long-term storage can be performed in the cloud. Such architectures require reliable

synchronization, workload orchestration, secure communication, and mechanisms for maintaining consistent twin state across distributed computing locations.

20 Federated Learning

Federated learning provides a potential approach for learning from data distributed across multiple factories, machines, or organizations without requiring all raw operational data to be transferred to a central repository. Local models can be trained using local data and model updates can then be aggregated. For industrial Digital Twins, this can support collaborative learning while reducing direct sharing of sensitive production data. Important challenges include heterogeneous data distributions, communication overhead, model poisoning, privacy protection, and maintaining consistent model performance across participating sites.

20.1 Multi-Sensor Fusion

Predictive maintenance can benefit from combining complementary measurements such as vibration, temperature, current, pressure, speed, load, and acoustic signals. Multi-sensor fusion can improve observability because a failure mechanism may not be clearly represented in a single sensor stream. Fusion can occur at the data, feature, or decision level. Future systems should also estimate sensor reliability so that a failed or degraded sensor does not disproportionately influence the Digital Twin or maintenance decision.

20.2 Explainable and Generative, Uncertainty-Aware AI

Industrial maintenance decisions require more than a prediction label. Operators may need to know which measurements contributed to an alert, how confident the system is, and what uncertainty surrounds a forecast. Explainable AI can provide feature importance, local explanations, or interpretable model outputs, while uncertainty estimation can communicate the reliability of predictions. Generative AI can provide natural-language explanations and operator assistance, but generated content should remain grounded in verified data and model outputs. For safety-critical applications, uncertainty and validation information should accompany any AI-generated recommendation.

20.3 Self-Healing Industrial Systems

Self-healing systems aim to detect abnormal conditions, determine an appropriate response, execute an approved corrective action, and verify the outcome. In the context of Digital Twins, this represents a progression from prediction toward closed-loop operation. A safe self-healing architecture should include constrained decision-making, authorization, fail-safe behavior, action verification, and human override. Autonomous actuation should therefore be treated as a controlled engineering function rather than as an unrestricted AI capability.

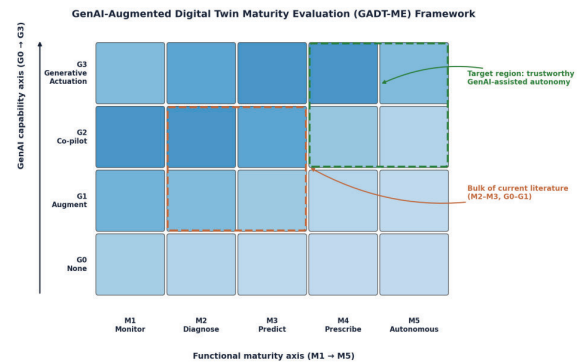


Figure 2: Proposed GenAI-Augmented Digital Twin Maturity Evaluation (GADT-ME) framework. Shading is illustrative of maturity progression.

20.4 Semantic and Interoperable Digital Twins

Industrial Digital Twins often operate across heterogeneous machines, controllers, databases, communication protocols, and enterprise applications. Semantic interoperability can help different components exchange information with consistent meanings rather than merely exchanging raw values. Future work should therefore investigate standardized information models, machine-readable asset descriptions, common semantic representations, and interoperable interfaces that allow twins to be integrated across production environments.

20.5 Accessible, GenAI-Assisted Digital Twins for SMEs

GenAI may make Digital Twin systems more accessible by providing natural-language interfaces for querying equipment state, summarizing alarms, explaining model outputs, generating maintenance documentation, and assisting with troubleshooting. For SMEs, such interfaces could reduce the expertise required to interact with complex analytics platforms. However, generated explanations and recommendations should be constrained by trusted industrial data, model outputs, access controls, and safety policies. Research should therefore focus on affordable architectures in which GenAI complements—not replaces—validated engineering and AI components.

21 A PROPOSED EVALUATION FRAMEWORK: GENAI-AUGMENTED DIGITAL TWIN MATURITY

The GenAI-Augmented Digital Twin Maturity Evaluation (GADT-ME) framework proposed in this review evaluates Digital Twin systems along two complementary dimensions: functional maturity and generative-AI capability. The framework is intended as an analytical taxonomy for comparing systems rather than as a claim that all reviewed studies implement every level.

21.1 Framework Axes

The first axis represents functional maturity. Five levels are used: M1, monitoring; M2, diagnosis; M3, prediction or prognostics; M4, prescriptive decision-making or optimization; and M5, autonomous operation. The second axis represents the role of generative AI: G0, no demonstrated GenAI capability; G1, GenAI augmentation; G2, GenAI co-pilot functionality; and G3, GenAI-enabled actuation. The two axes are intentionally separated because a system may have a high predictive maturity without using GenAI, or it may use GenAI for explanation while remaining at a diagnostic or predictive level.

21.2 Reading the Framework

A system should be assigned a maturity level according to the highest capability demonstrated by the evidence available for that system. For example, a Digital Twin that detects faults but does not forecast future degradation is classified at M2, whereas a system that estimates RUL is classified at M3. A system that recommends a maintenance action based on a prediction may reach M4, while validated autonomous execution of a corrective action is required for M5. GenAI coding follows the same evidence-based principle: natural-language explanation or data augmentation corresponds to G1, operator co-pilot functionality corresponds to G2, and GenAI directly participating in authorized actuation is required for G3.

22 Illustrative Scoring Procedure

The GADT-ME framework is qualitative and evidence-based rather than a universal numerical benchmark. For an individual study, the reviewer first identifies the highest demonstrated functional maturity (M1–M5) and then assigns the highest demonstrated GenAI capability (G0–G3). The resulting pair, such as M3/G1, summarizes the system's position in the framework. If a study does not demonstrate a maturity stage—for example, because it focuses on implementation determinants rather than a functioning maintenance system—the relevant axis can be recorded as not reported (NR) rather than inferred. This conservative procedure prevents a study from receiving a higher maturity level solely because a technology is mentioned without evidence of implementation.

The framework can subsequently be used to compare groups of studies by domain, sensor modality, deployment architecture, or maintenance task. Such comparisons should report the number of classifiable studies and should distinguish bibliographic or abstract-level evidence from independently verified full-text evidence.

23 DISCUSSION

The evidence synthesized in this review indicates that AI-enabled Digital Twins are increasingly capable of supporting monitoring, diagnosis, and predictive maintenance, but the transition from prediction to validated closed-loop action remains comparatively challenging. The technical pipeline requires reliable sensing, synchronized twin state, appropriate AI models, decision logic, secure communication, and controlled actuation. A weakness at any layer

can reduce the reliability of the overall system.

The analysis also shows that no single AI approach is sufficient for every manufacturing condition. Traditional machine learning can provide useful and comparatively interpretable models for structured sensor features; deep learning can capture complex temporal or signal patterns; unsupervised methods can address the scarcity of labelled failures; and hybrid or physics-informed methods can incorporate engineering knowledge. GenAI adds a different capability by supporting interaction, explanation, data augmentation, and recommendation drafting, but it requires grounding and safeguards before its outputs influence physical operations.

23.1 Practical Implications

For manufacturing practitioners, the findings support an incremental deployment strategy. Organizations can begin with reliable sensing and condition monitoring, establish a synchronized Digital Twin, and then add diagnosis, prediction, prescriptive analytics, and controlled actuation as evidence and validation increase. Edge computing can be used where latency is critical, while cloud resources can support training and fleet-level analysis. SMEs may particularly benefit from modular architectures, open interfaces, selective sensor deployment, and operator-oriented AI interfaces that reduce the expertise required to interpret system outputs.

For researchers, evaluation should extend beyond predictive accuracy. Important measures include false-alarm behavior, RUL error, inference and end-to-end latency, synchronization quality, robustness to sensor degradation and domain shift, cybersecurity, explainability, uncertainty, and the safety and reliability of any closed-loop action. These measures better reflect the requirements of an industrial cyber-physical system than model accuracy alone.

24 CONCLUSION

This structured review examined the integration of Artificial Intelligence (AI), Digital Twin (DT) technology, and predictive maintenance in smart manufacturing, with particular emphasis on the transition from condition monitoring and prediction toward prescriptive and closed-loop maintenance. The reviewed literature indicates that Digital Twins provide a cyber-physical representation of manufacturing assets by connecting physical equipment, sensor infrastructure, communication systems, virtual models, and analytical services. When AI is embedded within this architecture, Digital Twins can support fault diagnosis, anomaly detection, degradation assessment, Remaining Useful Life (RUL) estimation, and maintenance decision-making.

The analysis shows that traditional machine learning, deep learning, unsupervised anomaly detection, hybrid models, and physics-informed approaches provide complementary capabilities for predictive maintenance. Traditional machine-learning methods are useful for structured sensor data and fault classification, while deep-learning approaches can capture complex temporal and signal patterns. Unsupervised methods are particularly relevant where labelled industrial failure data are scarce. Hybrid

and physics-informed approaches provide a means of combining data-driven learning with engineering knowledge and physical constraints, thereby supporting more physically consistent degradation and RUL modelling.

A major finding of this review is the continuing prediction-to-action gap. Many reported Digital Twin systems identify or predict abnormal equipment behaviour but stop at an alarm, dashboard, or maintenance recommendation rather than demonstrating a complete and validated transition from prediction to safe corrective action. Moving toward closed-loop predictive maintenance therefore requires reliable decision-making, low-latency communication, secure actuation, accurate twin synchronization, uncertainty assessment, and appropriate human oversight. The transition from prediction to action should consequently be evaluated as an end-to-end cyber-physical process rather than as a machine-learning problem alone.

The review also identifies persistent challenges involving limited industrial failure data, domain shift, sensor reliability, latency, cybersecurity, explainability, interoperability, computational requirements, and deployment cost for small and medium-sized enterprises (SMEs). These challenges indicate that increasing model complexity alone is insufficient for industrial deployment. Practical systems require dependable sensing, robust data pipelines, edge-cloud coordination, secure communication, interpretable outputs, uncertainty awareness, and architectures that can be maintained under changing operating conditions.

The proposed GenAI-Augmented Digital Twin Maturity Evaluation (GADT-ME) framework provides a structured perspective for assessing Digital Twin systems according to functional maturity and generative-AI capability. The framework distinguishes progression from monitoring and diagnosis through prediction and prescription toward autonomous operation, while separately representing the contribution of generative AI. This perspective can support comparison of emerging systems that use GenAI for maintenance knowledge assistance, natural-language interaction, data augmentation, explanation, and recommendation generation. Because GenAI-enabled industrial actuation introduces additional safety and reliability concerns, generated recommendations should remain subject to validation, engineering constraints, and appropriate human or supervisory control before physical actions are executed.

Future research should therefore focus on hybrid edge-cloud Digital Twins, federated learning, multi-sensor fusion, explainable and uncertainty-aware AI, secure closed-loop actuation, self-healing industrial systems, semantic interoperability, and accessible GenAI-assisted Digital Twins for SMEs. Evaluation should extend beyond predictive accuracy to include false-alarm behaviour, RUL error, inference and end-to-end latency, synchronization quality, robustness to sensor degradation and domain shift, cybersecurity, explainability, uncertainty, and the safety and reliability of closed-loop actions. These measures better represent the requirements of an industrial cyber-physical system than model accuracy alone.

Overall, the literature demonstrates a continuing transition from “detect and predict” toward “understand, decide, and safely act.” Realizing this transition will require coordinated advances in AI modelling, Digital Twin synchronization, sensing and communication infrastructure,

secure control, and human-centred deployment. For manufacturing organizations, an incremental pathway beginning with reliable sensing and monitoring, followed by diagnosis, prediction, prescriptive analytics, and validated actuation, provides a practical basis for increasing system capability while maintaining control over operational risk. For researchers, the remaining gaps provide opportunities to develop reproducible evaluation protocols, interoperable architectures, trustworthy GenAI integration, and validated closed-loop Digital Twin systems for realistic industrial environments.

A PRIMARY-STUDY EVIDENCE MATRIX

Table 5: Primary-study evidence matrix for AI-enabled digital twins and predictive maintenance.

Year	Title	Venue	DOI	AI Method	Domain	Task	M	G	Quality
2019	Digital Twin for Machining Tool Condition Prediction	Procedia CIRP	10.1016/j.procir.2019.04.049	Deep learning/DSGRU	Machining/CNC	Tool condition prediction	M3	G0	Moderate
2019	The use of Digital Twin for predictive maintenance in manufacturing	International Journal of Computer Integrated Manufacturing	10.1080/0951192X.2019.1686173	Physics-based DT	Manufacturing robot	RUL/predictive maintenance	M3	G0	Moderate
2019	Methodology for enabling Digital Twin using advanced physics-based modelling in predictive maintenance	Procedia CIRP	10.1016/j.procir.2019.03.072	Physics-based modelling	Industrial robot	Predictive maintenance	M1	G0	Moderate
2020	A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin	Robotics and Computer-Integrated Manufacturing	10.1016/j.rcim.2020.101974	Hybrid DT + particle filtering	CNC	RUL/prediction	M3	G0	High
2020	Approach for a Holistic Predictive Maintenance Strategy by Incorporating a Digital Twin	Procedia Manufacturing	10.1016/j.promfg.2020.01.265	Simulation/statistical DT	Production machine	Predictive maintenance	M3	G0	Moderate
2021	Digital twin modeling for predictive maintenance of gearboxes in floating offshore wind turbine drivetrains	Forschungsingenieurwesen	10.1007/s10010-021-00468-9	DT degradation model	Wind turbine gearbox	Degradation/RUL	M3	G0	Moderate
2021	Prediction maintenance integrated decision-making approach supported by digital twin-driven cooperative awareness and interconnection framework	Journal of Manufacturing Systems	10.1016/j.jmsy.2020.08.001	Decision/optimization	Industrial maintenance	Maintenance decision support	M4	G0	Moderate
2022	Digital Twin Enabled Industry 4.0 Predictive Maintenance Under Reliability-Centred Strategy	IEEE	10.1109/ICEEICT53079.2022.9768590	ML/DT	Industry 4.0	Predictive maintenance	M3	G0	Moderate
2022	A Digital Twin Design for Maintenance Optimization	Procedia CIRP	10.1016/j.procir.2022.05.268	Degradation/RUL model	Milling machine	Maintenance optimization	M4	G0	Moderate
2022	Feature investigation with Digital Twin for predictive maintenance following a machine learning approach	IFAC-PapersOnLine	10.1016/j.ifacol.2022.04.182	Feature selection/ML	Steel production	PdM features	M2	G0	Moderate
2023	Digital twin-enhanced predictive maintenance for indoor climate	Energy and Buildings	10.1016/j.enbuild.2023.113738	LSTM autoencoder	Building systems	Failure prediction	M3	G0	Moderate
2023	A digital twin framework for prognostics and health management	Computers in Industry	10.1016/j.compind.2023.103948	Data-driven + physics	Manufacturing equipment	PHM	M2	G0	Moderate
2023	Digital Twins for predictive maintenance: A case study for a flexible IT-architecture	Procedia CIRP	10.1016/j.procir.2023.03.087	IoT/service architecture	Industrial asset	PdM case	M3	G0	Moderate
2023	Digital Twins for Predictive Maintenance	Procedia CIRP	10.1016/j.procir.2023.06.053	Statistical + ML	Virtual factory	PdM	M3	G0	Moderate
2023	Experience from implementing digital twins for maintenance in industrial processes	Journal of Intelligent Manufacturing	10.1007/s10845-023-02078-4	DT + anomaly/RUL analytics	Industrial process	Maintenance analytics	M3	G0	High
2023	Predictive maintenance of standalone steel industrial components powered by a dynamic reliability digital twin model with artificial intelligence	Reliability Engineering & System Safety	10.1016/j.res.2023.109859	AI regression	Steel components	Failure prediction	M3	G0	High

Year	Title	Venue	DOI	AI Method	Domain	Task	M	G	Quality
2024	Machine learning-based digital twin of a conveyor belt for predictive maintenance	International Journal of Advanced Manufacturing Technology	10.1007/s00170-024-14097-3	Machine learning	Conveyor	PdM	M3	G0	High
2024	Incremental learning with multi-fidelity information fusion for digital twin-driven bearing fault diagnosis	Engineering Applications of Artificial Intelligence	10.1016/j.engappai.2024.108212	Incremental/deep learning	Bearing	Fault diagnosis	M2	G0	High
2024	Twin data multimode collaborative transfer learning for bearing failure diagnosis	Engineering Applications of Artificial Intelligence	10.1016/j.engappai.2024.109142	Transfer learning	Bearing	Failure diagnosis	M2	G0	High
2024	Deep learning-based digital twin for intelligent predictive maintenance of rapier loom	Journal of Intelligent & Fuzzy Systems	10.3233/JIFS-233863	Deep learning	Rapier loom	PdM	M3	G0	Moderate
2024	Digital Twin-based Predictive Maintenance for Sheet Metal Bending	Procedia Computer Science	10.1016/j.procs.2024.01.050	Hybrid physics/data	Sheet-metal bending	PdM	M3	G0	Moderate
2024	Digital twin (DT)-based predictive maintenance of a 6G communication network	Procedia Computer Science	10.1016/j.procs.2024.06.058	AI/ML	6G network	PdM	M3	G0	Moderate
2024	Real-world prototyping and evaluation of digital twins for predictive facility maintenance	Journal of Building Engineering	10.1016/j.jobe.2024.110890	DT platform evaluation	Facilities	Predictive maintenance	M3	G0	High
2024	IoT and Digital Twin: a new perspective for Cultural Heritage predictive maintenance	Procedia Structural Integrity	10.1016/j.prostr.2024.09.334	IoT/DT	Cultural heritage	Predictive maintenance	M3	G0	Moderate
2024	From Sensors to Digital Twins toward an Iterative Approach for Existing Manufacturing Systems	Sensors	10.3390/s24051434	Sensor/DT integration	Manufacturing systems	Monitoring/integration	M1	G0	Moderate
2025	Data-Driven Digital Twin Framework for Predictive Maintenance of Smart Manufacturing Systems	Machines	10.3390/machines13060481	ML comparison	CNC turning	PdM	M3	G0	High
2025	Rolling bearings remaining useful life estimation using digital twin and physics-informed methods with uncertainty quantification	Engineering Applications of Artificial Intelligence	10.1016/j.engappai.2025.111070	Physics-informed NN	Rolling bearing	RUL	M3	G0	High
2025	Bridging gray-box modeling and machine learning: a digital twin approach to refrigeration system identification and predictive maintenance	Measurement: Digitalization	10.1016/j.measdig.2025.100018	Gray-box + ML	Refrigeration	Identification/PdM	M3	G0	Moderate
2025	Digital twin integration in metalworking: enhancing efficiency and predictive maintenance	Frontiers in Mechanical Engineering	10.3389/fmech.2025.1655565	Data fusion/deep learning	Metalworking	PdM	M3	G0	Moderate
2025	A simulation-based digital twin for data-driven maintenance scheduling of risk-prone production lines via actor critics	Flexible Services and Manufacturing Journal	10.1007/s10696-024-09579-1	Actor-critic RL	Production line	Maintenance scheduling	M3	G0	High
2025	Generative and Predictive AI for digital twin systems in manufacturing	Frontiers in Artificial Intelligence	10.3389/frai.2025.1655470	GenAI + predictive AI	Manufacturing/welding	Quality/PdM assistance	M3	G1	Moderate
2025	Investigating determinants of digital twins for predictive maintenance	Journal of Quality in Maintenance Engineering	10.1108/JQME-05-2024-0047	MCDM/DEMATEL/ISM	Industrial implementation	PdM determinants	NR	NR	Moderate
2025	Digital Twin-Driven Predictive Maintenance Using ML Models in Industry 5.0 Environments	IEEE CISES	10.1109/CISES66934.2025.11265639	ML	Industry 5.0	PdM	M3	G0	Moderate

Year	Title	Venue	DOI	AI Method	Domain	Task	M	G	Quality
2026	System and system-of-systems digital twins for predictive maintenance and root cause analysis	Journal of Intelligent Manufacturing	10.1007/s10845-025-02789-w	Real-time analytics/root cause	Ring rolling process	Root-cause analysis/PdM	M2	G0	High
2026	Physics-informed auto-encoder based on digital twin for rolling bearing fault diagnosis under imbalanced sample conditions	Engineering Applications of Artificial Intelligence	10.1016/j.engappai.2025.113017	Physics-informed autoencoder	Rolling bearing	Fault diagnosis	M2	G0	High

Note: The matrix contains the empirical primary/implementation records currently represented in the evidence map. M/G codes were assigned using the conservative GADT-ME coding protocol described in Section 9.4. NR denotes no demonstrated maturity stage and is excluded from the maturity denominator.

B REVIEW / SURVEY EVIDENCE MATRIX

Table 6: Review and survey evidence matrix used for landscape and contextual synthesis.

Year	Title	Venue	DOI	AI Method	Domain	Task	Quality
2020	Digital Twin for maintenance: A literature review	Computers in Industry	10.1016/j.compind.2020.103316	Literature review	Industrial maintenance	Review	High
2020	Digital Twin Models in Industrial Operations: A Systematic Literature Review	Procedia Manufacturing	10.1016/j.promfg.2020.02.084	Systematic review	Industrial operations	Review	High
2022	Predictive maintenance using digital twins: A systematic literature review	Information and Software Technology	10.1016/j.infsof.2022.107008	Systematic review	Industrial PdM	Review of 42 primary studies	High
2022	Digital Twin-Driven Machine Condition Monitoring: A Literature Review	Journal of Sensors	10.1155/2022/6129995	Literature review	Condition monitoring	Review	High
2022	Advances of Digital Twins for Predictive Maintenance	Procedia Computer Science	10.1016/j.procs.2022.01.348	Review	PdM	Review	Moderate
2022	Digital Twin for Integration of Design-Manufacturing-Maintenance: An Overview	Chinese Journal of Mechanical Engineering	10.1186/s10033-022-00760-x	Overview	Manufacturing	Review	High
2023	Overview of predictive maintenance based on digital twin technology	Heliyon	10.1016/j.heliyon.2023.e14534	Review	PdM	Review	High
2023	The advance of digital twin for predictive maintenance: The role and function of machine learning	Journal of Manufacturing Systems	10.1016/j.jmsy.2023.10.010	Review	PdM/ML	Review	High
2024	Artificial intelligence in digital twins—A systematic literature review	Data & Knowledge Engineering	10.1016/j.datak.2024.102304	Systematic review	AI + DT	Review of 149 studies	High
2024	Systematic review of predictive maintenance and digital twin technologies challenges, opportunities, and best practices	PeerJ Computer Science	10.7717/peerj-cs.1943	Systematic review	PdM + DT	Review	High

Year	Title	Venue	DOI	AI Method	Domain	Task	Quality
2024	Predictive maintenance in Industry 4.0: A systematic multi-sector mapping	CIRP Journal of Manufacturing Science and Technology	10.1016/j.cirpj.2024.02.003	Systematic mapping	Industry 4.0 PdM	Review	High
2025	AI-enhanced digital twins in maintenance: Systematic review, industrial challenges, and bridging research–practice gaps	Journal of Manufacturing Systems	10.1016/j.jmsy.2025.07.006	SLR + industry interviews	AI-DT maintenance	Review of 51 cases	High
2025	Systematic review of predictive maintenance practices in the manufacturing sector	Intelligent Systems with Applications	10.1016/j.iswa.2025.200501	Systematic review	Manufacturing PdM	Review	High
2025	Generative AI-Empowered Digital Twin: A Comprehensive Survey With Taxonomy	IEEE Transactions on Industrial Informatics	10.1109/TII.2025.3540473	Survey/taxonomy	GenAI + DT	Review	High
2025	Generative AI in AI-Based Digital Twins for Fault Diagnosis for Predictive Maintenance in Industry 4.0/5.0	Applied Sciences	10.3390/app15063166	State-of-the-art/review	GenAI + DT + PdM	Review	High
2025	Electronic Artificial Intelligence and Digital Twins in Industry 5.0: A Systematic Review and Perspectives	Machines	10.3390/machines13090755	Systematic review	AI + DT + Industry 5.0	Review	High
2025	Digital Twins, Extended Reality, and Artificial Intelligence in Sustainability Manufacturing Reconfiguration: A Systematic Literature Review	Sustainability	10.3390/su17052318	Systematic review	Manufacturing	Review	High
2025	Digital twin technology in wind turbine components: A review	Intelligent Systems with Applications	10.1016/j.iswa.2025.200535	Review	Wind energy DT	Review	High
2025	Digital twins in manufacturing: a unified conceptual framework	Annual Reviews in Control	10.1016/j.arcontrol.2025.101031	Conceptual review	Manufacturing DT	Review	Moderate
2026	AI-driven predictive maintenance for industry 4.0: a systematic review of models, methods, and challenges	International Journal of Advanced Manufacturing Technology	10.1007/s00170-026-17531-w	Systematic review	AI + PdM	Review	High
2026	AI-Driven Digital Twins for Manufacturing: A Review Across Hierarchical Manufacturing System Levels	Sensors	10.3390/s26010124	Review	AI + DT manufacturing	Review	High
2026	Generative AI for Predictive Maintenance for Manufacturing: A Survey	Procedia CIRP	10.1016/j.procir.2025.09.012	Survey	GenAI + PdM	Review	Moderate
2026	Exploring AI in Digital Twin: trends, challenges, benefits, and contributions	Digital Twin	10.1080/27525783.2026.2704992	Review	AI + DT	Review	High
2026	Digitalised Predictive Maintenance in Railways: A Systematic Review of AI, BIM, and Digital Twins	Infrastructures	10.3390/infrastructures11030087	PRISMA SLR	Railways	Review of 73 articles	High
2025	Digital twin innovations for induction motor monitoring and predictive maintenance: A 2020–2025 review	Next Research	10.1016/j.nexres.2025.100969	Review	Induction motor	Review of 60 studies	High

Year	Title	Venue	DOI	AI Method	Domain	Task	Quality
2025	A tutorial on digital twins for predictive maintenance	Woodhead Publishing	10.1016/B978-0-443-15476-8.00005-8	Tutorial/review	PdM	Tutorial	Moderate

Note: Review/survey records provide landscape and contextual evidence and are not counted as empirical maturity demonstrations.

C DOI-BASED REFERENCE VERIFICATION REGISTER

Table 7: DOI-based reference verification register for the evidence map.

Year	Title	Venue	DOI	Evidence Type; Bibliographic Verification	Full-Text Coding / Status
2019	Digital Twin for Machining Tool Condition Prediction	Procedia CIRP	10.1016/j.procir.2019.04.049	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2019	The use of Digital Twin for predictive maintenance in manufacturing	International Journal of Computer Integrated Manufacturing	10.1080/0951192X.2019.1686173	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2019	Methodology for enabling Digital Twin using advanced physics-based modelling in predictive maintenance	Procedia CIRP	10.1016/j.procir.2019.03.072	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2020	A hybrid predictive maintenance approach for CNC machine tool driven by Digital Twin	Robotics and Computer-Integrated Manufacturing	10.1016/j.rcim.2020.101974	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2020	Approach for a Holistic Predictive Maintenance Strategy by Incorporating a Digital Twin	Procedia Manufacturing	10.1016/j.promfg.2020.01.265	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2020	On the requirements of digital twin-driven autonomous maintenance	Annual Reviews in Control	10.1016/j.arcontrol.2020.08.003	Framework/architecture; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2021	Digital twin modeling for predictive maintenance of gearboxes in floating offshore wind turbine drivetrains	Forschungsingenieurwesen	10.1007/s10010-021-00468-9	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2021	Prediction maintenance integrated decision-making approach supported by digital twin-driven cooperative awareness and interconnection framework	Journal of Manufacturing Systems	10.1016/j.jmsy.2020.08.001	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2021	Holistic Concept Towards a Reference Architecture Model for Predictive Maintenance	Procedia CIRP	10.1016/j.procir.2021.11.241	Framework/architecture; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2021	Low-cost real-time multivariate process control from large sensor arrays (DOLPHINS)	Frontiers in Chemistry	10.3389/fchem.2021.734132	Adjacent/technical; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2022	Digital Twin Enabled Industry 4.0 Predictive Maintenance Under Reliability-Centred Strategy	IEEE	10.1109/ICEEICT53079.2022.9768590	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2022	A Digital Twin Design for Maintenance Optimization	Procedia CIRP	10.1016/j.procir.2022.05.268	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2022	Feature investigation with Digital Twin for predictive maintenance following a machine learning approach	IFAC-PapersOnLine	10.1016/j.ifacol.2022.04.182	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence

Year	Title	Venue	DOI	Evidence Type; Biblio-graphic Verification	Full-Text Coding / Status
2023	Digital twin-enhanced predictive maintenance for indoor climate	Energy and Buildings	10.1016/j.enbuild.2023.113738	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2023	A digital twin framework for prognostics and health management	Computers in Industry	10.1016/j.compind.2023.103948	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2023	Reference architecture for digital twin-based predictive maintenance systems	Computers & Industrial Engineering	10.1016/j.cie.2023.109099	Framework/architecture; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2023	Digital Twins for predictive maintenance: A case study for a flexible IT-architecture	Procedia CIRP	10.1016/j.procir.2023.03.087	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2023	Digital Twins for Predictive Maintenance	Procedia CIRP	10.1016/j.procir.2023.06.053	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2023	Experience from implementing digital twins for maintenance in industrial processes	Journal of Intelligent Manufacturing	10.1007/s10845-023-02078-4	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2023	Predictive maintenance of standalone steel industrial components powered by a dynamic reliability digital twin model with artificial intelligence	Reliability Engineering & System Safety	10.1016/j.ress.2023.109859	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	Machine learning- based digital twin of a conveyor belt for predictive maintenance	International Journal of Advanced Manufacturing Technology	10.1007/s00170-024-14097-3	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	Incremental learning with multi-fidelity information fusion for digital twin-driven bearing fault diagnosis	Engineering Applications of Artificial Intelligence	10.1016/j.engappai.2024.108212	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	Twin data multimode collaborative transfer learning for bearing failure diagnosis	Engineering Applications of Artificial Intelligence	10.1016/j.engappai.2024.109142	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	Deep learning-based digital twin for intelligent predictive maintenance of rapier loom	Journal of Intelligent & Fuzzy Systems	10.3233/JIFS-233863	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	Digital Twin-based Predictive Maintenance for Sheet Metal Bending	Procedia Computer Science	10.1016/j.procs.2024.01.050	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	Digital twin (DT)- based predictive maintenance of a 6G communication network	Procedia Computer Science	10.1016/j.procs.2024.06.058	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	Real-world prototyping and evaluation of digital twins for predictive facility maintenance	Journal of Building Engineering	10.1016/j.jobe.2024.110890	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	IoT and Digital Twin: a new perspective for Cultural Heritage predictive maintenance	Procedia Structural Integrity	10.1016/j.prostr.2024.09.334	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence

Year	Title	Venue	DOI	Evidence Type; Biblio-graphic Verification	Full-Text Coding / Status
2024	From Sensors to Digital Twins toward an Iterative Approach for Existing Manufacturing Systems	Sensors	10.3390/s24051434	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2024	State-of-the-art review and synthesis: A requirement-based roadmap for standardized predictive maintenance automation using digital twin technologies	Advanced Engineering Informatics	10.1016/j.aei.2024.102800	Framework/architecture; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	Data-Driven Digital Twin Framework for Predictive Maintenance of Smart Manufacturing Systems	Machines	10.3390/machines13060481	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	Rolling bearings remaining useful life estimation using digital twin and physics-informed methods with uncertainty quantification	Engineering Applications of Artificial Intelligence	10.1016/j.engappai.2025.111070	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	Bridging gray-box modeling and machine learning: a digital twin approach to refrigeration system identification and predictive maintenance	Measurement: Digitalization	10.1016/j.measig.2025.100018	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	Digital twin integration in metalworking: enhancing efficiency and predictive maintenance	Frontiers in Mechanical Engineering	10.3389/fmech.2025.1655565	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	A simulation-based digital twin for data-driven maintenance scheduling of risk-prone production lines via actor critics	Flexible Services and Manufacturing Journal	10.1007/s10696-024-09579-1	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	Method for the development and application of digital twins in manufacturing	Production Engineering	10.1007/s11740-025-01346-x	Framework/architecture; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	Generative and Predictive AI for digital twin systems in manufacturing	Frontiers in Artificial Intelligence	10.3389/frai.2025.1655470	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	Investigating determinants of digital twins for predictive maintenance	Journal of Quality in Maintenance Engineering	10.1108/JQME-05-2024-0047	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2025	Digital Twin-Driven Predictive Maintenance Using ML Models in Industry 5.0 Environments	IEEE CISES	10.1109/CISES66934.2025.112656399	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2026	System and system-of-systems digital twins for predictive maintenance and root cause analysis	Journal of Intelligent Manufacturing	10.1007/s10845-025-02789-w	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2026	Physics-informed auto-encoder based on digital twin for rolling bearing fault diagnosis under imbalanced sample conditions	Engineering Applications of Artificial Intelligence	10.1016/j.engappai.2025.113017	Primary; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence

Year	Title	Venue	DOI	Evidence Type; Biblio-graphic Verification	Full-Text Coding / Status
2026	A Critical Analysis and Roadmap for the Development and Implementation of Predictive Maintenance Digital Twins	Applied System Innovation	10.3390/asi9060123	Framework/architecture; DOI/publisher-index record identified	Bibliographically verified; maturity coding based on available publisher/index evidence
2020	Digital Twin for maintenance: A literature review	Computers in Industry	10.1016/j.compind.2020.103316	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2020	Digital Twin Models in Industrial Operations: A Systematic Literature Review	Procedia Manufacturing	10.1016/j.promfg.2020.02.084	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2022	Predictive maintenance using digital twins: A systematic literature review	Information and Software Technology	10.1016/j.infsof.2022.107008	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2022	Digital Twin-Driven Machine Condition Monitoring: A Literature Review	Journal of Sensors	10.1155/2022/6129995	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2022	Advances of Digital Twins for Predictive Maintenance	Procedia Computer Science	10.1016/j.procs.2022.01.348	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2022	Digital Twin for Integration of Design- Manufacturing- Maintenance: An Overview	Chinese Journal of Mechanical Engineering	10.1186/s10033-022-00760-x	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2023	Overview of predictive maintenance based on digital twin technology	Heliyon	10.1016/j.heliyon.2023.e14534	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2023	The advance of digital twin for predictive maintenance: The role and function of machine learning	Journal of Manufacturing Systems	10.1016/j.jmsy.2023.10.010	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2024	Artificial intelligence in digital twins—A systematic literature review	Data & Knowledge Engineering	10.1016/j.datak.2024.102304	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2024	Systematic review of predictive maintenance and digital twin technologies challenges,	PeerJ Computer Science	10.7717/peerj-cs.1943	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2024	Predictive maintenance in Industry 4.0: A systematic multi- sector mapping	CIRP Journal of Manufacturing Science and Technology	10.1016/j.cirpj.2024.02.003	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	AI-enhanced digital twins in maintenance: Systematic review, industrial challenges, and bridging research–practice gaps	Journal of Manufacturing Systems	10.1016/j.jmsy.2025.07.006	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	Systematic review of predictive maintenance practices in the manufacturing sector	Intelligent Systems with Applications	10.1016/j.iswa.2025.200501	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	Generative AI- Empowered Digital Twin: A Comprehensive Survey With Taxonomy	IEEE Transactions on Industrial Informatics	10.1109/TII.2025.3540473	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages

Year	Title	Venue	DOI	Evidence Type; Bibliographic Verification	Full-Text Coding / Status
2025	Generative AI in AI- Based Digital Twins for Fault Diagnosis for Predictive Maintenance in Industry 4.0/5.0	Applied Sciences	10.3390/app15063166	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	Electronic Artificial Intelligence and Digital Twins in Industry 5.0: A Systematic Review and Perspectives	Machines	10.3390/machines13090755	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	Digital Twins, Extended Reality, and Artificial Intelligence in Manufacturing Reconfiguration: A Systematic Literature Review	Sustainability	10.3390/su17052318	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	Digital twin technology in wind turbine components: A review	Intelligent Systems with Applications	10.1016/j.iswa.2025.200535	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	Digital twins in manufacturing: A unified conceptual framework	Annual Reviews in Control	10.1016/j.arcontrol.2025.101031	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2026	AI-driven predictive maintenance for industry 4.0: a systematic review of models, methods, and challenges	International Journal of Advanced Manufacturing Technology	10.1007/s00170-026-17531-w	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2026	AI-Driven Digital Twins for Manufacturing: A Review Across Hierarchical Manufacturing System Levels	Sensors	10.3390/s26010124	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2026	Generative AI for Predictive Maintenance for Manufacturing: A Survey	Procedia CIRP	10.1016/j.procir.2025.09.012	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2026	Exploring AI in Digital Twin: trends, challenges, benefits, and contributions	Digital Twin	10.1080/27525783.2026.2704992	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2026	Digitalised Predictive Maintenance in Railways: A Systematic Review of AI, BIM, and Digital Twins	Infrastructures	10.3390/infrastructures11030087	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	Digital twin innovations for induction motor monitoring and predictive maintenance: A 2020– 2025 review	Next Research	10.1016/j.nexres.2025.100969	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages
2025	A tutorial on digital twins for predictive maintenance	Woodhead Publishing	10.1016/B978-0-443-15476-8.00005-8	Review; DOI/publisher-index record identified	Verified: review/context record; not used for primary M/G percentages

Note: Bibliographic verification records identify the DOI/publisher-index record. Primary-study maturity codes use the conservative GADT-ME protocol and available publisher/index evidence; review/context records are separated from primary-study maturity calculations.

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Conflicts of interest/Competing interests

The authors declare that they have no conflicts of interest or competing interests that could have influenced the work reported in this manuscript.

Authors' contributions

All authors contributed to the conception and design of the study, literature search and analysis, interpretation of the findings, and preparation and revision of the manuscript. All authors have read and approved the final version of the manuscript.

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