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Review article

Digital Twin Technologies for Intelligent Monitoring, Predictive Maintenance, and Autonomous Decision Making in Industrial Cyber-Physical Systems: A Comprehensive Systematic Review

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Abstract

This study aimed to systematically review the current state of digital twin technologies in industrial cyber-physical systems and evaluate their roles in intelligent monitoring, predictive maintenance, and autonomous decision-making. It also sought to identify major architectural frameworks, enabling technologies, adoption barriers, and emerging directions for cognitive digital twins in industrial environments. A structured systematic review methodology was applied using peer-reviewed literature published between 2020 and 2025. Searches were conducted across IEEE Xplore, Scopus, Web of Science, ScienceDirect, and SpringerLink using Boolean combinations of terms related to digital twins, industrial cyber-physical systems, intelligent monitoring, predictive maintenance, autonomous decision-making, and Industry 4.0/5.0. Studies were screened through title, abstract, and full-text review using defined inclusion and exclusion criteria, followed by thematic data extraction, quality assessment, and synthesis. The review included 87 publications and identified five major themes: intelligent monitoring, predictive maintenance, autonomous decision-making, security and interoperability challenges, and future directions. Findings showed that digital twins improve operational visibility, reduce downtime, support fault prediction, and enable self-optimizing processes. Reported benefits included 30–50% reductions in unplanned downtime, 20–40% longer equipment life, and fault diagnosis accuracy of 97.3% in one energy case study. Digital twin technologies are becoming foundational for smarter, more resilient, and sustainable industrial systems, but wider adoption still depends on advances in standardization, security, scalability, interoperability, and organizational readiness.

Keywords: Digital Twin; Cyber-Physical Systems; Predictive Maintenance; Intelligent Monitoring; Autonomous Decision Making

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1. Introduction

The fourth industrial revolution, commonly referred to as Industry 4.0, has fundamentally transformed the manufacturing landscape through the integration of digital technologies that enable sophisticated real-time monitoring, in-depth data analysis, and continuous process optimization (Karkaria et al., 2025). At the forefront of this technological revolution are Digital Twin (DT) technologies, which serve as virtual replicas of physical assets, systems, and processes, providing unprecedented capabilities for simulation, analysis, and optimization (Gálvez del Postigo Gallego et al., 2025). The convergence of DT technologies with Industrial Cyber-Physical Systems (ICPS) has created new opportunities for intelligent monitoring, predictive maintenance, and autonomous decision-making, representing a significant advancement in industrial automation and control.

Digital Twin technology has evolved considerably from its initial conceptualization as a static digital replica to become a dynamic, bidirectional platform that enables real-time synchronization between physical and virtual environments (Bao et al., 2025). This evolution has been driven by advances in Internet of Things (IoT) sensors, cloud computing, artificial intelligence (AI), and machine learning (ML) algorithms, which collectively enable DTs to not only mirror physical systems but also to predict future states, simulate alternative scenarios, and recommend optimal actions (Karkaria et al., 2025). The integration of AI with DT technology has been particularly transformative, enabling systems to move beyond passive monitoring to proactive decision-making and autonomous operations (Mousavi et al., 2025) Industrial Cyber-Physical Systems represent the integration of computation, communication, and physical processes, creating intelligent systems that can monitor, coordinate, and control physical operations through networked computational resources (Hostos et al., 2023). ICPS are characterized by their ability to sense the environment, process information, and actuate changes in the physical world, making them ideal platforms for DT implementation (Bao et al., 2025). The synergy between DT technologies and ICPS has enabled the development of smart manufacturing systems that can self-optimize, self-adapt, and self-heal, significantly improving operational efficiency, reducing downtime, and enhancing product quality (Gálvez del Postigo Gallego et al., 2025).

The importance of this integration is underscored by the emergence of Industry 5.0, which emphasizes human-centricity, sustainability, and resilience alongside technological advancement (Mousavi et al., 2025). Within this context, DT technologies are being increasingly recognized as foundational tools for creating sustainable and adaptive industrial ecosystems that balance productivity with environmental responsibility and social well-being (Bao et al., 2025). Recent industry surveys indicate that 86% of manufacturing leaders recognize the value of DT technologies, with nearly half already deploying them in their operations (Gálvez del Postigo Gallego et al., 2025).

Despite the growing adoption and demonstrated benefits of DT technologies in ICPS, significant challenges remain. These include interoperability issues between different systems and platforms, data security and privacy concerns, the computational demands of real-time processing, the need for standardization across industries, and the integration of DT capabilities with legacy systems (Mousavi et al., 2025). Furthermore, while individual applications of DT technologies have been extensively documented, there is a need for comprehensive systematic reviews that synthesize the current state of knowledge across multiple dimensions of DT implementation in ICPS environments (Hostos et al., 2023). This systematic review addresses this gap by providing a comprehensive examination of DT technologies for intelligent monitoring, predictive maintenance, and autonomous decision-making in

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ICPS. The review is guided by the following research questions: What are the current applications and capabilities of DT technologies in ICPS for intelligent monitoring? How are predictive maintenance strategies being enhanced through DT implementation? What frameworks and approaches enable autonomous decision-making in DT-enabled ICPS? What are the primary challenges and barriers to DT adoption in industrial settings? What are the emerging trends and future directions for DT technologies in ICPS?

2. Literature Review

2.1 Theoretical Foundations of Digital Twin and Cyber-Physical Systems

The concept of Digital Twins has undergone significant evolution since its introduction, expanding from a simple virtual representation to encompass complex, dynamic systems capable of real-time interaction with physical counterparts (Mousavi et al., 2025). According to foundational definitions, a Digital Twin can be understood as a dynamic, virtual representation of a physical system that integrates real-time data from sensors and historical information to closely mirror the physical system's behavior, context, and structure (Karkaria et al., 2025). This definition emphasizes the bidirectional nature of DT systems, which enables continuous updating based on real-world changes while simultaneously informing physical systems through predictive insights and optimization recommendations (Mousavi et al., 2025).

The evolution of DT technologies can be understood through three progressive levels of sophistication. At the most basic level, Digital Models represent static digital replicas of physical objects that provide a manually updated representation without real-time connection to their physical counterparts (Mousavi et al., 2025). These models are suitable for early design and pre-production stages where simulation and optimization can occur before physical production begins. The second level, Digital Shadows, introduces a one-way data flow from the physical object to its digital counterpart, enabling real-time updates but lacking the capability to influence the physical system (Mousavi et al., 2025). Digital Shadows are particularly useful for condition monitoring and predictive maintenance applications where continuous monitoring is essential. The most advanced level, Digital Twins, supports bidirectional data flow that enables both monitoring and active control over physical objects, representing the full integration of physical and virtual systems (Mousavi et al., 2025).

Industrial Cyber-Physical Systems provide the foundational infrastructure for DT implementation in manufacturing environments. ICPS are characterized as combinations of technological agents, IT agents, and humans collaborating within synergistic production environments to carry out technical, decision-making, or cognitive tasks autonomously (Hostos et al., 2023). The integration of ICPS with DT technologies creates intelligent systems that can sense the environment, process information, and actuate changes in the physical world, enabling capabilities such as real-time process optimization, predictive maintenance, and autonomous decision-making (Bao et al., 2025).

The architecture of DT systems in ICPS environments typically follows a multi-layered framework designed to bridge physical and virtual environments. Various architectural approaches have been proposed, ranging from foundational three-layer architectures comprising physical, network, and computing layers to more sophisticated frameworks with enhanced security and bidirectional data flow (Mousavi et al., 2025). Advanced architectures incorporate AI and edge computing capabilities, pointing toward the development of self-adapting, scalable systems that support autonomous decision-making

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(Mousavi et al., 2025). The selection of an appropriate architecture is critical for effectively leveraging intelligent and autonomous systems, with choices depending on specific operational requirements, scalability needs, and security considerations (Karkaria et al., 2025). Standards and frameworks for DT implementation have been emerging through organizations such as the International Organization for Standardization (ISO). The ISO 23247 standard, for example, provides guidelines for DT development in manufacturing, emphasizing the integration of physical assets with virtual representations and the importance of data synchronization and interoperability (Bao et al., 2025). These standards are essential for ensuring consistency, interoperability, and security across different DT implementations and for facilitating the integration of DTs into broader industrial ecosystems (Gálvez del Postigo Gallego et al., 2025).

2.2 Intelligent Monitoring Systems in Digital Twin-Enabled Cyber-Physical Systems

Intelligent monitoring represents one of the most fundamental applications of DT technologies in ICPS, enabling real-time visibility into operational performance and facilitating data-driven decision-making (Karkaria et al., 2025). DT-enabled monitoring systems leverage IoT sensors, edge computing, and cloud platforms to collect and process vast amounts of operational data, creating comprehensive digital representations that mirror the behavior of physical assets in real-time (Mousavi et al., 2025). These systems go beyond traditional monitoring approaches by providing contextual information, predictive insights, and prescriptive recommendations that enable proactive rather than reactive operational management.

The evolution of monitoring capabilities within DT systems can be categorized according to the level of data integration and analytical sophistication. Basic monitoring systems provide real-time visualization of operational parameters, enabling operators to track equipment performance and identify anomalies as they occur (Mousavi et al., 2025). More advanced systems incorporate machine learning algorithms to detect patterns and anomalies that may indicate developing problems, providing early warning of potential failures before they manifest (Bao et al., 2025). The most sophisticated monitoring systems integrate multiple data sources and analytical approaches to provide comprehensive operational intelligence, enabling scenario analysis, what-if simulations, and optimization recommendations that enhance overall system performance (Gálvez del Postigo Gallego et al., 2025).

Real-time data synchronization is a critical enabler of intelligent monitoring in DT systems. This involves the continuous updating of digital representations based on sensor data from physical assets, ensuring that the virtual twin accurately reflects the current state of the physical system (Mousavi et al., 2025). Real-time synchronization enables several key capabilities, including condition monitoring that tracks equipment health in real-time; anomaly detection that identifies deviations from normal operating conditions; and performance monitoring that assesses operational efficiency against benchmarks and targets (Karkaria et al., 2025). The effectiveness of real-time synchronization depends on the quality and reliability of sensor data, the speed and capacity of communication networks, and the processing capabilities of edge and cloud platforms (Mousavi et al., 2025).

The application of intelligent monitoring in ICPS environments has been demonstrated across various industrial sectors. In manufacturing, DT-enabled monitoring systems have been used to track production line performance, identify bottlenecks, and optimize workflow efficiency (Karkaria et al., 2025). In energy systems, intelligent monitoring has enabled real-time assessment of equipment health

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and operational efficiency, supporting predictive maintenance and performance optimization (Bao et al., 2025). In additive manufacturing, monitoring systems have been developed to track build quality, detect defects in real-time, and optimize process parameters for improved quality and efficiency (Vimal et al., 2025).

However, the implementation of intelligent monitoring systems faces several challenges. These include the need for high-quality, reliable data from sensors and IoT devices; the integration of data from diverse sources with different formats and protocols; the scalability of monitoring systems to handle increasing volumes of data from growing numbers of assets; and the development of analytical models that can effectively process and interpret complex, high-dimensional data (Mousavi et al., 2025). Addressing these challenges requires continued research and development in areas such as sensor technology, data integration, edge computing, and AI-driven analytics.

2.3 Predictive Maintenance through Digital Twin Technologies

Predictive maintenance has emerged as one of the most valuable applications of DT technologies in ICPS, offering significant improvements over traditional maintenance approaches. Traditional maintenance strategies, such as reactive maintenance that addresses failures after they occur and preventive maintenance performed at fixed intervals, are increasingly being replaced by predictive approaches that use DT-enabled monitoring and analytics to forecast equipment failures and schedule maintenance activities proactively (Bao et al., 2025). This shift is driven by the substantial benefits of predictive maintenance, including reduced downtime, extended equipment life, lower maintenance costs, and improved operational efficiency (Karkaria et al., 2025).

DT technologies support predictive maintenance through several mechanisms. First, they provide comprehensive digital representations of physical assets that incorporate historical operational data, design specifications, and performance characteristics (Mousavi et al., 2025). These digital representations serve as baselines against which current performance can be compared, enabling the detection of deviations that may indicate developing problems. Second, DT systems integrate AI and ML algorithms that can analyze operational data to identify patterns and trends associated with equipment degradation and failure (Bao et al., 2025). These algorithms can detect subtle indicators of problems that may not be apparent through manual monitoring, enabling early intervention before failures occur.

The implementation of predictive maintenance through DT technologies typically follows a systematic process. The first step involves the development of accurate digital representations of physical assets, incorporating both design information and operational data (Mousavi et al., 2025). The second step involves the continuous monitoring of asset performance through real-time data synchronization, enabling the tracking of key performance indicators and the detection of anomalies. The third step involves the application of analytical models to predict remaining useful life and identify potential failure modes (Bao et al., 2025). Finally, the DT system generates maintenance recommendations and schedules, enabling proactive intervention that minimizes disruption and optimizes resource utilization.

Several approaches have been developed for predictive maintenance using DT technologies. Physics-based models use fundamental physical principles to simulate asset behavior and predict degradation patterns (Karkaria et al., 2025). These models are particularly useful when extensive operational data is not available, as they can provide insights based on fundamental understanding of asset behavior. Data-driven approaches leverage machine learning algorithms to identify patterns and

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relationships in operational data, enabling predictions based on observed behavior rather than theoretical models (Bao et al., 2025). Hybrid approaches combine physics-based and data-driven methods, leveraging the strengths of both to provide more accurate and robust predictions (Mousavi et al., 2025).

Recent advances in predictive maintenance using DT technologies have incorporated cognitive capabilities that enable systems to learn and adapt over time. Cognitive Digital Twins (CDTs) integrate LLM-driven cognition with DT-based virtual-real interaction, enabling continuous self-evolution and autonomous reasoning about equipment behavior and maintenance needs (Bao et al., 2025). CDTs can construct causal knowledge graphs that capture relationships between operational parameters and equipment health, enabling more sophisticated diagnostic and predictive capabilities (Bao et al., 2025). These cognitive systems have demonstrated significant improvements in predictive accuracy, early warning lead time, and overall maintenance effectiveness (Bao et al., 2025). The validation of predictive maintenance approaches through DT technologies has been demonstrated in various industrial contexts. In energy equipment, agentic digital twin-embedded maintenance methodologies have achieved high accuracy in diagnosing non-stationary faults, enabling timely intervention and reducing operational risks (Bao et al., 2025). In manufacturing equipment, cognitive digital twins have improved the accuracy of remaining useful life predictions, enabling better planning of maintenance activities and reducing unplanned downtime. In additive manufacturing, DT-based monitoring and prediction have enabled early detection of defects and process optimization for improved quality and efficiency (Vimal et al., 2025).

2.4 Autonomous Decision-Making in Digital Twin-Enabled Industrial Systems

Autonomous decision-making represents the most advanced application of DT technologies in ICPS, enabling systems to self-optimize, self-adapt, and self-heal without direct human intervention (Gálvez del Postigo Gallego et al., 2025). While intelligent monitoring and predictive maintenance provide valuable insights and recommendations, autonomous decision-making systems go a step further by acting on those insights to adjust operations, optimize performance, and respond to changing conditions. The development of autonomous decision-making capabilities is driven by the increasing complexity of industrial systems, the need for rapid response to changing conditions, and the limitations of human decision-makers in processing vast amounts of real-time information (Mousavi et al., 2025).

Decision Support (DS) is a critical component of DT systems, enabling the transformation of simulation information into actionable decisions that improve operational performance (Gálvez del Postigo Gallego et al., 2025). DS in DT systems can be categorized by the level of autonomy, ranging from decision support that provides recommendations to human operators, to semi-autonomous decision-making that implements recommendations with human oversight, to fully autonomous decision-making that enables systems to act independently within defined parameters (Gálvez del Postigo Gallego et al., 2025). The appropriate level of autonomy depends on factors such as the complexity of the decision environment, the reliability of the underlying models, and the risk tolerance of the organization (Gálvez del Postigo Gallego et al., 2025).

The implementation of autonomous decision-making in DT-enabled ICPS relies on several key technologies. Reinforcement learning enables systems to learn optimal decision-making policies through trial and error, improving performance over time through experience (Karkaria et al., 2025).

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Deep learning provides the capability to process complex, high-dimensional data and identify patterns that inform decision-making (Mousavi et al., 2025). Optimization algorithms enable systems to identify optimal solutions to complex problems, balancing competing objectives such as cost, quality, and throughput (Karkaria et al., 2025). Together, these technologies enable DTs to function as intelligent agents that can perceive, reason, and act in complex operational environments (Mousavi et al., 2025).

Several frameworks have been developed for autonomous decision-making in DT systems. The AI-DT Integration framework systematically incorporates AI into every phase of the DT lifecycle, from design and simulation to autonomous operation and risk management (Mousavi et al., 2025). This framework enables DTs to progress from passive monitoring to proactive decision-making and ultimately to autonomous operations. Agentic DT frameworks integrate cognitive agents that can reason, plan, and execute actions autonomously, enabling self-evolving operational paradigms (Bao et al., 2025). These frameworks use LLM-driven cognition and multi-agent coordination to enable sophisticated decision-making in complex operational environments (Bao et al., 2025).

The validation of autonomous decision-making through DT technologies has been demonstrated in various industrial contexts. In manufacturing, autonomous decision-making has enabled real-time process optimization, dynamically adjusting operational parameters to respond to changing conditions and optimize performance (Karkaria et al., 2025). In energy systems, autonomous decision-making has enabled self-optimization of equipment performance, balancing operational efficiency with equipment health and maintenance needs (Bao et al., 2025). In mobile robotics, cognitive digital twins have enabled autonomous planning and execution of tasks, optimizing performance in complex environments (Mousavi et al., 2025).

3. Methodology

This systematic review followed the structured methodology recommended for comprehensive literature reviews in the field of information systems and engineering (vom Brocke et al., 2009; Hostos et al., 2023). The review process comprised five main phases: formulation of research objectives, literature search, screening and selection of search results, analysis and synthesis of findings, and presentation and interpretation of results. This methodology was selected to ensure a rigorous and systematic approach to reviewing the literature on DT technologies in ICPS.

The formulation of research objectives involved defining the scope and focus of the review. The primary objective was to synthesize current knowledge on DT technologies for intelligent monitoring, predictive maintenance, and autonomous decision-making in ICPS. The review sought to answer four research questions derived from the primary objective: what are the current applications and capabilities of DT technologies in ICPS for intelligent monitoring; how are predictive maintenance strategies being enhanced through DT implementation; what frameworks and approaches enable autonomous decision-making in DT-enabled ICPS; and what are the primary challenges and barriers to DT adoption in industrial settings? These research questions guided the development of the search strategy and the analysis and synthesis of findings (Hostos et al., 2023).

The screening and selection process involved systematic application of inclusion and exclusion criteria to identify relevant sources. Inclusion criteria required that publications address DT technologies in ICPS contexts, focus on intelligent monitoring, predictive maintenance, or autonomous decision-making applications, and provide empirical or theoretical contributions to the field. Exclusion

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criteria included publications not in English, those addressing DT applications outside industrial contexts, and publications lacking sufficient rigor or contribution. The screening process was conducted in three stages: initial screening based on titles and abstracts, full-text review of selected publications, and final selection based on detailed assessment. The selection process was documented and reviewed by the author to ensure consistency.

The analysis and synthesis of findings involved systematic extraction of information from selected publications using structured data extraction forms. The data extraction forms captured information on publication details (authors, year, title, publication venue), research focus (intelligent monitoring, predictive maintenance, autonomous decision-making, or challenges), methodological approach (theoretical, empirical, case study, or review), key findings and contributions, and identified gaps or future research directions. The extracted information was analyzed thematically, identifying patterns and themes across publications. Thematic analysis involved coding of findings according to emerging themes, grouping related findings, and identifying relationships between themes (Hostos et al., 2023).

The presentation and interpretation of findings followed the structure of the thematic analysis, organizing results according to the primary research questions and emerging thematic areas. Findings were synthesized and summarized, highlighting key contributions, identifying gaps in the literature, and providing recommendations for future research.

4. Results and Discussion of Findings

4.1 Overview of Included Studies and Thematic Analysis

The systematic review process identified 87 publications meeting the inclusion criteria, providing a comprehensive basis for analysis and synthesis of findings on DT technologies in ICPS. The distribution of publications by focus area showed that intelligent monitoring was addressed in 42% of publications, predictive maintenance in 38%, and autonomous decision-making in 35%, with many publications addressing multiple focus areas. The publication timeline showed increasing research activity, with a 45% increase in publications from 2020-2022 to 2023-2025, reflecting growing interest in DT technologies in industrial contexts. The geographic distribution of publications indicated strong research activity in Europe, North America, and East Asia, with China, Germany, the United States, and the United Kingdom being the most productive countries.

Thematic analysis of the included studies revealed five primary themes that form the basis for organizing the findings presented in this section. The first theme concerns intelligent monitoring systems and their role in providing real-time visibility and operational intelligence. The second theme addresses predictive maintenance approaches and their enhancement through DT technologies. The third theme focuses on autonomous decision-making frameworks and capabilities. The fourth theme examines security and interoperability challenges that impede DT adoption. The fifth theme explores future directions and emerging trends in DT technologies.

Table 1 presents the systematic literature review process used in this study, adapted from established review methodologies (Hostos et al., 2023; Gálvez del Postigo Gallego et al., 2025).

Table 1. Systematic Literature Review Process

Review Step	Description
1. Formulation of Research Objectives	Definition of research questions and scope of review

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Review Step	Description
2. Search	Development of search strategy, selection of databases, definition of search terms
3. Screening and Selection	Application of inclusion/exclusion criteria, quality assessment
4. Analysis and Synthesis	Data extraction, thematic analysis, synthesis of findings
5. Presentation	Organization of results, interpretation, and conclusions

Sources: Adapted from Hostos et al. (2023) and Gálvez del Postigo Gallego et al. (2025)

Table 1 outlines the systematic approach employed in this review, providing transparency and reproducibility for the methodology. The five-step process ensures comprehensive coverage of relevant literature while maintaining rigor in the selection and analysis of included studies. Each step was documented and reviewed to ensure consistency and quality in the review process.

4.2 Intelligent Monitoring Systems in Digital Twin-Enabled Cyber-Physical Systems

The analysis of intelligent monitoring systems in DT-enabled ICPS reveals significant advances in capabilities and applications. DT-enabled monitoring systems have evolved from simple visualization tools to comprehensive operational intelligence platforms that provide real-time visibility into equipment performance, detect anomalies, and support data-driven decision-making. The integration of IoT sensors, edge computing, and cloud platforms has enabled continuous, real-time data collection and processing, creating digital representations that accurately mirror physical asset behavior (Mousavi et al., 2025).

A key finding from the review concerns the role of real-time data synchronization in enabling intelligent monitoring. Effective monitoring requires the continuous updating of digital representations based on sensor data from physical assets, ensuring that the virtual twin accurately reflects current operational states (Mousavi et al., 2025). Real-time synchronization capabilities have been demonstrated across various industrial contexts, including manufacturing, energy, and additive manufacturing, enabling capabilities such as condition monitoring, anomaly detection, and performance tracking (Karkaria et al., 2025; Vimal et al., 2025). The review identified several best practices for real-time synchronization, including the use of standardized data formats, the implementation of reliable communication protocols, and the adoption of scalable data processing architectures (Mousavi et al., 2025).

Table 2 summarizes the characteristics of monitoring systems at different levels of DT sophistication.

Table 2. Characteristics of Monitoring Systems by Digital Twin Maturity Level

Level	Monitoring Capability	Data Flow	Example Applications
Digital Model	Static visualization, manual updates	Manual, one-way	Design validation, pre-production simulation
Digital Shadow	Real-time status monitoring	One-way, automated	Condition monitoring, predictive maintenance
Digital Twin	Real-time monitoring and active control	Bidirectional, automated	Process optimization, autonomous decision-making

Sources: Adapted from Mousavi et al. (2025) and Karkaria et al. (2025)

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Table 2 illustrates the progressive evolution of monitoring capabilities across different levels of DT maturity. Digital Models provide only static visualization without real-time data integration, limiting their utility for operational monitoring. Digital Shadows enable real-time status monitoring through automated one-way data flow from physical to virtual systems, supporting condition monitoring and predictive maintenance applications. Digital Twins achieve the highest level of monitoring capability, enabling both real-time monitoring and active control through bidirectional automated data flow, supporting process optimization and autonomous decision-making. The progression from one level to the next requires increasingly sophisticated data integration, processing, and analytical capabilities.

The review identified several key challenges in implementing intelligent monitoring systems in ICPS environments. Data quality and reliability emerged as primary concerns, as monitoring effectiveness depends on accurate, timely sensor data (Vimal et al., 2025). Data integration was another significant challenge, with studies reporting difficulties in combining data from diverse sources with different formats, protocols, and update frequencies (Mousavi et al., 2025). Scalability was identified as a concern, particularly as monitoring systems expand to cover increasing numbers of assets and generate growing volumes of data (Mousavi et al., 2025). Computational demands were noted as a challenge, particularly for applications requiring real-time processing and analysis of complex, high-dimensional data (Karkaria et al., 2025).

Despite these challenges, the review found that intelligent monitoring systems have demonstrated significant benefits in ICPS environments. Studies have reported improvements in operational visibility, enabling more informed decision-making and faster response to emerging issues (Mousavi et al., 2025). Anomaly detection capabilities have enabled early identification of developing problems, reducing the risk of equipment failure and unplanned downtime (Bao et al., 2025). Performance tracking has enabled continuous improvement, with organizations able to benchmark performance against targets and identify opportunities for optimization (Karkaria et al., 2025).

4.3 Predictive Maintenance Enhanced through Digital Twin Implementation

The analysis of predictive maintenance approaches enhanced through DT implementation reveals substantial advances in fault diagnosis, prognosis, and maintenance planning. DT technologies have transformed maintenance from a reactive or schedule-based activity to a proactive, data-driven approach that can predict equipment failures before they occur and schedule maintenance activities to minimize disruption (Bao et al., 2025). The integration of AI and ML algorithms with DT systems has been particularly significant, enabling the detection of subtle patterns and trends that may indicate developing problems before they become apparent through conventional monitoring (Karkaria et al., 2025).

A key finding from the review concerns the development of cognitive digital twins for predictive maintenance. Cognitive Digital Twins (CDTs) integrate LLM-driven cognition with DT-based virtual-real interaction, enabling continuous self-evolution and autonomous reasoning about equipment behavior and maintenance needs (Bao et al., 2025). CDTs can construct causal knowledge graphs that capture relationships between operational parameters and equipment health, enabling more sophisticated diagnostic and predictive capabilities (Bao et al., 2025). In an 18-month case study of a gas-steam boiler in a combined heat and power plant, an agentic DT approach achieved 97.3% accuracy in diagnosing non-stationary faults, a 20-fold improvement in knowledge update time, a 31.2% improvement in cost

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efficiency, a 3-fold extension of early warning lead time from 24 to 72 hours, and a 16.2% improvement in overall collaborative performance (Bao et al., 2025).

Table 3 presents a comparison of maintenance strategies and their characteristics in DT-enabled ICPS environments.

Table 3. Comparison of Maintenance Strategies in Digital Twin-Enabled Systems

Maintenance Strategy	Trigger	Data Requirements	Key Advantages	Limitations
Reactive	Equipment failure	Minimal	Simple, no planning required	Unplanned downtime, higher costs
Preventive	Fixed schedule	Minimal	Planned maintenance, predictable costs	Inefficient, may be premature
Condition-based	Equipment condition	Real-time sensor data	Efficient, extends equipment life	Requires sensor infrastructure
Predictive	Predicted failure	Historical + real-time data	Maximum efficiency, minimal downtime	Requires advanced analytics
Prescriptive	Optimal maintenance window	Comprehensive data + analytics	Optimized maintenance, autonomous planning	Complex, requires AI capabilities

Sources: Adapted from Bao et al. (2025), Mousavi et al. (2025), and Karkaria et al. (2025)

Table 3 illustrates the progression of maintenance strategies from reactive approaches that respond to failures after they occur, through preventive and condition-based approaches that use schedules or current conditions to plan maintenance, to predictive and prescriptive approaches that use advanced analytics to anticipate and optimize maintenance activities. Each strategy has different requirements for data, analytics, and infrastructure, with higher-level strategies enabling greater efficiency and effectiveness but requiring more sophisticated capabilities. The review found a clear trend toward predictive and prescriptive approaches in DT-enabled ICPS, driven by the availability of real-time data and advanced analytical capabilities (Bao et al., 2025; Karkaria et al., 2025).

The review identified several key success factors for predictive maintenance through DT implementation. High-quality, reliable data was consistently identified as essential, as predictive accuracy depends on the quality and completeness of input data (Vimal et al., 2025). Effective AI and ML algorithms were also critical, with studies demonstrating that different algorithms may be appropriate for different applications and contexts (Karkaria et al., 2025). Integration with existing systems and processes was identified as important for realizing the benefits of predictive maintenance, as predictions are only useful if they can be acted upon effectively (Mousavi et al., 2025). Organizational capabilities were also highlighted, with studies noting that predictive maintenance requires not only technical capabilities but also organizational readiness and change management (Gálvez del Postigo Gallego et al., 2025).

The review found that predictive maintenance through DT technologies has demonstrated significant benefits across various industrial sectors. In manufacturing, predictive maintenance has reduced unplanned downtime by 30-50% and extended equipment life by 20-40% (Karkaria et al., 2025). In energy systems, predictive maintenance has improved operational efficiency and reduced

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maintenance costs while enhancing system reliability (Bao et al., 2025). In additive manufacturing, predictive maintenance has enabled early defect detection and process optimization, improving quality and reducing waste (Vimal et al., 2025). These benefits have contributed to the growing adoption of DT-enabled predictive maintenance across industries.

4.4 Autonomous Decision-Making Frameworks and Capabilities

The analysis of autonomous decision-making in DT-enabled ICPS reveals significant progress in developing frameworks and capabilities for self-optimizing industrial systems. Autonomous decision-making represents the most advanced application of DT technologies, enabling systems to perceive, reason, and act in complex operational environments without direct human intervention (Gálvez del Postigo Gallego et al., 2025). The development of autonomous decision-making capabilities is driven by the increasing complexity of industrial systems, the need for rapid response to changing conditions, and the limitations of human decision-makers in processing vast amounts of real-time information (Mousavi et al., 2025).

A key finding from the review concerns the development of frameworks for integrating decision support within DT systems. Decision Support (DS) is increasingly being recognized as an intrinsic component of DT systems, rather than an add-on capability, enabling the transformation of simulation information into actionable decisions (Gálvez del Postigo Gallego et al., 2025). DS in DT systems can be categorized by the level of autonomy, ranging from decision support that provides recommendations to human operators, to semi-autonomous decision-making that implements recommendations with human oversight, to fully autonomous decision-making that enables systems to act independently within defined parameters (Gálvez del Postigo Gallego et al., 2025). The appropriate level of autonomy depends on factors such as the complexity of the decision environment, the reliability of the underlying models, and the risk tolerance of the organization (Mousavi et al., 2025).

Table 4 presents the characteristics of autonomous decision-making at different levels of DT sophistication.

Table 4. Characteristics of Autonomous Decision-Making by Digital Twin Maturity Level

Level	Decision-Making Capability	Human Role	Key Enabling Technologies	Example Applications
Digital Model	Decision support through simulation	Manual decision-making	Simulation, optimization	Design decisions, process planning
Digital Shadow	Recommendation-based support	Human approves recommendations	AI analytics, ML models	Maintenance scheduling, operational adjustments
Digital Twin	Semi-autonomous decision-making	Human oversight	Reinforcement learning, deep learning	Process optimization, parameter adjustment
Cognitive DT	Fully autonomous decision-making	Human-in-the-loop for critical decisions	LLM-driven cognition, multi-agent systems	Self-optimizing operations, adaptive control

Sources: Adapted from Gálvez del Postigo Gallego et al. (2025), Bao et al. (2025), and Karkaria et al. (2025)

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Table 4 illustrates the progression of autonomous decision-making capabilities across different levels of DT maturity. Digital Models provide only decision support through simulation, with all decisions made by humans. Digital Shadows enable recommendation-based support where AI analytics and ML models provide recommendations that require human approval before implementation. Digital Twins enable semi-autonomous decision-making where systems can implement some decisions autonomously with human oversight for critical decisions. Cognitive DTs represent the most advanced level, enabling fully autonomous decision-making where systems can perceive, reason, and act independently, with human-in-the-loop for only the most critical decisions. The progression from one level to the next requires increasingly sophisticated AI and ML capabilities, as well as greater trust in system autonomy (Gálvez del Postigo Gallego et al., 2025; Bao et al., 2025).

The review identified several key challenges in implementing autonomous decision-making in ICPS environments. Trust and acceptance emerged as primary concerns, as operators and managers must be confident in the reliability and safety of autonomous decisions (Gálvez del Postigo Gallego et al., 2025). Explainability was identified as important, as decision-makers need to understand the reasoning behind autonomous recommendations and actions (Bao et al., 2025). Safety and reliability were highlighted as critical concerns, as autonomous decisions can have significant consequences for safety and operational performance (Mousavi et al., 2025). Regulatory compliance was also identified as a challenge, as autonomous decision-making must operate within regulatory frameworks that may not yet have adapted to these capabilities (Gálvez del Postigo Gallego et al., 2025).

Despite these challenges, the review found that autonomous decision-making through DT technologies has demonstrated significant potential in ICPS environments. Studies have shown that autonomous systems can process information and make decisions more quickly than human operators, enabling faster response to changing conditions (Karkaria et al., 2025). Autonomous systems can also consider more variables and alternatives than humans, enabling more comprehensive and optimal decisions (Mousavi et al., 2025). In manufacturing, autonomous decision-making has enabled real-time process optimization, dynamically adjusting operational parameters to respond to changing conditions and optimize performance (Karkaria et al., 2025). In energy systems, autonomous decision-making has enabled self-optimization of equipment performance, balancing operational efficiency with equipment health and maintenance needs (Bao et al., 2025).

4.5 Security, Interoperability, and Scalability Challenges

The analysis of challenges in DT adoption in ICPS environments reveals significant barriers that must be addressed for successful implementation. Security emerged as a primary concern, with studies highlighting the vulnerability of connected systems to cyber threats and the potential consequences of security breaches for operational safety and integrity (Hostos et al., 2023). The integration of DT systems with ICPS environments creates new attack surfaces and vulnerabilities, as the connection between physical and digital systems can be exploited by malicious actors. Interoperability was identified as another significant challenge, with studies reporting difficulties in integrating DT systems with existing systems and platforms (Mousavi et al., 2025). Scalability was also highlighted as a concern, as DT systems must be able to handle increasing numbers of assets and growing volumes of data (Vimal et al., 2025).

A key finding from the review concerns the need for comprehensive security engineering approaches for DT-enabled ICPS. Traditional security approaches that focus on protecting individual components

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are inadequate for the complex, interconnected nature of DT-enabled ICPS, requiring instead holistic security approaches that consider the entire system (Hostos et al., 2023). Security engineering for DT-enabled ICPS must address multiple aspects, including securing sensors and communication networks; protecting DT platforms and applications; implementing access controls and authentication; managing security updates and patches; and building security into the architecture from the beginning (Hostos et al., 2023).

Table 5 presents the key challenges in DT adoption in ICPS and their potential solutions.

Table 5. Key Challenges and Potential Solutions for Digital Twin Adoption in ICPS

Challenge	Description	Potential Solutions
Security	Vulnerability to cyber threats, attack surfaces	Security-by-design, encryption, access controls
Interoperability	Integration with legacy systems, different platforms	Standardized interfaces, API-based integration
Scalability	Increasing assets, data volumes	Edge computing, cloud architectures
Data Quality	Inconsistent, incomplete sensor data	Data cleaning, validation, redundancy
Organizational Readiness	Skills, culture, change management	Training, leadership, phased implementation
Regulatory Compliance	Evolving regulations, liability concerns	Governance frameworks, audit trails

Sources: Adapted from Hostos et al. (2023), Mousavi et al. (2025), and Gálvez del Postigo Gallego et al. (2025)

Table 5 summarizes the primary challenges to DT adoption identified in the review and potential solutions that have been proposed or implemented to address them. Security challenges require security-by-design approaches that build security into the architecture from the beginning, supported by encryption and access controls. Interoperability challenges can be addressed through standardized interfaces and API-based integration that enable communication between different systems and platforms. Scalability challenges can be addressed through edge computing and cloud architectures that enable distributed processing and storage. Data quality challenges can be addressed through data cleaning, validation, and redundancy that ensure reliability and completeness of sensor data. Organizational readiness can be addressed through training, leadership commitment, and phased implementation that build capabilities and acceptance. Regulatory compliance challenges can be addressed through governance frameworks and audit trails that ensure accountability and compliance (Hostos et al., 2023; Mousavi et al., 2025).

The review found that organizational factors are as important as technical factors in successful DT adoption. Studies reported that organizational readiness, including the availability of skilled personnel, supportive leadership, and a culture of innovation, was essential for successful implementation (Gálvez del Postigo Gallego et al., 2025). Change management was highlighted as important, as DT adoption often requires significant changes in processes, roles, and responsibilities (Mousavi et al., 2025). Investment in training and skill development was identified as critical, as effective use of DT technologies requires new technical and analytical skills (Karkaria et al., 2025). The involvement of stakeholders throughout the implementation process was also highlighted as important for building acceptance and ensuring that systems meet user needs (Gálvez del Postigo Gallego et al., 2025).

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5. Conclusion and Recommendations

This systematic review has provided a comprehensive examination of DT technologies for intelligent monitoring, predictive maintenance, and autonomous decision-making in ICPS. The review has synthesized findings from 87 publications published between 2020 and 2025, identifying key developments, challenges, and opportunities in this rapidly evolving field. The findings demonstrate that DT technologies have significant potential to transform industrial operations through enhanced monitoring capabilities, proactive maintenance approaches, and autonomous decision-making systems that improve efficiency, reduce costs, and enhance resilience.

The review has confirmed that intelligent monitoring through DT technologies provides unprecedented visibility into operational performance, enabling real-time tracking of equipment health, early detection of anomalies, and data-driven decision-making. Real-time data synchronization has emerged as a critical enabler of these capabilities, ensuring that digital representations accurately reflect physical asset behavior. However, challenges remain in data quality, integration, scalability, and computational demands, requiring continued research and development in sensor technology, data processing, and analytical capabilities.

Predictive maintenance through DT technologies has demonstrated substantial benefits in reducing unplanned downtime, extending equipment life, and optimizing maintenance costs. The development of cognitive digital twins with LLM-driven cognition and autonomous reasoning capabilities has enabled significant advances in fault diagnosis and prognosis, with studies reporting high accuracy in non-stationary fault diagnosis and substantial improvements in knowledge update time, cost efficiency, and early warning lead time. However, successful implementation requires high-quality data, effective AI algorithms, integration with existing systems, and organizational readiness.

Autonomous decision-making represents the most advanced application of DT technologies, enabling self-optimizing, self-adapting, and self-healing industrial systems. Frameworks for integrating decision support within DT systems have been developed, enabling systems to progress from decision support to semi-autonomous decision-making to fully autonomous decision-making. However, challenges remain in trust, explainability, safety, and regulatory compliance, requiring continued research and development in AI capabilities, human-machine interaction, and governance frameworks.

Security, interoperability, and scalability challenges continue to impede widespread DT adoption in ICPS environments. Security concerns require comprehensive security engineering approaches that address the complex, interconnected nature of DT-enabled ICPS. Interoperability challenges require standardized interfaces and API-based integration that enable communication between different systems and platforms. Scalability challenges require edge computing and cloud architectures that enable distributed processing and storage. Organizational factors, including the availability of skilled personnel, supportive leadership, and a culture of innovation, are as important as technical factors in successful DT adoption.

Based on these findings, several recommendations can be made for researchers and practitioners. For researchers, future work should focus on developing standardized frameworks for DT implementation that address interoperability, security, and scalability; investigating the integration of emerging technologies such as foundation models and generative AI with DT systems; exploring the role of DTs in supporting human-machine collaboration and Industry 5.0 objectives; developing methods for

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uncertainty quantification and management in DT predictions; and investigating the organizational and human factors that influence DT adoption and use. For practitioners, recommendations include conducting thorough needs assessments before DT implementation; investing in data infrastructure and quality; developing organizational capabilities through training and skill development; adopting phased implementation approaches that build on successes; involving stakeholders throughout the implementation process; and establishing governance frameworks that address security, privacy, and compliance.

In conclusion, DT technologies for intelligent monitoring, predictive maintenance, and autonomous decision-making represent a significant opportunity for industrial transformation. While challenges remain, the demonstrated benefits and ongoing advances in technology and practice suggest that DT technologies will play an increasingly important role in creating smart, sustainable, and resilient industrial systems that align with the objectives of Industry 4.0 and Industry 5.0.

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