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Is it worth developing Digital Twins for Industrial Maintenance? Current Trends and first Assessment Elements

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Digital Twin (DT) has emerged as a cornerstone technology in industrial maintenance, providing dynamic virtual representations of physical assets that enable real-time monitoring, predictive analytics, and performance optimization. While its technical benefits are widely acknowledged, questions persist regarding its actual profitability and environmental sustainability.
Based on previous works, this paper provides an updated overview examining how emerging technologies, particularly artificial intelligence (AI) and augmented reality (AR), are reshaping DT applications in industrial maintenance contexts. It synthesizes the latest academic and industrial advancements to outline key trends, methodological innovations, and representative case studies across multiple sectors. A specific focus is placed on the convergence of machine learning and AI-driven predictive maintenance with immersive visualization technologies, which together improve data interpretation, operational decision-making, and operator training.
In this study, several dimensions are considered: the maturity level of DT implementations, the types of industrial equipment observed, the quantity and nature of data collected (sensor data, operational parameters, environmental variables), and the specific maintenance strategies applied (corrective or preventive, the latter encompassing time-based, condition-based, and predictive approaches). The analysis also compares applications across sectors such as energy, manufacturing, and transportation to evaluate their respective levels of adoption and return on investment.
Beyond conceptual and technical dimensions, the study seeks to determine the conditions under which Digital Twins constitute sustainable and cost-effective solutions for industrial maintenance. To address this issue, an evaluation framework is proposed, integrating both qualitative and quantitative metrics, including economic and environmental costs, to assess performance throughout the DT life cycle, from design to operation.
This dual perspective enables a holistic understanding of how DT generate value across different industrial ecosystems. The results of this research are expected to provide strategic insights for industrial stakeholders, thereby supporting evidence-based decision-making regarding technology investment, operational optimization, and the transition toward more resilient and sustainable industrial systems.

Keywords: Digital twin, industry, maintenance, augmented reality, virtual reality

1 Introduction

A Digital Twin (DT) refers to a dynamic digital representation of a physical asset, system, or process, continuously updated through data exchange across its lifecycle. Unlike a standalone mathematical model, a DT typically combines models with (near) real-time data flows, explicit lifecycle anchoring, and operational services (e.g., monitoring, diagnosis, what-if simulation) to support decision-making. In industrial maintenance, DTs are increasingly promoted as enablers of predictive decision-making, operational optimization, and sustainability improvements. However, beyond technological feasibility, their actual economic and environmental relevance remains insufficiently assessed, particularly in real industrial contexts.

To address these challenges and provide a structured assessment of current practices, this study adopts a systematic literature-based approach combining quantitative classification and qualitative analysis. It extends Viaron et al. (2024), and Table 1 directly continues the previous study with publications published in 2024 and 2025. The review characterizes the selected publications by geographical distribution, industrial sector, DT maturity level, enabling technologies, and maintenance strategies (corrective vs preventive, including time-based/systematic and data-driven approaches such as condition-based/predictive maintenance).

The remainder of the paper is organized as follows: Section 2 details the review methodology and classification criteria. Section 3 reports the main results and trends. Section 4 provides a focused analysis of high-maturity manufacturing-oriented DT applications and discusses implications for maintenance decision support, including digital maturity and user experience (UX) considerations.

2 Review Methodology

Several dimensions are considered: the maturity level of DT implementations, the types of industrial equipment observed, the quantity and nature of data collected (sensor data, operational parameters, environmental variables), and the maintenance strategies applied. These strategies include corrective maintenance and preventive maintenance approaches, such as time-based or systematic maintenance (scheduled at fixed intervals), condition-based maintenance (triggered by equipment state), and predictive maintenance (anticipating failures through data analysis). The analysis also compares applications across sectors such as energy, manufacturing, and transportation to evaluate their respective levels of adoption and return on investment.

2.1 Literature Selection and Scope

The literature was identified through a Google Scholar search using the query: allintitle: Maintenance "Digital Twin".

Reviews, overviews, and studies related to BIM, facility management, supply chain, infrastructure, urban systems, buildings, bridges, aviation, aquaculture, art, and construction were excluded in order to retain publications specifically focused on industrial maintenance contexts. The analysis was limited to English-language publications published in 2024 or 2025, ensuring a focused dataset of recent industrial maintenance-oriented Digital Twin applications.

2.2 Analysis Dimensions and Evaluation Criteria

Each selected publication was systematically coded using a predefined analysis grid composed of five dimensions: geographical scope, industrial sector, DT maturity level, maintenance strategy, and enabling technologies.

DT maturity was classified according to a five-level scale ranging from Mirror and Shadow representations to Control, Cognitive, and Collaborative Digital Twins. Maintenance approaches were categorized as corrective maintenance, preventive maintenance, time-based (systematic) preventive maintenance, condition-based maintenance, predictive maintenance, or not specified. Enabling technologies were identified based on explicit mentions of artificial intelligence (AI), industrial Internet of Things (IIoT), and immersive technologies such as augmented reality (AR), virtual reality (VR), and extended reality (XR).

This standardized classification ensured consistency across heterogeneous studies and enabled cross-comparison without relying on subjective interpretation.

2.3 Value-Oriented Selection and Assessment Procedure

A total of 197 publications were included in the review process. Each document was thoroughly read and assessed using a cross-validation procedure involving three engineering students specializing in industrial engineering.
The validation process was conducted using an overlap-based approach, whereby each publication was subjected to independent review by at least two assessors. Discrepancies in the classification were resolved through collaborative discussion, thereby ensuring a uniform interpretation and classification of the publications. The application of this procedure to the entire dataset of publications was driven by the objective of enhancing methodological rigor. This approach contributed to reducing individual bias and improving the reliability of the data extraction process.

3 Results of the analysis

Fig. 1 indicates an increase in the number of publications over the period 2018–2025 across all regions. Europe and Asia exhibit the highest values throughout the period considered, reaching 38 and 44 publications respectively in 2025. Africa and America show lower but steadily increasing numbers of publications, reaching 17 and 18 publications respectively by 2025. In contrast, Oceania remains marginal in terms of publication output, with a maximum annual increase of one publication over the period.

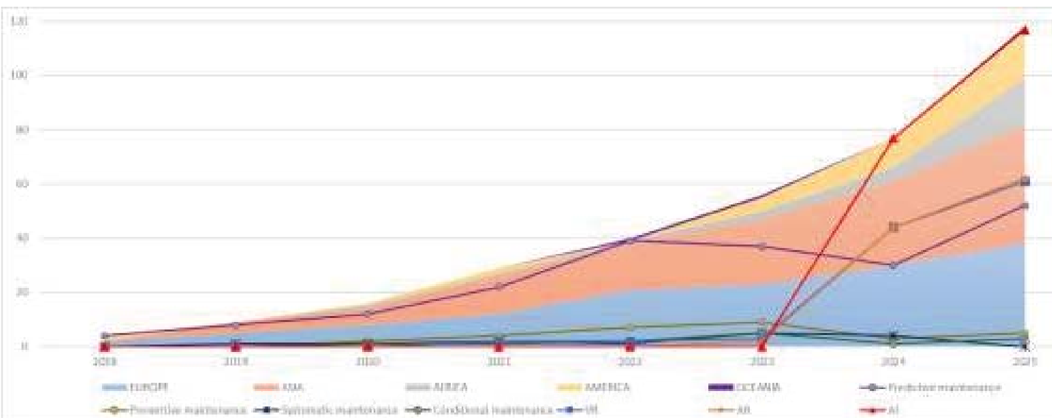

Table 1 shows that Europe and Asia each account for approximately 40 % of the total publications (139 and 140 respectively), followed by America with 11 % (39), Africa with 8 % (28), and Oceania with 1 % (3). This distribution highlights the dominant role of European and Asian research ecosystems in the development of Digital Twin applications for industrial maintenance, while other regions remain less represented despite a gradual increase in publication activity.

Regarding maintenance strategies, the literature is predominantly focused on predictive maintenance, which represents 78 % of the publications (204). Preventive maintenance accounts for 11 % (30), while time-based (systematic) maintenance and condition-based maintenance represent 5 % (14) and 5 % (13) of the publications respectively. This strong emphasis on predictive maintenance reflects the growing integration of data-driven approaches within Digital Twin architectures, where sensor data and advanced analytics enable the anticipation of failures and the optimization of maintenance planning.

From a technological perspective, 112 publications (27 %) refer to virtual reality (VR) and 108 publications (26 %) refer to augmented reality (AR). Artificial intelligence (AI) is mentioned in 194 publications (47 %) in 2024 and 2025. These results suggest an increasing convergence between data-driven predictive models and immersive visualization technologies, which together support improved interpretation of operational data, operator training, and decision-making in industrial environments.

Table 1. Summary of the selected publications and their classification across regions, maintenance strategies, and enabling technologies.

Category	2018	2019	2020	2021	2022	2023	2024	2025	Total	%
ASIA	0	4	6	14	17	24	31	44	140	40,1%
EUROPE	2	5	8	12	21	23	30	38	139	39,8%
AMERICA	2	0	1	2	0	5	11	18	39	11,2%
AFRICA	0	0	1	1	1	3	5	17	28	8,0%
OCEANIA	0	0	0	0	1	1	0	1	3	0,9%
Predictive maintenance	4	8	12	22	39	37	30	52	204	78,2%
Preventive maintenance	0	0	2	4	7	9	3	5	30	11,5%
Time-based (systematic) maintenance	0	1	1	2	1	5	4	0	14	5,3%
Condition-based maintenance	0	0	1	1	2	5	1	3	13	5,0%
AI							77	117	194	46,9%
VR	0	0	0	2	2	3	44	61	112	27,0%
AR	0	0	0	0	0	2	44	62	108	26,1%

3.1 Orientation and technology focus

The analyzed publications are distributed across several industrial categories. Manufacturing accounts for 26 publications (13%), energy for 33 publications (17%), transportation for 23 publications (12%), civil engineering for 19 publications (10%), and health-related applications for 1 publication (1%).

The largest category corresponds to state-of-the-art contributions, which represent 93 publications (48%) of the total dataset of publications.

Table 1. Orientation and Technology Focus

Type of industry	Number of publications	% Distribution
State of art	93	48%
Energy	33	17%
Manufacturing	26	13%
Transportation	23	12%
civil engineering	19	10%
Health	1	1%

3.2 Digital Twin Maturity Levels

The distribution of publications by Digital Twin (DT) maturity level shows that Level 1 (Mirror) and Level 4 (Cognitive) are the most prevalent, with 98 and 82 publications respectively.

In contrast, Level 2 (Shadow), Level 3 (Control), and Level 5 (Collaborative) remain less common, indicating that intermediate or fully collaborative Digital Twin implementations are still relatively limited in the current literature.

Table 2. Digital Twin Maturity Levels

Level of digital twins	Number of publications
Level 1 (Mirror)	98
Level 4 (Cognitive)	82
Level 2 (Shadow)	6
Level 5 (Collaborative)	6
Level 3 (Control)	3

The maturity analysis reveals a marked dichotomy between rudimentary Mirror DT and more advanced Cognitive implementations. Mirror-level systems remain widely used for monitoring and visualization purposes, whereas Cognitive Digital Twins increasingly incorporate data-driven models for diagnosis and predictive analysis. The limited presence of intermediate maturity levels suggests that development pathways are not always incremental. Many studies either remain at descriptive levels or directly target intelligent functionalities without a formalized validation of intermediate control stages.

A complementary geographical analysis was conducted to assess whether DT research maturity differs across continents. Despite variations in the volume of publications across regions, the distribution of maturity levels appears relatively balanced worldwide. No continent concentrates a significantly higher share of advanced DT levels, suggesting a globally homogeneous progression of Digital Twin research maturity.

3.3 Technology Stack Distribution

The term "artificial intelligence" (AI) is mentioned in almost all publications, reaching 99% in state-of-the-art studies and 100% in all sector-specific groups.

Table 3. Technology Stack Distribution

Type of industry	AI	AR VR	IoT
State-of-the-art	99%	51%	10%
Energy	100%	67%	6%
Manufacturing	100%	54%	12%
Transportation	100%	48%	13%
Civil engineering	100%	63%	16%
Health	100%	100%	0%

This pervasive presence indicates a dominant trend within the existing literature. However, in many cases the term "AI" is used as a generic label. In practice, it often refers to machine learning (ML) techniques or related data-driven methods rather than to fully autonomous artificial intelligence systems in the strict sense.

Furthermore, several publications mention AI only in the context of literature reviews or state-of-the-art analyses, without implementing AI-based models within operational Digital Twin architectures.

The presence of AR and VR technologies shows greater variability, with percentages ranging from 48% in the transportation sector to 100% in health-related publications. In contrast, the explicit presence of IoT technologies remains comparatively limited, with values ranging from 6% to 16% across sectors.

The predominance of generic studies, combined with the widespread reference to AI, suggests that a significant portion of the literature focuses on technological architectures and conceptual frameworks rather than on domain-specific maintenance implementations directly aligned with industrial use cases.

From a technological standpoint, immersive technologies such as augmented reality (AR), virtual reality (VR), and extended reality (XR) are increasingly integrated to support visualization, operator interaction, and training activities. Nevertheless, their adoption remains secondary compared to AI-driven analytical capabilities.

The relatively limited explicit documentation of IoT infrastructures, despite their fundamental role in data acquisition, suggests that these technologies are often considered implicit enabling components rather than central research contributions.

3.4 Overall Findings

The present study indicates that current Digital Twin research in industrial maintenance is primarily oriented toward analytical performance and technological integration rather than toward comprehensive lifecycle evaluation. Although economic profitability and environmental sustainability are frequently cited as major motivations for Digital Twin adoption, the literature still provides limited quantitative evidence supporting these claims. This observation highlights the need for structured evaluation frameworks capable of assessing Digital Twin implementations beyond technical feasibility, particularly in terms of long-term cost-effectiveness, operational value, and environmental impact within real industrial contexts.

4 Impact Analysis

In addition to the overall dataset of 197 publications, a focused subset of 19 studies was selected for further analysis. The selection criteria were restricted to manufacturing-oriented applications and to Digital Twin maturity levels 3 (Control), 4 (Cognitive), and 5 (Collaborative), ensuring that only advanced and operationally relevant implementations were retained.

These selected publications were then examined in greater detail in order to extract additional information where available, including the type of twinned object, DT maturity level, functional characteristics, enabling technologies, user experience (UX) aspects, and communication protocols. This targeted analysis aims to provide a more detailed technical characterization of high-maturity Digital Twin implementations in industrial maintenance contexts.

However, it should be noted that not all dimensions could be systematically reported, as the level of technical detail varies significantly across publications.

4.1 Equipment, Maturity, and User Experience

User experience (UX) emerged as a key factor influencing both the ecological footprint and the overall sustainability performance of a Digital Twin (DT). To incorporate this dimension into the assessment framework, the study draws on the DT Capabilities Periodic Table (Elbaroudi et al., 2025). This model defines five progressive levels of UX maturity, each representing an increasing degree of interactivity, immersion, and integration between the user and the digital environment.

Within this analytical framework, UX was examined in parallel with equipment characteristics and DT maturity indicators, providing a multidimensional perspective that connects technological capability with human interaction quality. This integrated approach highlights that digital maturity extends beyond technical sophistication; it also depends on how effectively the Digital Twin supports intuitive, efficient, and sustainable user engagement throughout the system lifecycle.

Table 4. The evaluation grid used to evaluate the impacts of a DT

	Maturity	Equipment	UX
L1	Mirror	No new equipment	Basic visualizations
L2	Shadow	IoT	Advanced visualization
L3	Control	One simple user terminal	3D modeling
L4	Cognitive	One augmented user terminal	Extended Reality (XR)
L5	Collabora tive	Multiple user terminals	Gamification

By applying this reference framework to the publications included in our literature review, it was observed that most studies were positioned either at Level 1 of DT maturity (Mirror), characterized by static visualization of digital replicas, or at Level 4 (Cognitive). The latter has become increasingly prevalent since 2024, reflecting the growing integration of immersive technologies such as AR, VR, and XR to enhance user interaction.

This evolution has occurred in parallel with the rising influence of artificial intelligence, indicating a convergence between cognitive automation and experiential design within Digital Twin development.

While these advancements demonstrate significant progress in both technological sophistication and user engagement, they also introduce important cost implications. Implementing immersive and AI-driven Digital Twin solutions often requires substantial investments in computational models, specialized equipment, and large-scale data infrastructures. These economic and resource considerations highlight the need for balanced strategies that maximize innovation benefits without compromising accessibility or sustainability.

To interpret the ecological and economic impacts of a Digital Twin, a scoring approach is proposed based on three criteria: DT maturity, equipment acquisition, and UX level, each evaluated on a scale from 1 to 5. The total score (TS) corresponds to the sum of the three criteria and therefore ranges from 3 to 15, where higher scores indicate greater ecological and economic impacts.

Scores can be categorized as follows:

- Low Impact: $TS \leq 6$
- Medium Impact: $7 \leq TS \leq 10$
- High Impact: $TS \geq 11$

4.2 Convergence of Artificial Intelligence and Machine Learning in Predictive Maintenance

DT technology has significantly improved maintenance applications through the integration of artificial intelligence (AI) and machine learning (ML) techniques. AI supports advanced reasoning and complex data analysis, while ML enables Digital Twins to continuously improve their performance by learning from operational data collected from industrial systems. Together, these technologies transform the Digital Twin into a dynamic decision-support tool capable of predicting failures and optimizing maintenance strategies.

A review of the literature indicates that only three studies meet the criteria for truly operational Digital Twins applied to real Observable Manufacturing Elements (OMEs). These studies demonstrate the implementation of AI- and ML-based Digital Twin approaches for predictive maintenance in specific industrial systems, highlighting the growing convergence between intelligent algorithms and digital representations of physical assets.

4.3 Case Study: Application to an Observable Manufacturing Element (OME)

Across the selected studies, predictive maintenance strategies vary considerably, relying on different artificial intelligence (AI), machine learning (ML), and Long Short-Term Memory (LSTM) models. The choice of predictive approach largely depends on the characteristics of the equipment involved, referred to here as the Observable Manufacturing Element (OME). This observation highlights the strong relationship between predictive methodology and the operational characteristics of the monitored industrial system.

4.3.1 Application for a Winding Machine

Kerkeni et al. (2025) propose a data-driven Digital Twin (DT) designed for unsupervised anomaly detection on a monofilament winding machine, a critical element in textile spinning processes. The proposed DT leverages real-time sensor data to identify geometric defects and support predictive maintenance, thereby reducing downtime and improving product quality.

According to the proposed evaluation grid, this implementation reaches Control DT maturity (Level 3), employs IoT-based monitoring equipment, and provides a 3D visualization interface, resulting in a total score of TS = 8 (3 + 2 + 3). The Digital Twin can therefore be classified as a medium-impact DT, integrating closed-loop predictive capabilities while maintaining moderate equipment and user experience requirements.

4.3.2 Application to a CNC System

In their 2025 study, Khan et al. present a data-driven Digital Twin for the predictive maintenance of a ROMI E280 CNC turning machine used in smart manufacturing environments. The proposed DT enables the monitoring and prediction of key process indicators, including surface quality and energy consumption, with the aim of supporting both maintenance planning and operational decision-making.

Based on the proposed evaluation grid, this implementation reaches Cognitive DT maturity (Level 4), relies on limited additional equipment, and provides a structured 3D user interface, resulting in a total score of TS = 10. The Digital Twin is therefore positioned at the upper boundary of the medium-impact category, reflecting a balance between advanced predictive capabilities and moderate ecological and economic impacts.

4.3.3 Application to an Engine Cylinder Cleaning System

In their 2025 study, Wang and Guo propose a Digital Twin concept for the predictive maintenance of an engine cylinder cleaning production line in the automotive industry. The DT relies on real-time operational data to anticipate failures and support maintenance decision-making for this critical Observable Manufacturing Element.

According to the proposed evaluation grid, this implementation reaches Cognitive DT maturity (Level 4), requires dedicated data acquisition equipment, and provides a basic interactive visualization interface, resulting in a total score of TS = 9 (4 + 3 + 2). The Digital Twin is therefore classified as a medium-impact DT, combining advanced predictive capabilities with controlled equipment and user experience requirements.

5 Conclusion

Despite significant technological progress, particularly in AI-driven predictive maintenance and immersive visualization, the development of fully operational Digital Twins (DTs) remains limited. This situation is largely explained by the lack of standardized methodologies for their design, deployment, and lifecycle management.

Although high-maturity DT implementations demonstrate strong potential for monitoring, predictive maintenance, decision support, and user interaction, most existing applications remain either experimental or restricted to early maturity levels such as Mirror systems, while Cognitive DT implementations remain limited.

The analysis conducted in this study highlights the importance of jointly considering technological capabilities, equipment requirements, and user experience when assessing the ecological and economic impacts of DT implementations. The proposed evaluation framework therefore provides a structured perspective for analyzing technological maturity and sustainability implications in industrial maintenance contexts.

Future research should focus on the development of robust design frameworks and empirical evaluation methods capable of assessing DT implementations beyond technical feasibility, particularly in terms of long-term economic viability, operational performance, and environmental sustainability. Advancing such evaluation approaches will be essential to support the transition from conceptual prototypes toward fully operational and sustainable Digital Twin solutions in industrial environments.

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