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Integration of Enterprise Resource Planning (ERP) with Artificial Intelligence- and Data Analytics-Based Predictive Maintenance: A Systematic Literature Review Using the PRISMA Method

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ABSTRACT
The integration of Enterprise Resource Planning (ERP) systems with Artificial Intelligence (AI) and data analytics-based predictive maintenance is a pillar of industrial digital transformation in the industry 4.0 and 5.0 era. However, a comprehensive understanding of integration patterns, AI methods, benefits, and challenges remains scattered across the literature. This study conducts a Systematic Literature Review (SLR) using the PRISMA protocol to map the current state of ERP integration with AI-based predictive maintenance. A search was performed on the Scopus database, yielding 59 initial articles that were reduced to 10 final open-access articles published between 2024 and 2026. The results show that the dominant AI methods are Long Short-Term Memory (LSTM) and ensemble learning (XGBoost, Random Forest), often combined with Digital Twin technology. ERP integration patterns range from decision support to full bidirectional integration via OPC-UA and REST API protocols. Key benefits include up to 40% improvement in mean time to failure (MTTF), a 30% reduction in maintenance costs, and a return on investment (ROI) of 42.5%. The main challenges include data quality, legacy system interoperability, cybersecurity, and limited multi-site validation.

INTRODUCTION

The development of industrial technology in recent decades has been marked by a major transformation in the fields of automation, digitalization, and intelligent maintenance (Bhadra et al., 2023; Lee et al., 2020; Marques et al., 2026; Pech et al., 2021; Singh, 2020). In modern manufacturing and process industry environments, maintaining the optimal performance of mechanical systems is a critical factor that affects operational continuity, cost efficiency, and sustainability. Among various strategies, predictive maintenance (PdM) is emerging as a key approach in asset management that offers the ability to predict potential failures and plan interventions before damage occurs (Nozari & Szmelter-Jarosz, 2025). This approach has proven to be superior to conventional reactive and preventive maintenance, as it is able to reduce unplanned downtime and extend the life of the equipment (Rakholia et al., 2025).

In line with this, the Enterprise Resource Planning (ERP) system functions as the digital backbone of modern industrial organizations (Al-Amin, 2023; Bitkowska et al., 2024;

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Halimuzzaman et al., 2024; Halimuzzaman & Sharma, 2024; Kopishynska et al., 2023; Kowsar & Rahman, 2022). ERP integrates operational, financial, and maintenance data in one centralized environment to manage resources and processes (Haekal et al., 2025). When connected with artificial intelligence and data analytics technologies, ERP capabilities evolve beyond administrative control towards real-time machine monitoring, maintenance scheduling, and automated decision-making (Ouled Laghzal & Abdelmajid, 2025).

The convergence between ERP, predictive maintenance, and Artificial Intelligence (AI) opens up opportunities for the creation of a multi-layered framework that connects physical machines, virtual simulations, and predictive analytics (Davlatov et al., 2026). This integration not only enables real-time condition monitoring and predictive diagnostics, but also supports strategic decision-making for resource allocation and maintenance optimization (Chatterjee et al., 2025). This approach directly contributes to the evolution of autonomous and self-sustaining industrial systems, which is a major goal in advanced machine design and automation research.

A variety of artificial intelligence methods have been developed to support such integration, ranging from ensemble learning equipped with Explainable AI techniques to improve prediction transparency (Liu & Meng, 2025), to deep learning architectures and clustering algorithms for unattended anomaly detection (Martínez-García et al., 2025). A number of studies have also integrated AI with wireless networks and the Internet of Things (IoT) to support dynamic resource allocation and predictive maintenance (Koukaras et al., 2025).

Nonetheless, most research and applications still treat the three layers independently or only at the level of data exchange. The main problem that arises is the lack of a comprehensive and structured understanding of how ERP systems are integrated with AI-based predictive maintenance and data analytics, what AI methods are most effective, and the benefits and challenges that come with such integration. The existing literature is still scattered and fragmented in various industrial domains, so a systematic literature review is needed that is able to map the current condition comprehensively. This gap is the main motivation for this research, which is to unite the perspectives of ERP and AI-based predictive maintenance in one structured systematic review.

Based on this background, this study uses the Systematic Literature Review (SLR) method with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol, which is directed to answer four research questions (Research Question / RQ) as follows: (RQ1) Artificial Intelligence method and what data analytics are used in ERP integration with predictive maintenance; (RQ2) how the pattern and level of integration between ERP systems and AI-based predictive maintenance systems; (RQ3) what are the measurable benefits and impacts of integrating ERP with AI-based predictive maintenance; and (RQ4) what are the challenges and research gaps that are still open in this field. These four questions are the basis for the process of selection, extraction, and analysis of literature in the next section. This research offers both theoretical and practical benefits. Theoretically, it contributes a comprehensive mapping of ERP–AI predictive maintenance integration that has not been systematically compiled in previous literature, serving as a foundation for future research in information systems, industrial engineering, and artificial intelligence. Practically, it provides a reference for practitioners and decision-makers in designing integration strategies and selecting appropriate AI methods based on organizational needs and infrastructure, while the identification of research gaps and challenges such as interoperability, cybersecurity, and multi-location validation offers guidance for researchers and technology developers to focus on the most pressing issues.

METHOD

This research used the Systematic Literature Review (SLR) method by following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) 2020 protocol (Moher et al., 2019). PRISMA was chosen because it provides a structured and transparent workflow through four main stages, namely identification, screening, eligibility, and inclusion. This approach ensures that the literature selection process can be replicated and accounted for scientifically.

Search Strategies and Data Sources

Literature searches are carried out on the Scopus database as the main source of indexed and internationally reputable scientific publications. The search string is structured using keyword combinations with Boolean operators as follows:

Inclusion and Exclusion Criteria

The inclusion and exclusion criteria applied in this study are presented in Table 1.

Table 1. Inclusion and Exclusion Criteria

Criteria Inclusion	Exclusion Criteria
In the form of scientific journal articles	In the form of a book, book chapter, or non-article proceedings
Written in English	Written in a language other than English
Berstatus open access	Not fully accessible (closed access)
Published in the range of 2018–2026	Published outside the range of 2018–2026
Relevant to ERP integration, predictive maintenance, and AI/data analytics	Irrelevant to the topic of ERP–predictive maintenance–AI integration

Source: Authors' adaptation of PRISMA 2020 flow diagram

Stages of PRISMA Selection

The literature selection process follows four stages of PRISMA. At the identification stage, an initial search of the Scopus database yielded 59 articles. At the screening stage, restrictions are made based on the type of document (only articles) that leave 15 articles, followed by English restrictions that still leave 15 articles. At the eligibility stage, the open access status restriction leaves 12 articles, and the 2018–2026 range restriction still leaves 12 articles. In the final stage (inclusion), after a thorough reading of the relevance of the content, 10 final articles were obtained that were analyzed in depth. The PRISMA flowchart is presented in Figure 1, while a summary of the number of articles at each stage is presented in Table 2.

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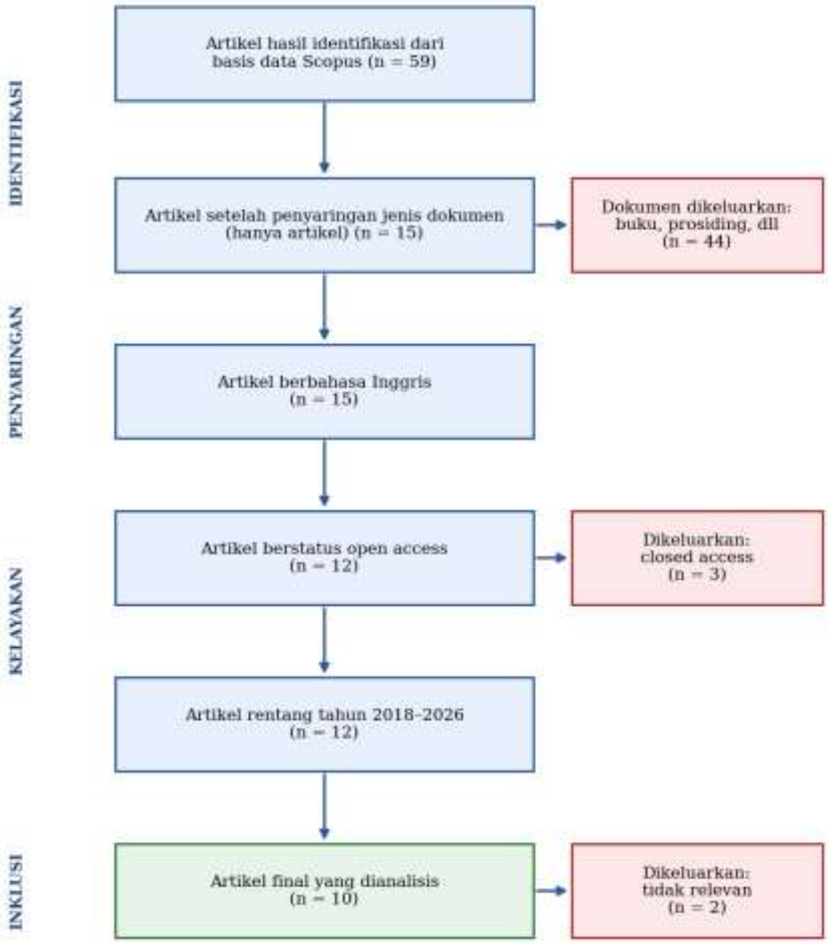

Figure 1. Literature Selection Flowchart with the PRISMA Protocol

Source: Authors' compilation based on PRISMA 2020 guidelines

Table 2. Summary of the PRISMA Selection Flow

Stages	Activities	Quantity
Identification	Initial search results on the Scopus database	59
Screening	Document type restrictions (articles only)	15
Screening	Language restrictions (English)	15
Eligibility	Open access state restrictions	12
Eligibility	2018–2026 range restrictions	12
Inclusions	Content relevance selection (full-text review)	10

Source: Authors' compilation based on PRISMA 2020 selection process

Data Extraction and Analysis

Each selected article is analyzed to extract key information including: the identity of the article (author, year, journal, publisher), AI/data analytics methods used, integration patterns with ERP systems, measurable results and impacts, and research challenges and gaps. The extracted data were then analyzed thematically to answer the four research questions, and analyzed descriptively to map publication trends and publisher distribution.

RESULT AND DISCUSSION

Publication Characteristics and Trends

A total of 10 final articles that passed the PRISMA selection were analyzed in this study. Based on the distribution of the year of publication, an interesting trend can be seen as shown in Figure 2. The majority of articles (7 articles) will be published in 2025, followed by 2 articles in 2026, and 1 article in 2024. This pattern indicates that the topic of integrating ERP with AI-based predictive maintenance is an emerging field of research that has attracted increasing academic attention in recent years.

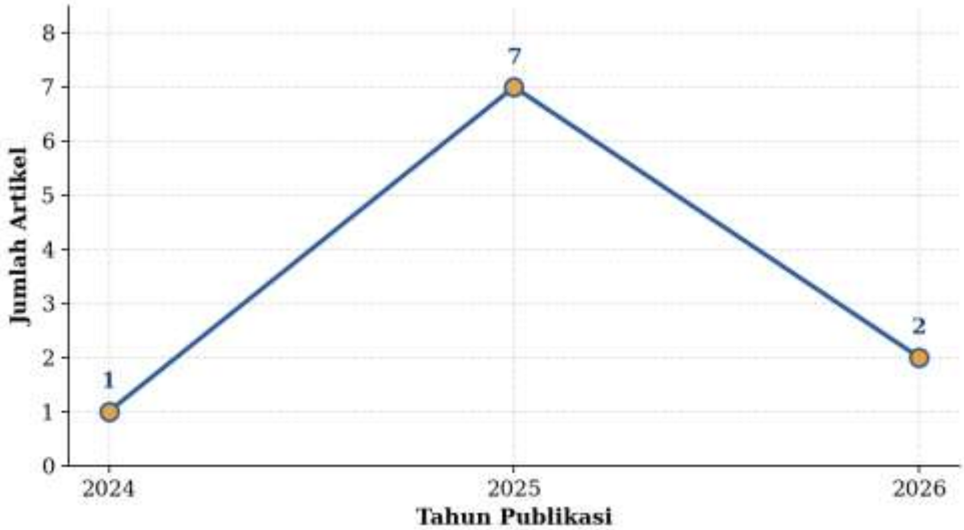

Figure 2. Trend in Number of Publications per Year (2024–2026)

Source: Authors' analysis of selected articles

In terms of publisher distribution, as shown in Figure 3, MDPI publishers dominate with 4 articles, followed by various other publishers such as IIETA, Springer Nature, Oeconomia Copernicana, Elsevier (ScienceDirect), Science and Information Organization, and IJIEM, each with 1 article. The dominance of MDPI shows that open access publishers play a significant role in the dissemination of research in this field.

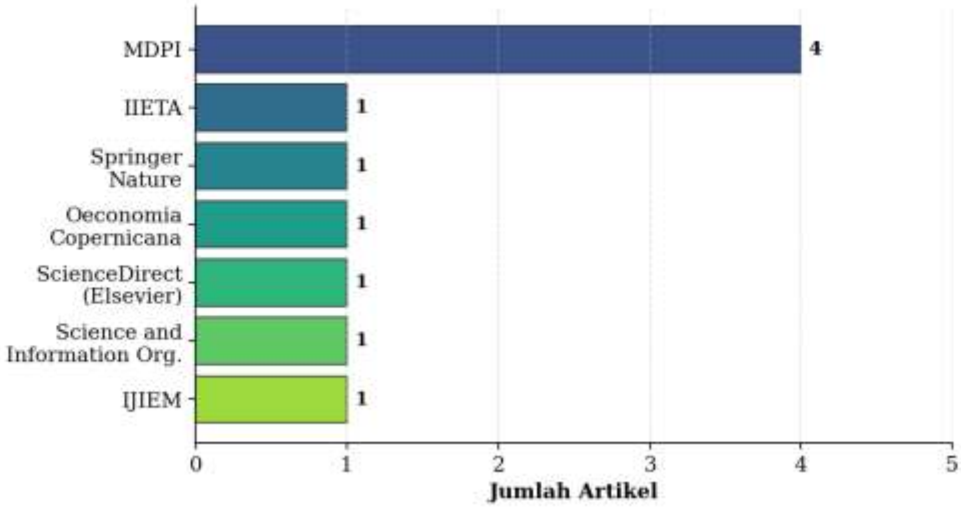

Figure 3. Distribution of Articles by Publisher

Source: Authors' analysis of selected articles

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A summary of the characteristics of the ten selected articles is presented comprehensively in Table 3.

Table 3. Summary of Selected Articles

NO	Author (Year)	Journal/Publisher	AI Method	ERP Integration Pattern
1	Davlatov et al. (2026)	DAYS	LSTM + Ensemble ML + Digital Twin	Multi-location MES/ERP integration (edge-cloud)
2	Nozari & Szmelter-Jarosz (2025)	Machines (MDPI)	Hybrid LSTM + Physics Digital Twin	Full two-way via OPC-UA & REST API (Odoo)
3	Martínez-García et al. (2025)	J. Industrial Info. Integration (Elsevier)	Clustering + Machine Learning	Process monitoring, no direct ERP
4	Liu & Meng (2025)	Applied Sciences (MDPI)	Bow-ExhiBoost + Curse (Ash)	Decision supporters
5	Ouled Laghzal & Abdelmajid (2025)	IJACSA	CNN, Neural Network, Deep Learning	MES/ERP/PLM as a critical enabler
6	Koukaras et al. (2025)	Applied Sciences (MDPI)	LSTM + Isolation Forest + RL	Resource management (5G/IoT)
7	Sendhil Nathan et al. (2026)	Scientific Reports (Springer)	DFB-ML (Random Forest)	Parts supply chain management
8	Haekal et al. (2025)	MMEP (IIETA)	ANN, SVM, RF, KNN (AI Ladder)	Directly to the ERP module (work order)
9	Rakholia et al. (2025)	Information (MDPI)	AI + IoT (ML pada SCADA/ERP)	Direct SCADA + ERP + sensor
10	Chatterjee et al. (2025)	Copernican Economy	ML + Digital Twin + XR	ERP in the industrial metaverse

Source: Authors' compilation of selected articles

AI and Data Analytics Methods (RQ1)

The results of the analysis of 10 articles show the diversity of AI and data analytics methods used, as visualized in Figure 4. Digital Twin technology was the most widely used (4 articles), followed by Long Short-Term Memory (LSTM) and Random Forest which were used in 3 articles each.

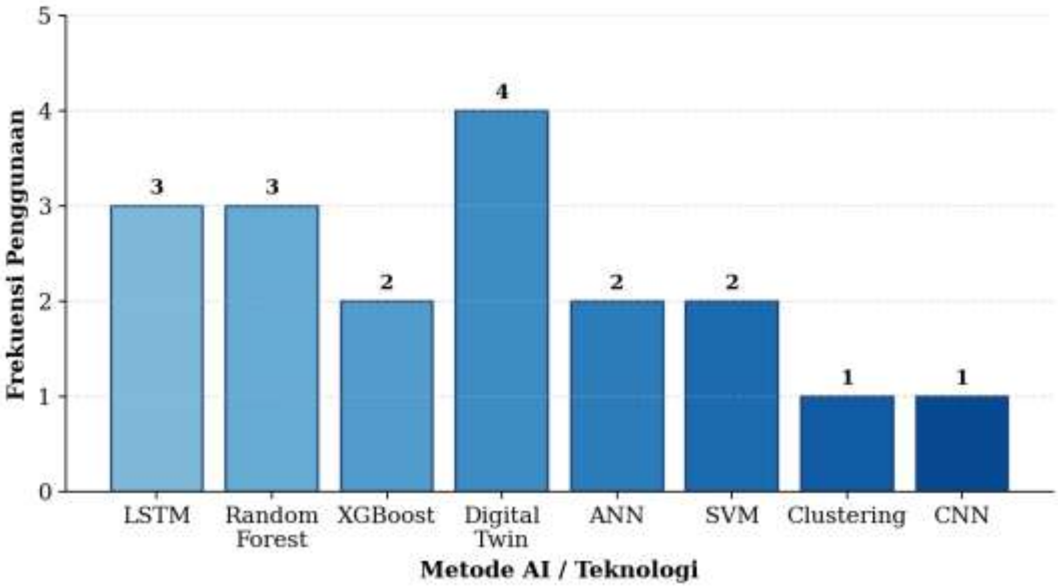

Figure 4. Frequency Distribution of AI Method Use

Source: Authors' analysis of selected articles

LSTM, a deep learning architecture based on a recurrent neural network, excels at handling time series data and is used by Nozari & Szmelter-Jarosz (2025), Davlatov et al. (2026), and Koukaras et al. (2025) to predict equipment degradation trends and detect anomalies. Ensemble learning methods, especially eXtreme Gradient Boosting (XGBoost) and Random Forest, are also widely used. Liu & Meng (2025) developed a BO-XGBoost model optimized with Bayesian Optimization and equipped with SHAP (Shapley Additive Explanations) to improve the interpretability of the model (Explainable AI), achieving an R^2 accuracy of 0.971. Sendhil Nathan et al. (2026) used Random Forest in the framework of Decay-Function-Blended Machine Learning, while Haekal et al. (2025) compared four classifiers, namely ANN, SVM, Random Forest, and KNN.

Other approaches found include clustering algorithms for unattended anomaly detection (Martínez-García et al., 2025) as well as a hybrid physics-data model approach. An important trend observed is the use of Digital Twin technology as a complement to AI methods, where Digital Twin acts as a virtual representation of physical equipment in real-time. In addition, the need for Explainable AI is increasing to meet the demands of transparency in high-risk industrial environments.

ERP Integration Patterns and Levels (RQ2)

The analysis reveals three levels of integration patterns between ERP and predictive maintenance systems, with the distribution as shown in Figure 5.

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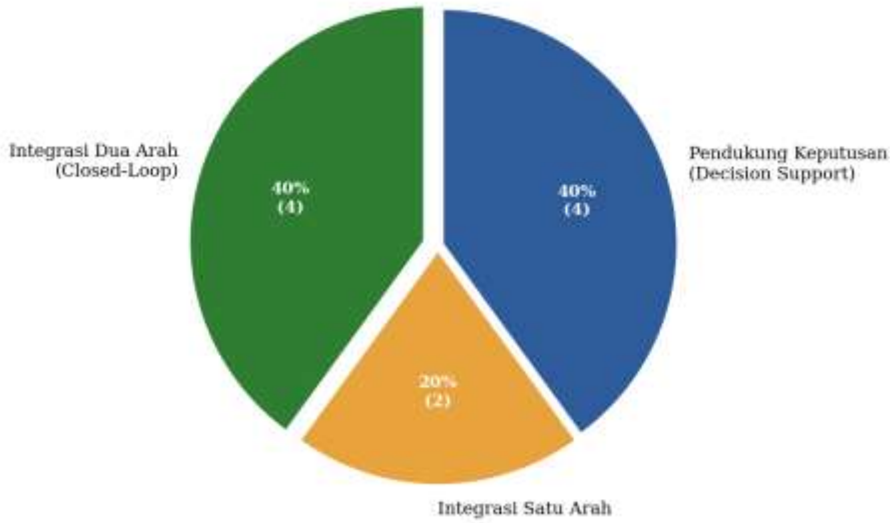

Figure 5. Distribution of ERP–Predictive Maintenance Integration Patterns

Source: Authors' analysis of selected articles

The first level is integration as decision support, where AI predictions are simply information inputs without automatic links to the ERP system, as seen in Liu & Meng (2025) and Martínez-García et al. (2025). The second level is one-way integration, where the output of a predictive model automatically triggers actions on the ERP maintenance module, such as the creation of an automated work order. This pattern was found in Haekal et al. (2025) who used the AI Ladder (Collect–Organize–Analyze–Infuse) framework to link rail defect detection from UAV imagery to ERP maintenance modules, and Rakholia et al. (2025) who integrated SCADA and ERP data on the production line.

The third and most mature level is bidirectional/closed-loop integration, where ERP and predictive systems influence each other in a closed feedback cycle. Nozari & Szmelter-Jarosz (2025) are the best example of a three-layer architecture (ERP–Digital Twin–Predictive Analytics) connected through the OPC-UA protocol and REST API, where the Digital Twin not only simulates the behavior of the equipment but also actively updates the maintenance policy on the ERP. Davlatov et al. (2026) also implemented deep integration with multi-location MES/ERP ecosystems. These findings suggest that industry-standard communication protocols such as OPC-UA and REST APIs are key enablers in achieving mature integration.

Measurable Benefits and Impacts (RQ3)

The integration of ERP with AI-based predictive maintenance provides measurable benefits both technically and economically. Comparison of pre- and post-integration performance in the Nozari & Szmelter-Jarosz (2025) study is visualized in Figure 6.

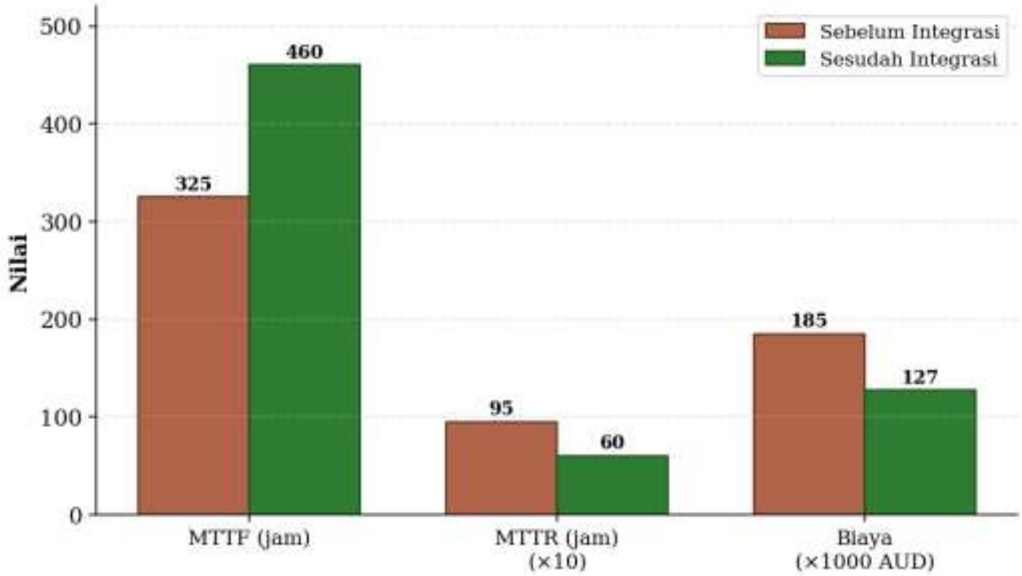

Figure 6. Comparison of Performance Before and After Integration
Source: Authors' adaptation from Nozari & Szmelter-Jarosz (2025)

In terms of reliability, mean time to failure (MTTF) increased by 40% (from 325 hours to 460 hours) and mean time to repair (MTTR) decreased by 35% (from 9.5 hours to 6.0 hours). From an economic perspective, annual maintenance costs decreased by 30% and return on investment (ROI) reached 42.5% in the first year. In terms of prediction accuracy, various studies show high performance: Liu & Meng (2025) achieved an R^2 of 0.971 with a MAPE of 5.5%; Nozari & Szmelter-Jarosz (2025) recorded a classification accuracy of 94% with an AUC of 0.92; and Sendhil Nathan et al. (2026) obtained a Safe MAPE of 4.36%. A summary of the measurable impact is presented in Table 4.

Table 4. The Measurable Impact of AI-Based ERP–Predictive Maintenance Integration

Indicator	Results	Source
Mean Time to Failure (MTTF)	Increased by 40%	Nozari & Szmelter-Jarosz (2025)
Mean Time to Repair (MTTR)	Decreased 35%	Nozari & Szmelter-Jarosz (2025)
Maintenance Costs	Decreased by 30%	Nozari & Szmelter-Jarosz (2025)
Return on Investment (ROI)	42.5% (first year)	Nozari & Szmelter-Jarosz (2025)
Prediction Accuracy (R^2)	0.971 (MAPE 5.5%)	Liu & Meng (2025)
Classification Accuracy/AUC	94% / 0,92	Nozari & Szmelter-Jarosz (2025)
Safe MAPE Peramalan	4,36%	Sendhil Nathan et al. (2026)
Production Efficiency	Increased 15% (average)	Ouled Laghzal & Abdelmajid (2025)

Source: Authors' compilation based on measurable impact data reported in selected articles as cited in the table

Research Challenges and Gaps (RQ4)

Despite offering significant benefits, ERP integration with AI-based predictive maintenance still faces a number of challenges. The first challenge is the quality and availability of data; faulty sensors or inconsistent data flows can degrade prediction accuracy and trigger incorrect maintenance alerts, as emphasized by Nozari & Szmelter-Jarosz (2025) and Koukaras et al. (2025). The second challenge is interoperability with legacy systems;

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Combining heterogeneous information systems and ensuring compatibility between industrial communication protocols (OPC-UA, MQTT) with enterprise systems remains a technical constraint for large-scale deployment.

The third challenge is cybersecurity, where the increasing number of IoT endpoints expands the attack surface so that it requires strict encryption, authentication, and network segmentation. The fourth challenge is the model interpretability (black box effect), especially in complex deep learning models, thus driving the need for Explainable AI as offered by Liu & Meng (2025) through SHAP.

The research gaps identified include: (1) limited validation in one location so that generalizations to other industries are still weak; (2) the use of reinforcement learning for autonomous decision-making has not been optimal; (3) the lack of fully closed-loop two-way integration; and (4) the need for a more comprehensive implementation and time-to-value cost analysis. These gaps open up promising opportunities for further research and become recommendations for future research directions.

CONCLUSION

This study has conducted a systematic literature review using the PRISMA protocol on 10 selected articles on ERP integration with AI-based predictive maintenance and data analytics published in the 2024–2026 range. The results of the study answered the four research questions as follows. First, the dominant AI methods are LSTM and ensemble learning (XGBoost, Random Forest), which are heavily combined with Digital Twin technology and the trend towards Explainable AI. Second, the ERP integration pattern is divided into three levels, namely decision support, one-way integration, and full-loop two-way integration, where the OPC-UA protocol and REST API are the key enablers. Third, the integration provides measurable benefits in the form of an increase in MTTF of up to 40%, a reduction in maintenance costs of up to 30%, ROI of up to 42.5%, and high prediction accuracy. Fourth, key challenges include data quality, legacy system interoperability, cybersecurity, and model interpretability, with research gaps in the form of multi-location validation limitations, reinforcement learning utilization, full closed-loop integration, and comprehensive economic analysis. Thus, the integration of ERP with AI-based predictive maintenance is an important pillar of digital transformation towards a smart and self-sustaining industrial system according to the principles of Industry 4.0 and 5.0. This research contributes in the form of an integration roadmap and the identification of research gaps that can be a reference for researchers and practitioners. The limitation of this research lies in the use of a single database (Scopus) and the relatively limited number of final articles. Further research is suggested to expand database sources (e.g. Web of Science and IEEE Xplore), increase the number of articles, and conduct quantitative meta-analyses to strengthen the generalization of findings.

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REFERENCE

Al-Amin, M. (2023). History, features, challenges, and critical success factors of enterprise resource planning (ERP) in the era of Industry 4.0. *European Scientific Journal*.

Bhadra, P., Chakraborty, S., & Saha, S. (2023). Cognitive IoT meets robotic process automation: The unique convergence revolutionizing digital transformation in the Industry 4.0 era. In *Confluence of Artificial Intelligence and Robotic Process Automation* (pp. 355–388). Springer.

Bitkowska, A., Dziembek, D., & Gzik, T. (2024). Enterprise resource planning based on cloud computing (Cloud ERP). *Journal of Software & Systems Development, 2024*.

Chatterjee, S., Kliestik, T., Rowland, Z., & Bugaj, M. (2025). Immersive collaborative business process and extended reality-driven industrial metaverse technologies for economic value co-creation in 3D digital twin factories. *Oeconomia Copernicana, 16*(1), 125–161. https://doi.org/10.24136/oc.3596

Davlatov, S., Zayniyev, A., Zokirov, J., Temirova, M., Uljaeva, S., Khudayberganov, K., Matkarimov, I., & Van Truong, C. (2026). Integration of digital twin technology and Industry 4.0 principles for real-time structural health monitoring in smart manufacturing facilities. *International Journal of Industrial Engineering and Management, 17*(1), 1–20. https://doi.org/10.24867/IJIEM-400

Haekal, J., Mu'min, R., Adriansyah, A., Paduloh, Sjarifudin, D., Nuryono, A., Rosihan, R. I., Tambunan, E. B. M., & Yaakop, S. N. K. (2025). AI ladder-based intelligent enterprise resource planning for predictive railway track maintenance from UAV imagery. *Mathematical Modelling of Engineering Problems, 12*(10), 3577–3592. https://doi.org/10.18280/mmep.121023

Halimuzzaman, M., & Sharma, J. (2024). The role of enterprise resource planning (ERP) in improving the accounting information system for organizations. In *Revolutionizing the AI-Digital Landscape* (pp. 263–274).

Halimuzzaman, M., Sharma, J., & Khang, A. (2024). Enterprise resource planning and accounting information systems: Modeling the relationship in manufacturing. In *Machine Vision and Industrial Robotics in Manufacturing* (pp. 418–434). CRC Press.

Kopishynska, O., Utkin, Y., Makhmudov, K., Kalashnik, O., Moroz, S., & Somych, M. (2023). Digital transformation of resource management of territorial communities based on the cloud ERP system in the concept of Industry 4.0. *Journal of Systemics, Cybernetics and Informatics, 21*(2), 21–29.

Koukaras, C., Hatzikraniotis, E., Mitsiaki, M., Koukaras, P., Tjortjis, C., & Stavrinides, S. G. (2025). Revolutionising educational management with AI and wireless networks: A framework for smart resource allocation and decision-making. *Applied Sciences, 15*(10), 5293. https://doi.org/10.3390/app15105293

Kowsar, M. M., & Rahman, M. A. (2022). Enterprise resource planning and customer relationship management integration: A systematic review of adoption models and organizational impact. *Review of Applied Science and Technology, 1*(2), 26–52.

Lee, J., Ni, J., Singh, J., Jiang, B., Azamfar, M., & Feng, J. (2020). Intelligent maintenance systems and predictive manufacturing. *Journal of Manufacturing Science and Engineering, 142*(11), 110805.

Liu, H., & Meng, X. (2025). Explainable ensemble learning model for residual strength forecasting of defective pipelines. *Applied Sciences, 15*(7), 4031. https://doi.org/10.3390/app15074031

Marques, E. L. de O., Lucas, R. E. C., & Borges, J. M. (2026). Digital transformation in industrial maintenance: An overview of Industry 4.0 technologies, their advantages and challenges. *International Journal of Quality & Reliability Management, 43*(7), 1938–1953.

Martínez-García, F. M., Molina García, A., Gómez de León, F. C., & Alarcón, M. (2025). Distillation anomaly and fault detection based on clustering algorithms. *Journal of*

\

Industrial Information Integration, 45, 100970. https://doi.org/10.1016/j.jii.2025.100970

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009/2019). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Open Medicine, 3*(3), e123–e130. Reprinted in *Respiration, 97*, 576–584.

Nathan, B. S., Reddy, B. V. S., Sujan, V. S. S., Sastry, C. C., Krishnaiah, J., & Jitpichitchai, S. (2026). A machine learning framework for long-term forecasting of spare part demand in end-of-life product scenarios. *Scientific Reports, 16*, 1394. https://doi.org/10.1038/s41598-025-31171-2

Nozari, H., & Szmelter-Jarosz, A. (2025). A predictive maintenance approach for composting plants based on ERP and digital twin integration. *Machines, 13*(12), 1123. https://doi.org/10.3390/machines13121123

Ouled Laghzal, S., & Abdelmajid, E. O. (2025). Integrating artificial intelligence into continuous improvement for automotive manufacturing. *International Journal of Advanced Computer Science and Applications, 16*(11). https://doi.org/10.14569/IJACSA.2025.0161187

Pech, M., Vrchota, J., & Bednář, J. (2021). Predictive maintenance and intelligent sensors in smart factory. *Sensors, 21*(4), 1470.

Rakholia, R., Suárez-Cetrulo, A. L., Singh, M., & Carbajo, R. S. (2025). Integrating AI and IoT for predictive maintenance in Industry 4.0 manufacturing environments: A practical approach. *Information, 16*(9), 737. https://doi.org/10.3390/info16090737

Singh, H. (2020). *Artificial intelligence and robotics transforming industries with intelligent automation solutions*. SSRN. https://doi.org/10.2139/ssrn.5267868