Enhancing predictive maintenance capabilities by integrating artificial intelligence: systematic review

Thippeswamy G. N[1], Neelambike S[1], Sanjay Pande M. B[2]
[1]Department of Information Science and Engineering, GM University, Davanagere, India
[2]Department of Computer Science and Engineering, GM University, Davanagere, India

Article Info

Article history:

Received Jul 17, 2025
Revised Dec 30, 2025
Accepted Jan 11, 2026

Keywords:

Adaptive structuration theory
Artificial intelligence
Facility operations and maintenance
Operational cost reduction
Predictive maintenance

ABSTRACT

Organizations are under pressure to increase productivity and lower operating costs because facility operations and maintenance (O&M) account for a significant portion of a facility's life-cycle cost. By facilitating real-time monitoring and data-driven decision-making, artificial intelligence (AI) has become a promising catalyst for enhancing predictive maintenance. In order to investigate how AI can be combined with predictive maintenance to lower operational and maintenance overhead, this systematic review examines peer-reviewed studies that have been published in the last five years. Using an evidence-based review methodology and adaptive structuration theory (AST), the study synthesized results from 14 excellent publications. Unbiased maintenance planning, cost-effective resource utilization, and AI-enabled operational visibility emerged as three key themes. According to the review, AI-driven predictive maintenance greatly increases operational effectiveness and reduces costs; however, successful implementation necessitates better data governance and organizational preparedness.

Corresponding Author:

Thippeswamy G. N.
Department of Information Science and Engineering, GM University
Davanagere, India
Email: neelais@gmail.com

1. INTRODUCTION

The operational and the maintenance phase takes into consideration nearly 70–80% of a facility's total life-cycle cost [1]. Buildings across the United States collectively spend more than $50 billion annually on operation and maintenance activities, placing considerable financial strain on organizations. Routine maintenance is essential to preserve asset performance, avoid failures, and retain operational continuity throughout the building's lifespan [2]–[4].

To manage rising costs, organizations increasingly seek data-driven approaches to improve operational efficiency. Studies indicate that artificial intelligence (AI) can reduce redundancies, accelerate maintenance processes, and enhance decision-making accuracy within facility management programs [5]. This systematic review evaluates the potential of AI-enabled predictive maintenance to lower facility operations and maintenance (O&M) expenses.

The findings contribute to facility managers, technology leaders, and stakeholders by offering an evidence-based understanding of how AI tools improve responsiveness, reduce labor requirements, and support data-driven investment decisions [6]–[9].

2. PROPOSED FRAMEWORK (OPTIONAL)

Before discussing the methodology, a conceptual representation of the AI-enabled predictive maintenance process is introduced. The Figure 1 framework illustrates the evolution of industrial maintenance from a simple "watch-and-wait" approach to a sophisticated, AI-driven strategy. Rather than treating maintenance as a series of isolated repair tasks, this model treats it as a continuous lifecycle of data and intelligence. Here is how the process unfolds:

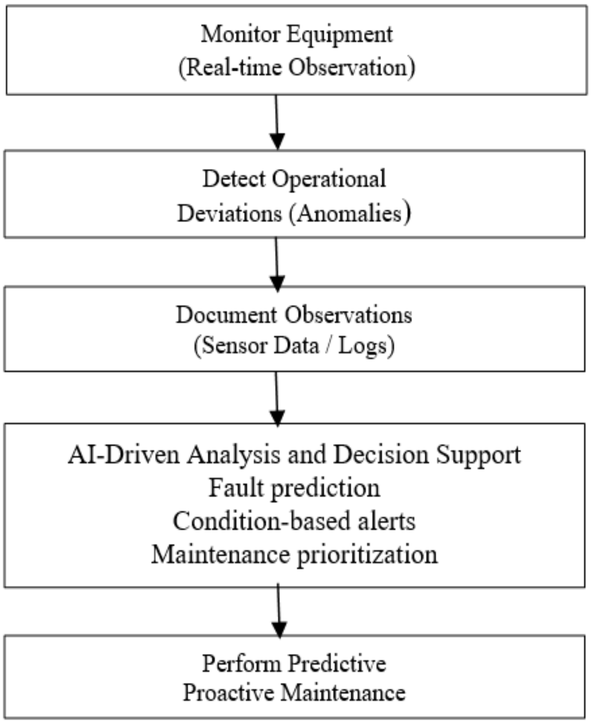

Figure 1. The AI-enhanced maintenance workflow

The vigilant eye (monitor equipment) the cycle begins with the fundamental layer of Real-time Observation. Much like a doctor checking a patient's vitals, sensors and monitoring tools keep a constant watch on the equipment's heartbeat. This isn't about deep analysis yet; it is simply about ensuring the machinery is running and gathering the raw signals of operation.

Catching the whisper (detect operational deviations) before a machine fails, it usually "whispers"a slight vibration, a minor temperature spike, or a delay in processing. In this stage, the system identifies these Operational Deviations or Anomalies. It captures the subtle cues that indicate the equipment is drifting away from its standard performance baseline, even if the machine hasn't failed yet.

The digital paper trail (document observations) observation without memory is useless. In this phase, the system documents observations by logging sensor data and anomaly reports. This builds a historical record, transforming fleeting moments of "weird behavior" into a structured dataset. This data serves as the fuel for the next, critical step.

The "Brain" of the operation (ai-driven analysis) this is the transformative step. Instead of drowning human operators in raw logs, the AI-Driven Analysis engine steps in to make sense of the noise. It performs three critical cognitive tasks:

- Fault prediction: it looks into the future, using historical patterns to predict *when* a part will fail.
- Condition-based alerts: it filters out false alarms, notifying technicians only when specific conditions warrant attention.
- Maintenance prioritization: it acts as a triage nurse, telling the team which machine needs immediate help and which one can wait, optimizing resource allocation.

Preventive maintenance at last, the realization is put into practice. Predictive or proactive maintenance can be carried out by the team thanks to the intelligence gathered upstream. Technicians step in at the perfect time to save money, avoid downtime, and prolong the asset's life rather than rushing to fix a breakdown (reactive) or replacing parts that are still good (preventive).

3. RESEARCH METHODOLOGY

This approach employs an evidence-based methodology to offer timely suggestions within constrained resource frameworks [6]. Evidence-based management research utilizes diverse study designs to collect peer-reviewed, scholarly data on management concerns and develop well-supported research conclusions for informed decision-making purposes. AST analysis serves as a theoretical framework, as illustrated in Figure 2. The framework draws on concepts from the AST as outlined in reference [10]–[12]. The person responsible for maintenance supervises the functioning of an asset within a building's supporting structure. The technician verifies that the facility asset complies with its pre-defined operational specifications. The technician makes a record of the observations according to the set procedural rules. The technician subsequently conducts maintenance at a level that restores the asset to its standard operational parameters. This activity streamlines existing methods by evaluating an asset's functional attributes and conducting proactive maintenance before a failure occurs through the use of the asset's data. The person responsible for maintenance supervises the functioning of an asset within a building's supporting structure. The technician verifies that the facility asset complies with its pre-defined operational specifications. The technician makes a record of the observations according to the set procedural rules.

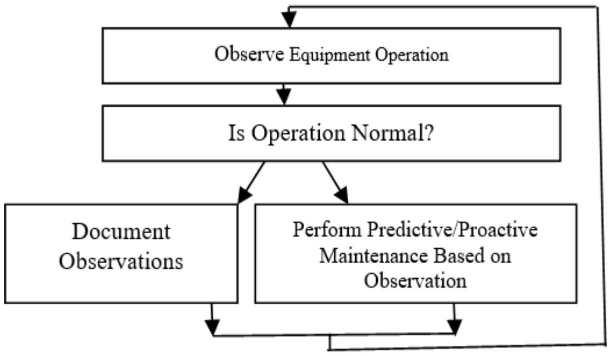

Figure 2. Predictive maintenance framework

3.1. Evaluation of critical qualities

The study selection followed a structured screening and quality evaluation process to ensure methodological rigor and relevance to the research objectives. An initial pool of studies was identified through systematic searches of selected digital libraries using predefined keywords and inclusion criteria. Seventeen articles that met the screening requirements were subjected to quality appraisal using the TAPUPAS framework. This assessment evaluated studies based on transparency, accuracy, purposivity, utility, propriety, accessibility, and specificity. Each criterion was scored on a three-point scale, resulting in a maximum possible score of 21 per article. The detailed appraisal criteria and scoring outcomes are presented in table, with Table 1 summarizing the assessment structure and Table 2 reporting individual study scores. Studies achieving an overall score of 14 or higher, without receiving the lowest score in any assessment category, were considered suitable for inclusion. Articles that scored the lowest value in any criterion were excluded due to concerns regarding methodological robustness. Following this evaluation, three studies were excluded, resulting in a final set of fourteen articles retained for synthesis. This quality-based screening ensured that only methodologically sound and relevant studies contributed to the subsequent analysis, thereby strengthening the reliability of the review findings [13].

Quality appraisal of selected studies: this table presents the quality appraisal results of the studies included in the systematic review. The TAPUPAS (transparency, accuracy, purposivity, utility, propriety, accessibility, and specificity) framework was employed to evaluate the methodological quality of each selected article. This framework is widely used for assessing qualitative, quantitative, and mixed-methods research. Each study was assessed across seven predefined criteria, with individual scores assigned on a three-point scale. The maximum achievable score for each article was 21. Studies scoring 14 or above, without receiving the lowest score in any criterion, were considered methodologically sound and retained for synthesis. Articles that scored the lowest value in any assessment criterion were excluded due to concerns regarding reliability or validity. Table 1 summarizes the aggregated quality scores across all criteria, while Table 2 presents the individual evaluation outcomes for each retained study. This appraisal process ensured that only robust and credible studies contributed to the final analysis.

Table 1. Summary of quality appraisal scores

Criterion	Description	Score Range
T	Transparency	1–3
A	Accuracy	1–3
P	Purposivity	1–3
U	Utility	1–3
Pr	Propriety	1–3
A	Accessibility	1–3
S	Specificity	1–3
Total	Maximum possible score	21

Table 2. Quality appraisal results for included studies

Article ID	T	A	P	U	Pr	A	S	Total Score	Decision
A1	3	3	2	3	2	3	2	18	Included
A2	2	3	2	3	2	2	2	16	Included
A3	3	2	3	2	2	3	2	17	Included
…	…	…	…	…	…	…	…	…	…

3.2. Procedure

Professionals in facility management have implemented a variety of maintenance strategies to improve the effectiveness, efficiency, and responsiveness of operations. $50 billion was spent on outsourcing maintenance and repair in 2016, according to a 2018 national institute of standards and technology (NIST) report written by D. Thomas [14]. The same report estimated that predictive maintenance could potentially save between 15% to 98% of total maintenance costs, although exact figures remain unverified. Research by Kim et al. confirms that multiple maintenance approaches have maintained operational continuity, helping conserve resources for broader business needs. Currently, the industry applies three main strategies: preventive, corrective, and predictive maintenance. Preventive maintenance follows a scheduled routine based on OEM or industry guidelines, involving regular replacement of parts and protective materials. Corrective maintenance is reactive, conducted after equipment fails or no longer functions effectively, restoring machinery to operational status. The growth of AI technologies, including neural networks, robotics, expert systems, and machine learning, has revolutionized predictive models and data analysis in facilities management. Deep learning allows machines to assess data, thereby continually improving maintenance approaches. Applications of AI span areas such as speech recognition, language processing, visualizations, and automated decision-making, with growing relevance in energy management and system optimization [15]–[17]. Tan and colleagues introduced MIGRATE, a machine learning system that uses a three-step framework consisting of disaggregation and activity forecasting to predict energy load profiles.

3.3. Research question

Researchers utilizing CIMO logic create review questions, conduct design science research to address these queries, and generate evidence-based outcomes and recommendations to inform data-driven decision-making processes. This article employs design science research to address the question driving its content. The CIMO framework used to develop the research question is outlined in Table 3, which shows the CIMO table. The existing body of knowledge on AI research is expected to be augmented by the introduction of a new method for integrating AI into the facility's maintenance procedures. The approach is expected to offer a fair, peer-reviewed, and evidence-based assessment of the existing body of research carried out in the last 5 years. Readers of this article should leave with the knowledge that AI boosts the efficiency of maintenance operations, reduces costs, and enhances the facility management program.

Table 3. CIMO Model for AI-based predictive maintenance

CIMO element	Guiding question	Description (based on article)
Context (C)	Which individuals, relationships, institutional configurations, or broader frameworks are the subject being researched?	Property or asset management system; infrastructure and specialized knowledge base; operational data sources relevant for predictive maintenance.
Intervention (I)	What is the event or action being implemented? What activities or processes are being investigated?	Utilizing AI techniques for predictive maintenance methodology in property/asset management.
Mechanism (M)	What are the underlying processes that explain the connection between intervention and outcome? In what situations are these mechanisms activated or deactivated?	AI-driven operational data review; technology-supported decision-making; predictive models identifying maintenance needs in advance.
Outcome (O)	What are the consequences of the intervention? How will the situation be resolved? How can the outcomes be measured? What are the intended or unintended consequences?	Decrease in upkeep expenses; fewer unexpected failures; improved asset lifecycle; outcomes measurable through cost savings, system uptime, and maintenance records.

3.4. Coding

A structured quality appraisal was conducted to assess the methodological rigor of the studies selected for synthesis. Seventeen articles were initially evaluated using the TAPUPAS assessment framework, which is widely recognized for its applicability across qualitative, quantitative, and mixed-methods research designs. The assessment criteria and scoring outcomes are documented in table.

Each study was evaluated across multiple quality dimensions, with a maximum attainable score of 21. Studies achieving a cumulative score of 14 or higher, without receiving the lowest score in any individual criterion, were considered methodologically robust and suitable for inclusion. Conversely, studies receiving the lowest score in at least one criterion were excluded due to concerns regarding validity or reliability.

Following this appraisal process, three studies were excluded, resulting in a final set of fourteen articles retained for detailed analysis. Among these, the majority employed quantitative research methods, while a smaller number adopted qualitative and mixed-methods approaches. This distribution reflects the predominance of data-driven evaluation techniques within the domain under investigation.

Although the TAPUPAS framework provides a comprehensive and systematic means of quality assessment, it is acknowledged that the scoring process involves a degree of subjectivity. To mitigate potential bias, evaluations were conducted with careful adherence to predefined criteria; however, subjective interpretation remains an inherent limitation of self-review-based appraisal methods.

The initial coding phase involved categorizing 14 selected articles using a total of 19 codes, including 16 deductive codes based on the adaptive structuration theory's concepts of structure, system, and outcome, and 3 inductive codes derived from the analysis. The researcher in the second coding cycle condensed these codes to create more thorough categories, revealing patterns and common traits throughout the entire dataset. This stage entailed decreasing the 19 codes and related article excerpts to six preliminary classifications, which were then further refined and consolidated into three definitive categories, as detailed in table. The categories were operationalized by employing the AST framework. According to Saldana's framework, the process of forming themes arose from these categories, which identify patterned responses or meanings within the data and offer a deeper understanding of the research question.

4. THEORY

Adaptive structuration theory (AST) examines how groups and organizations adopt and use information and communication technologies in practice. DeSanctis and Poole conceptualize AST as a lens through which organizational change can be understood from two complementary perspectives: the structural features embedded within advanced technologies and the structures that emerge through the interaction of human actors with these technologies. This perspective highlights the importance of technological integration, user engagement, and the development of context-specific operational practices.

Within the AST framework, the core variables of task, people, and technology are analyzed individually to understand their respective roles and interactions in organizational processes [18]–[22]. The fundamental elements of the theory include structures, systems, and outcomes, which together explain how technology influences organizational routines and decision-making. Although AST has been criticized for adopting an optimistic stance and for diverging from Anthony Giddens' original structuration theory, these limitations have been acknowledged in the literature. Despite such critiques, AST continues to be widely applied in contemporary research due to its relevance in analyzing technology-mediated organizational practices.

5. RESULTS

Results from coding and findings, based on the AST and the CIMO model, as well as the central research question of "How can AI be used with predictive maintenance to decrease O&M expenses in facility operations?" demonstrate several key insights from the reviewed literature. Integrating advanced technologies into facility management has been demonstrated to enhance operational efficiency through real-time monitoring of systems, the early identification of performance problems, and the provision of support for predictive maintenance strategies. Frameworks including the industrial data analysis improvement cycle and digital twin models help in visualizing system health and detecting initial signs of equipment deterioration, particularly in components such as air handling units.

Research also suggests that predictive tools, such as neural networks, support vector machines, and decision trees, improve decision-making by removing personal bias and providing data-driven evaluations for repair and investment planning. These tools facilitate reduced labor requirements, prevent unwarranted replacements, and improve safety through timely warnings. Scheduling repairs during periods of low demand and having technicians prepared with precise diagnostic information supports predictive maintenance in reducing system downtime. The use of modeling systems also facilitates the effective management of mechanical, electrical, and plumbing infrastructure, leading to resource optimization and cost savings. Overall, the results confirm that predictive technologies, when implemented strategically, result in improved system uptime, proactive maintenance, reduced operational downtime, and more efficient allocation of facility resources.

CERQual provides a transparent and systematic framework for assessing the reliability of qualitative research results [23]–[25]. To establish credibility in research findings, a comprehensive evaluation of the confidence in the results is required, involving a systematic assessment of the data. CERQual consists of four critical components to assess the grading criteria: methodological limitations, coherence, data adequacy, and relevance. The CERQual terms and grading criteria are detailed in table.

The CERQual criteria were used to evaluate each finding for this REA, with the results documented in table. The CERQual assessment assigns moderate confidence levels to findings 1, 2, and 3. The overall rating is a reflection of the level of confidence in the research quality in relation to the context of the review question. All 14 articles were published over the past five years, are relevant to the research question and have undergone peer review. Hence, there is no cause for concern regarding the confidence of these articles or the results.

6. DISCUSSION

Facility management is evolving through the integration of AI, which is proving valuable in optimizing O&M. Current literature reveals multiple successful implementations of AI in managing individual systems within facility operations. These systems operate in alignment with adaptive structuration theory, where AI supports monitoring and predictive maintenance. Through deep learning, AI continuously observes system behavior and identifies anomalies, initiating control actions or alerting technicians with suggested resolutions.

When fully integrated, AI can manage entire facility systems, monitor conditions in real-time, and issue automated work orders through systems like CMMS. It contributes to reducing downtime, extending system life, and optimizing resource use. The system learns and adapts from data, helping decision-makers act on accurate insights. AI’s role in analyzing work orders, prioritizing tasks, and adjusting operational settings minimizes manual processes. As a result, organizations benefit from improved efficiency, faster response times, and reduced staffing demands.

In facility management, the implementation of AI should be started with limited, targeted applications, which then aim to achieve ambitious long-term goals, as studies suggest that only specific AI components have so far shown proven efficiency and cost-saving potential as shown in Figure 3. A full-scale transition is currently unwarranted due to issues like insufficient high-quality real-world data to train AI algorithms and a scarcity of detailed equipment fault records. In cases where full automation is not cost-effective, a partially automated, sensor-driven system linked to a building management system can be installed to track operations and suggest enhancements. AI implementation should be driven by a company-wide effort, supported by effective senior management. Executive leaders should create a business charter to steer the adoption process, address risks, align with technological and business opportunities, and establish data governance policies and necessary competencies. Final conceptual framework of theory as shown in Figure 3.

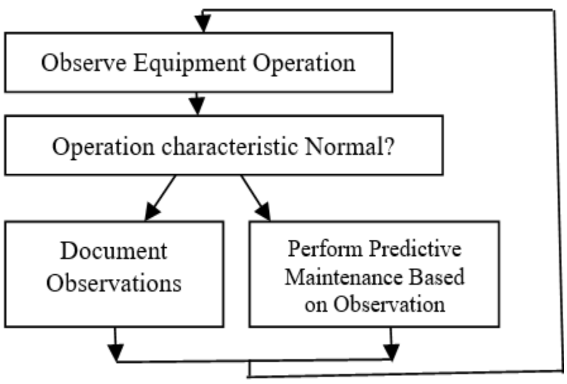

Figure 3. Final conceptual framework of theory

7. CONCLUSION

This study investigates how AI can be utilized with predictive maintenance to reduce the expenses linked to O&M in facility operations management. This study investigated academic research on adopting AI technology through the AST framework, aiming to provide guidance for facility management executives in making informed choices. This study investigated existing research on predictive maintenance and found that integrating AI with predictive maintenance in a facility operations programme will lead to cost savings in labor hours, analysis time, and provide unbiased predictive maintenance and investment recommendations. More investigation is required to determine the process of acquiring and maintaining full operational capabilities with AI. Examples of AI in real-life facility management programs should also be studied and recorded for potential use in future research studies. Studies have shown that AI can lower facility operation costs, and this study has demonstrated the potential for even greater AI adoption. Future research will need to determine the further repercussions of AI implementation. A central focus of the scholarship review is that AI constitutes a new paradigm with considerable benefits, which is being utilized across all sectors.

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Thippeswamy G. N.	✓	✓	✓	✓	✓	✓		✓	✓	✓	✓	✓	✓	
Neelambike S		✓				✓	✓	✓	✓	✓	✓	✓	✓	
Sanjay Pande M. B.	✓		✓	✓			✓			✓	✓			✓

C : Conceptualization
M : Methodology
So : Software
Va : Validation
Fo : Formal analysis
I : Investigation
R : Resources
D : Data Curation
O : Writing - Original Draft
E : Writing - Review & Editing
Vi : Visualization
Su : Supervision
P : Project administration
Fu : Funding acquisition

CONFLICT OF INTEREST STATEMENT

The authors state that they do not have any known financial conflicts of interest or personal connections that may have potentially affected the research presented in this paper. The authors state that they have no conflict of interest.

DATA AVAILABILITY

Data will be made available on request.

REFERENCES

[1] J. Garcia, L. Rios-Colque, A. Peña, and L. Rojas, "Condition monitoring and predictive maintenance in industrial equipment: an NLP-assisted review of signal processing, hybrid models, and implementation challenges," *Applied Sciences (Switzerland)*, vol. 15, no. 10, p. 5465, May 2025, doi: 10.3390/app15105465.

[2] K. Lefrouni and S. Taibi, "Artificial intelligence techniques for industrial predictive maintenance: a systematic review of recent advances," *Journal Europeen des Systemes Automatises*, vol. 58, no. 4, pp. 653–668, Apr. 2025, doi: 10.18280/jesa.580401.

[3] Y. Mahale, S. Kolhar, and A. S. More, "A comprehensive review on artificial intelligence driven predictive maintenance in vehicles: technologies, challenges and future research directions," *Discover Applied Sciences*, vol. 7, no. 4, p. 243, Mar. 2025, doi: 10.1007/s42452-025-06681-3.

[4] Ş. Yıldırım, A. D. Yücekaya, M. Hekimoğlu, M. Ucal, M. N. Aydin, and İ. Kalafat, "AI-driven predictive maintenance for workforce and service optimization in the automotive sector," *Applied Sciences (Switzerland)*, vol. 15, no. 11, p. 6282, Jun. 2025, doi: 10.3390/app15116282.

[5] C. Tsallis, P. Papageorgas, D. Piromalis, and R. A. Munteanu, "Application-wise review of machine learning-based predictive maintenance: trends, challenges, and future directions," *Applied Sciences (Switzerland)*, vol. 15, no. 9, p. 4898, Apr. 2025, doi: 10.3390/app15094898.

[6] L. Ismail, A. Abdelmoti, A. Basu, A. D. E. Berini, and M. Naouss, "A systematic review of digital twin-driven predictive maintenance in industrial engineering: taxonomy, architectural elements, and future research directions," Sep. 2025, [Online]. Available: http://arxiv.org/abs/2509.24443

[7] A. D. Scaife, "Improve predictive maintenance through the application of artificial intelligence: A systematic review," *Results in Engineering*, vol. 21, p. 101645, Mar. 2024, doi: 10.1016/j.rineng.2023.101645.

[8] I. Rojek, M. Jasiulewicz-Kaczmarek, M. Piechowski, and D. Mikołajewski, "An artificial intelligence approach for improving maintenance to supervise machine failures and support their repair," *Applied Sciences (Switzerland)*, vol. 13, no. 8, p. 4971, Apr. 2023, doi: 10.3390/app13084971.

[9] M. Ahern, D. T. J. O'Sullivan, and K. Bruton, "Implementation of the IDAIC framework on an air handling unit to transition to proactive maintenance," *Energy and Buildings*, vol. 284, p. 112872, Apr. 2023, doi: 10.1016/j.enbuild.2023.112872.

[10] M. Bidollahkhani and J. M. Kunkel, "Revolutionizing system reliability: the role of ai in predictive maintenance strategies," Apr. 2024, [Online]. Available: http://arxiv.org/abs/2404.13454

[11] R. Haque, A. Bajwa, N. A. Siddiqui, and I. Ahmed, "Predictive maintenance in industrial automation: a systematic review of Iot sensor technologies and Ai algorithms," *American Journal of Interdisciplinary Studies*, vol. 5, no. 1, pp. 01–30, Mar. 2024, doi: 10.63125/hd2ac988.

[12] P. Sharna, "Predictive maintenance in IT infrastructure using machine learning," *International Transactions on Machine Learning (ITML)*, vol. 6, no. 6, 2024.

[13] K. T. Huynh, H. C. Vu, T. D. Nguyen, and A. C. Ho, "A predictive maintenance model for k-out-of-n:F continuously deteriorating systems subject to stochastic and economic dependencies," *Reliability Engineering and System Safety*, vol. 226, p. 108671, Oct. 2022, doi: 10.1016/j.ress.2022.108671.

[14] P. Vrignat, F. Kratz, and M. Avila, "Sustainable manufacturing, maintenance policies, prognostics and health management: A literature review," *Reliability Engineering and System Safety*, vol. 218, p. 108140, Feb. 2022, doi: 10.1016/j.ress.2021.108140.

[15] F. Öhlinger, L. Greimel, R. Glawar, and W. Sihn, "An approach for AI-based forecasting of maintenance orders for MRO scheduling," *IFAC-PapersOnLine*, vol. 55, no. 10, pp. 2312–2317, 2022, doi: 10.1016/j.ifacol.2022.10.053.

[16] L. Reichsthaler, T. Madreiter, J. Giner, R. Glawar, F. Ansari, and W. Sihn, "An AI-enhanced Approach for optimizing life cycle costing of military logistic vehicles," *Procedia CIRP*, vol. 105, pp. 296–301, 2022, doi: 10.1016/j.procir.2022.02.049.

[17] D. K. Abideen, A. Yunusa-Kaltungo, P. Manu, and C. Cheung, "A systematic review of the extent to which BIM is integrated into operation and maintenance," *Sustainability (Switzerland)*, vol. 14, no. 14, p. 8692, Jul. 2022, doi: 10.3390/su14148692.

[18] Y. A. Yucesan, A. Dourado, and F. A. C. Viana, "A survey of modeling for prognosis and health management of industrial equipment," *Advanced Engineering Informatics*, vol. 50, p. 101404, Oct. 2021, doi: 10.1016/j.aei.2021.101404.

[19] M. Marocco and I. Garofolo, "Integrating disruptive technologies with facilities management: A literature review and future research directions," *Automation in Construction*, vol. 131, p. 103917, Nov. 2021, doi: 10.1016/j.autcon.2021.103917.

[20] D. Kim, S. Lee, and D. Kim, "An applicable predictive maintenance framework for the absence of run-to-failure data," *Applied Sciences (Switzerland)*, vol. 11, no. 11, p. 5180, Jun. 2021, doi: 10.3390/app11115180.

[21] D. Tan, M. Suvarna, Y. Shee Tan, J. Li, and X. Wang, "A three-step machine learning framework for energy profiling, activity state prediction and production estimation in smart process manufacturing," *Applied Energy*, vol. 291, p. 116808, Jun. 2021, doi: 10.1016/j.apenergy.2021.116808.

[22] V. Marinakis, "Big data for energy management and energy-efficient buildings," *Energies*, vol. 13, no. 7, p. 1555, Mar. 2020, doi: 10.3390/en13071555.

[23] M. Fernandes, A. Canito, V. Bolón-Canedo, L. Conceição, I. Praça, and G. Marreiros, "Data analysis and feature selection for predictive maintenance: A case-study in the metallurgic industry," *International Journal of Information Management*, vol. 46, pp. 252–262, Jun. 2019, doi: 10.1016/j.ijinfomgt.2018.10.006.

[24] X. Gao and P. Pishdad-Bozorgi, "BIM-enabled facilities operation and maintenance: A review," *Advanced Engineering Informatics*, vol. 39, pp. 227–247, Jan. 2019, doi: 10.1016/j.aei.2019.01.005.

[25] M. P. Gallaher, A. C. O'Conor, J. L. Dettbarn, and L. T. Gilday, "Cost analysis of inadequate interoperability in the U.S. capital facilities industry," Aug. 2004, doi: 10.6028/NIST.GCR.04-867.

BIOGRAPHIES OF AUTHORS

Mr. Thippeswamy G. N is a research scholar in the Department of Information Science and Engineering at GM University, Davangere, India. He holds a Master's degree in Computer Science and Engineering and is currently pursuing his Ph.D. under the supervision of Dr. Neelambike S and co-supervision of Dr. Sanjay Pande M B. His research focuses on machine learning, data visualization, and software development for real-time applications. He has presented his work at various conferences and is actively engaged in developing innovative solutions in his area. His research interests include machine learning, data visualization, and software systems. He can be contacted at email: thippeswamy@gmit.ac.in.

Dr. Neelambike S is a Professor and Head in the Department of Information Science and Engineering at GM University, Davangere, India. She holds a Ph.D. in Computer Science and Engineering with expertise in machine learning, data engineering, and augmented reality. She has made significant contributions to curriculum development, research guidance, and interdisciplinary projects. She has published numerous research papers, authored textbooks, and holds patents in her areas of work. Her research interests include machine learning, data engineering, augmented reality applications, and curriculum design in engineering education. She can be contacted at email: neelambikes@gmit.ac.in.

Dr. Sanjay Pande M. B is an Professor and Principal in the Department of Computer Science and Engineering at GM University, Davangere, India. He holds a Ph.D. in Computer Science and an MBA, specializing in data mining, cloud computing, and software engineering. He has contributed to several funded projects, research publications, and industrial collaborations. Dr. Sanjay Pande has guided multiple postgraduate and doctoral scholars and has been actively involved in academic administration. His research interests include data analytics, cloud computing, software systems, and data mining. He can be contacted at email: sanjaypandemb@gmit.ac.in.