



Self-Learning Health Assurance for Connected Fleets

Christopher Wilson
Asst Professor

Abstract

This research presents a framework for asset health and fleet resilience in connected IoT environments, enabled by machine intelligence and predictive analytics. The framework combines analytical methods with a system-level architecture for service delivery, aiming to deliver and validate predictive maintenance analytics at scale. It addresses the interests of OEMs, Industry 4.0 initiatives, and sustainability goals framed around Environmental, Social, and Governance (ESG) objectives. Its domain spans asset health, predictive maintenance, and resilient fleet operations, with a resilience perspective centered on governing predictive maintenance practices, calibrating organizational risk tolerance, and balancing autonomy against human oversight. Data-driven analytics, alongside distributed data management and governance, are most salient in the IoT and Sensor Data Management research areas. The hypotheses and evaluation criteria presented here draw on both literature-based guidance and lens-based reasoning.

Asset health predictive analytics are best evaluated through successful project delivery; at scale, this requires embedding analytics within a production service that problem owners and users can discover and adopt. A systematic approach to service delivery therefore accelerates project realization and broadens coverage. In mission-critical settings, service consumption becomes mandatory, meaning the acceptable risk balance is effectively determined by the service itself. The development team functions as the gatekeeping authority for service quality, shaping analytics, shadow data processing, and incident detection. Within this structure, knowledge gaps are closed by selecting appropriate predictive maintenance methods, service consumption enables validation testing, and security requirements govern shadow data processing.

Keywords—Predictive analytics; operational resilience; industrial systems; prognostic health management; Internet of Things; asset health; connected systems; machine learning; artificial intelligence; autonomy; safety; governance; security.

1. INTRODUCTION

For several decades, governments and industry have invested heavily in sensors and technology to assist asset health, predictive maintenance, and resilient connected (fleet) operations, yet full autonomy remains elusive. These efforts were predicated on the belief that more data and advanced analytics would lead to optimally reliable, available, maintainable, and safe (RAMS) fleets, deployed and operated with sophistication to approach perfect operations. The reality is that the vast majority of fleets remain operated with simple rules such as "replace it on condition—if it fails, it must have been on condition". Critical-hire operations in the oil and gas sector are governed with 100% human oversight, and dual-operating railways are not yet relying on an advanced risk governance framework. New Autonomous Industrial Intelligence (AII) frameworks for Predictive Asset Health and Resilient Connected Fleet Operations (PAH-RCFO) are needed to define AI as the "artificial capacity to presume basic asset health risks in response to changing system conditions and fluid operating requirements" undertaken by autonomous agents (humans or machines) engaged in the RAMS, either fully or in a Human-in-the-loop mode. Such PAH-RCFO frameworks provide the information foundation to move appoint autonomous agents onto the critical trusted path at an acceptable and justifiable operational risk. The PAH-RCFO itself enables agents to derive high-value decisions but in itself is not an Autonomous-Safety-Critical Intelligence.

Defining the full sweet spot of credit, autonomy acceptance, and AI methods for a diversified operating portfolio remains an ongoing challenge. The AII-for-PAH-RCFO framework integrates smart function of Assistive, Collaborative, Partial, Full and Autonomous with Incident Acceptance Tolerance. A summary of the key method domains enables the articulation of appropriate supervisory risk governance measures aligned with the Justified degree of Autonomy while standardizing the associated collaboration and intervention actions, including human-in-the-loop intervention when necessary. Enabling a reliability, availability, maintainability and safety (RAMS) analysis requires asset conditions to be batched with Changing internal and external Context and Environment variables, and the associated impact on safe system operation for all fleet members using a framework of min-max loss ratios during ageing and learning. Electric-propulsion fleets allow marginal-cost based flight streamlining of route profiles and the calculation of noise and emission contours.

Mathematical Formulas:

(1) Asset Health Index

$$AHI = \frac{\sum_{i=1}^n w_i x_i}{\sum_{i=1}^n w_i}$$

where:

- (x_i) = normalized sensor measurement
- (w_i) = feature importance weight

(2) Remaining Useful Life

$$RUL = T_f - T_c$$

where

- (T_f) = predicted failure time
- (T_c) = current operating time

(3) Failure Probability

$$P(F) = 1 - e^{-\lambda t}$$

where

- (λ) = failure rate
- (t) = operating time

(4) Fleet Resilience Score

$$FR = \frac{A \times R}{D}$$

where

- (A) = availability

- (R) = reliability
- (D) = downtime

(5) Predictive Maintenance Cost

$$C_{PM} = C_M + C_D$$

where

- (C_M) = maintenance cost
- (C_D) = downtime cost

(6) Prediction Accuracy

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN}$$

(7) Mean Squared Error

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

(8) Risk Score

$$Risk = Probability \times Impact$$

2. Theoretical Foundations and Conceptual framing

Investigate the nature of intelligence in industrial systems, the role of predictive analytics, the importance of resilience, and the use of autonomy; connect these themes to asset health, fleet operations, and IoT/sensor networks; and establish a model of autonomous industrial intelligence along with its core constructs.

The growing perception of an age of convergence, in which the physical and digital realms are seamlessly intertwined, is reflected in the emergence of a new lexicon: Industry 4.0, the Industrial Internet of Things (IIOT), Intelligent Connected Operations, and Autonomous Industrial Intelligence. The Intelligent Connected Operation paradigm enables the integration of physical and cyber supply chain assets through real-time data exchange, a process that ultimately culminates in full operational automation. An important advantage of autonomous systems is the ability to trade off the human-in-the-loop computation paradigm in favor of improved reliability and availability. Risk acceptance depends on the criticality of each operation in the process. It is a well-known fact that sensor networks embedded in the operation of equipment have become a basic and essential element for equipment condition monitoring, and that these data can be used to assess equipment health and predict failures.

Table 1. Autonomous Industrial Intelligence Framework Components

Layer	Main Components	Purpose
Data Layer	IoT Sensors, Maintenance Logs, Environmental Data	Collect operational data
Edge Layer	Edge AI, TinyML, Feature Extraction	Local processing
Analytics Layer	ML Models, Statistical Models	Predict failures
Decision Layer	Risk Engine, Fleet Optimizer	Maintenance decisions
Governance Layer	Security, Data Provenance, Policy Engine	Compliance and trust

Table 2. Industrial Data Sources

Data Source	Example	Frequency	Usage
IoT Sensors	Temperature, Vibration	Real-time	Health monitoring
Fleet GPS	Vehicle location	Seconds	Fleet optimization
Maintenance Records	Repair history	Daily	Failure prediction
Weather Data	Temperature, Humidity	Hourly	Context awareness
Equipment Logs	System events	Continuous	Anomaly detection

3. Architecture of the Autonomous Industrial Intelligence Framework

System-level architecture, core data flows, and interoperability requirements for the Autonomous Industrial Intelligence framework and its integrated components are defined, and the interfaces to external components, systems, and services, along with key features of the data acquisition and ingestion modules, specified. Autonomous systems offer the opportunity for family of systems to operate jointly, creating a connected fleet with greater resilience. The ADS and its associated elements implement the prediction layer of the framework. These systems receive data from IoT/sensor networks that track the health status of assets, infrastructure development and environmental conditions, enabling predictive asset health management and unit- and connected fleet-based behavior optimization

Components and associated intelligent systems are expected to enable autonomous operation tempered by overall operational sustainability. These predefined design criteria allow for a clear articulation of the framework architecture, key data flows and interoperability delineation required to support tailored input and output interactions with

integrated systems performing distinct tasks. Preceding sections have established the nature of the underlying data requirements and the main themes being monitored through health analytics. Data provision for the framework therefore relies on an extensive family of monitoring datasets with common attributes supported by sensors, log files or maintenance records. Each dataset is aligned with the prediction pipeline of the Family of Systems, resourced through historical collection or near real-time data feeds. Conformance to latency requirements for monitoring responsibility delineates the specific classes of patents being defined as products or services within the connected family of systems.

Table 3. Algorithms Used

Algorithm	Purpose	Framework Module
Random Forest	Fault Prediction	Predictive Analytics
Decision Tree	Explainable Diagnosis	Asset Health
ARIMA	Time-Series Forecasting	Remaining Useful Life
Survival Analysis	Failure Probability	Prognostics
Reinforcement Learning	Fleet Optimization	Autonomous Decision Engine
Autoencoder	Anomaly Detection	Monitoring

Table 4. Evaluation Metrics

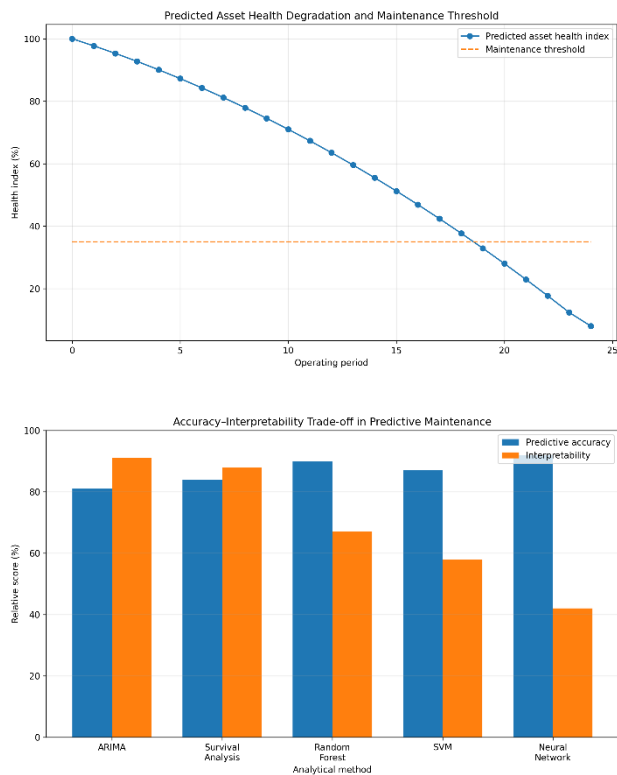
Metric	Description
Accuracy	Fault prediction correctness
Precision	Correct positive predictions
Recall	Failure detection capability
F1-score	Overall classification performance
RMSE	Remaining useful life prediction error
Latency	Decision response time
Availability	Fleet operational uptime

A. Data Acquisition and Ingestion

Data sources for the Autonomous Industrial Intelligence Framework range from sensors and production logs to asset maintenance history and external environment information feeds. The nature and granularity of data vary significantly, determined by the underlying physical phenomena, the operational scale of the monitored assets and fleets, the requirements of various predictive analytics applications, and the integration and interaction with other components. Data

ingestion and preparation procedures must also ensure that data quality is adequate for the intended applications and that data provenance is captured.

For forecast denoising and novel-event detection, high-frequency streaming data from low-cost sensors and edge devices (microcontroller units) are leveraged. These data are processed on edge devices with limited sensors and actuation resources, using tinyML-based pipelines comprising feature extraction and labelling to produce compressed features as prepared for ML-based predictive analytics. High-value complex assets—such as fleet vehicles—possessing on-board processing capabilities rely on techniques dedicated to confined-edge devices and edge-fog cloud architectures, where distributed ML processing balances data transfer loads and associated latencies. In parallel, and more strategically, data quality control using digital twins and other assets, combined with product and maintenance records, manages longer-term Asset Management Lifecycles (AML), providing production logs to higher-level decision support.

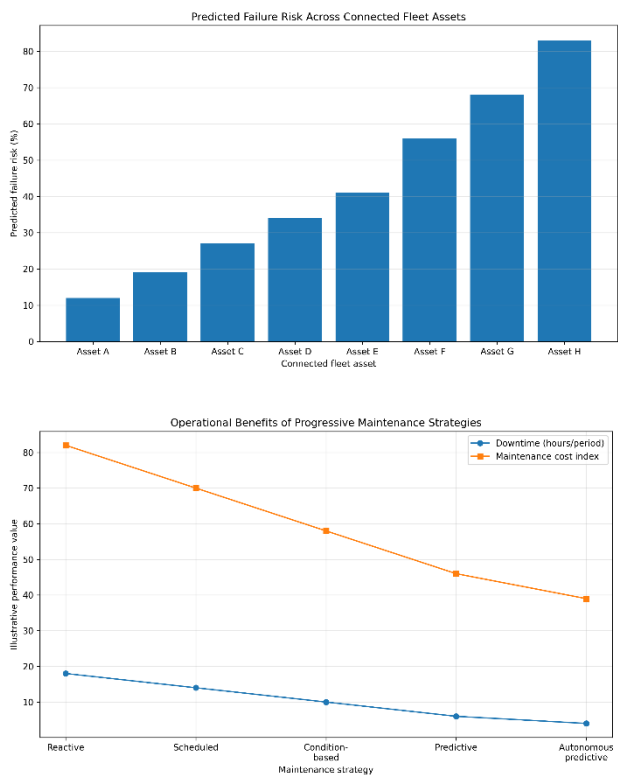


4. Methods and Algorithms

A diverse set of algorithms and methodological approaches is required to address the various processes encapsulated within the Autonomous Industrial Intelligence Framework, including prognostics, anomaly detection, optimization, decision-making, and incident-management readiness. Where supervision is possible, supervised methods will be used; otherwise, unsupervised learning approaches will be preferred until supervised instantiation becomes feasible. The requirement for actuation feedback will justify human-in-the-loop governance only for machine-learning-based control/actuation policy optimization. Reinforcement learning will be employed to tune behavioural agents without a clearly defined reward function. Governance and risk will

dictate method selection on a task-by-task basis to ensure model interpretability, calibration or validation against real-world outcomes, and uncertainty quantification of the predictions subsequently.

The Autonomous Industrial Intelligence Framework uses both traditional statistical methods and modern ML/AI techniques. The modelling of predictive-maintenance tasks using traditional approaches offers benefits in terms of understanding, interpretation, computational requirements, and uncertainty quantification, which are critical to ensuring the operational reliability of the underlying system or equipment. Model types such as classical regression and survival analysis are considered interpretable. Moreover, appropriate Poisson models can provide the decision support of a maintenance scheduling policy controlling downtime for a fleet of sensors. Classical methods, specifically ARIMA, remain the state-of-the-art solution for time-series forecasting due to their mathematical foundations, statistical properties, low computing-time requirements, extensive literature support, and data-driven tuning through identification tests and residual analysis. Consequently, no ML/AI predictive-maintenance methods have surpassed their accuracy and practicality. Nevertheless, ML/AI better captures complex dependencies and therefore supports predictive—prescriptive models in anomaly detection, process control, incident response, and support systems for fleet operations.



A. Machine Learning and Statistical Methods

Machine learning algorithms typically outperform traditional statistical methods when adequate datasets are available. Random forests, support vector machines, and neural networks can model complex relationships, explore non-linear dependencies, and improve accuracy by aggregating predictions from multiple base models.

However, they are often considered “black boxes.” Decision trees, whereas less accurate, can also be interpreted and visualized. Algorithms pretrained on large external datasets and subsequently fine-tuned for target applications enhance performance even in data-scarce domains. Moreover, approaches embedding additional domain knowledge can further alleviate training data scarcity. Models using domain knowledge are less prone to overfitting and usually extend beyond ideal training conditions. Nonetheless, highly capable ML methods demand high computational power, and ML-trained black-box models need to be properly validated and risk mitigated, failing to fulfill safety-by-design requirements for high-reliability or high-safety applications.

Critical-sequence rupture-prediction models for cyber-physical industrial assets with an external dependency on the Internet rely on human-machine-safety collaboration to mitigate the impact of executive-level failures in the external-pull submodule using risk-tolerance adjustment as an additional risk-mitigation and restoration method. Within the Asset Health evaluation module, time-to-failure models enabling prognostics-based predictive-asset-health evolution utilize heuristic methods and executive-down risky scenario-cum-sustenance reliance change-factor models. Failure-prediction methods utilize statistical (survival-analysis and reliability-function-based failure-time modelling) and ML (decision-tree and random-forest) techniques. Their application requires either the availability of a sizeable dataset with labelled historical failure data (supervised learning) or the absence of such data (unsupervised learning) because ML black-box models must be validated and risk-mitigated before deployment in higher-reliability and-safety systems.

5. Governance, Security, and Safety Considerations

Computation and information technology (IT) have profoundly changed how organizations operate, creating complex interdependencies that expose them to novel risks. Statistically rare events, often termed black swan events, and their associated cascading effects, also known as systemic risks, can threaten the viability of entire organizations or even the global economy. Consequently, traditional methods for governing, managing, and operating organizations are becoming increasingly obsolete. New approaches to governance, management, and operations are needed to develop advanced adaptive processes so that organizations can thrive instead of merely surviving.

Within this domain, governance can be understood as selecting and enforcing policies that determine how pervasive computing and communications are used, handcrafted in a top-down manner for the entire organization. Stakeholder and risk analysis underpin the policy definition. Management defines processes that fulfil the goals of the organization without executing them and monitors their performance and risks. Emerging, self-organizing, bottom-up processes function outside management monitoring and control, creating new opportunities and threats. Finally, operational decisions determine what will be done next to achieve organizational goals, assign who will do it, and set resource levels. Traditional risk management is still important but has

been complemented by resilience engineering that emphasizes the capacity to prepare for and respond to unpredictable dangers, often by exploiting them. Digital twins mimic physical entities in real time, enabling autonomous and semi-autonomous operations. To establish risk-tolerant autonomy, the consequences of errors need to be tolerated or controlled. These three views – governance, management, and operations – differ mainly in the hierarchical level at which they are applied and help frame considerations on governance, security, and safety aspects of automated processes.

A. Data Governance and Provenance

An effective data governance framework underpins the entire data ecosystem, spanning data ownership, access controls, retention policies, and provenance tracking. A structured hierarchy of data assets and users enables the assignment of clear ownership rights, as well as the creation of logical access control lists. Automated monitoring, detection, and notification of attempted unauthorized access further strengthen the data governance framework. For connected fleet operations, the ability to expose and utilize highly curated datasets from multiple parties empowers fleet operators, Original Equipment Manufacturers (OEMs), and third-party services for predictive maintenance and further solution development. Classification of data assets also enhances the ability to define appropriate retention policies aligned with business objectives. Intermodal asset flow between organizations, however, complicates data retention decisions. A proper governance framework can help navigate the trade-offs between information preservation and dwindling storage costs, ultimately defining the best approach for specific datasets.

Finally, data provenance supports the capture of data asset lineage across the entire pipeline. In asset health, provenance aids the establishment of digital twins, direct quantification of remaining useful life, and other derived health attributes, while evidencing the process through which the final derivative was generated. For other areas such as predictive maintenance, usage data provenance is essential to ascertain the fitness for purpose and quality of predicted outcomes. Digital twins' trustworthiness hinges not only on the quantity but also the quality of the data underpinning the physics-based component. Digital twins employed for advanced applications require data quality justifying the predicted solution in a court of law. The best way to guarantee this level of data quality is through strict direct data collection from the asset. This is especially true for datasets feeding into machine learning methods, for which a clearly defined provenance enables the certification of the dataset employed for training and hence the appropriate quantification of uncertainty on the predicted solution.

6. Conclusion

The interplay of asset health, predictive maintenance, and resilience of connected fleet operations of industrial assets is critical and forms the main objective of this paper. Following a comprehensive literature survey, and focusing on end user needs, a series of research questions were articulated, along with a set of hypotheses—which delineate the expected

behaviour of the system that would resolve these questions—and success metrics to gauge their validity. An integrated Autonomous Industrial Intelligence Framework is proposed whose theory base consists of the three domains of asset health, predictive maintenance, and resilience of connected fleet operations, and which leverages several data science methods and algorithms from related areas of signalling, control, finance, supply chain, and operations research. Data is acquired primarily from internal sources, including sensors, system/asset log files, maintenance records, and data mart repositories acting as data lakes feeding the framework.

Novelty detection, forecasting, regression, trajectory prediction, clustering and other machine learning methods permit proactive operational actions with a human-in-the-loop approach suitable for autonomous industrial operations. A closer inspection of response surfaces associated with these techniques, especially novelty detection and clustering, ensures user acceptance for resilience covering the four reliability, availability, maintainability, safety (RAMS) and security dimensions. Conversely the deployment of RAMS and security policies for assets operating under automated control is recast in terms of a suitable risk attitude of not performing the upkeep and oversight of a complete industrial complex as a single entity, but of multiple interacting fleets of connected and autonomous industrial assets.

REFERENCES

1. Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., & Elger, G. (2021). Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. *Reliability Engineering & System Safety*, 215, 107864.
2. Markudova, D., Mishra, S., Cagliero, L., Vassio, L., Mellia, M., Baralis, E., Salvatori, L., & Loti, R. (2021). Preventive maintenance for heterogeneous industrial vehicles with incomplete usage data. *Computers in Industry*, 130, 103468.
3. Safavi, S., Safavi, M. A., & Hamid, H. (2021). Multi-sensor fault detection, identification, isolation and health forecasting for autonomous vehicles. *Sensors*, 21(7), 2547.
4. Yandamuri, U. S., Loganathan, R., Davuluri, P. S. L. N., Rani, P. R. S., Kolla, S. H., & Nagubandi, A. R. (2026). Adaptive Intelligence Networks for Humancentered Enterprise Automation and Governance. In 2026 Third International Conference on Innovations in Cybersecurity and Data Science (ICICDS) (pp. 678–683). IEEE. 2026 Third International Conference on Innovations in Cybersecurity and Data Science (ICICDS). <https://doi.org/10.1109/icicds70526.2026.11604640>
5. Jain, M., Vasdev, D., Pal, K., & Sharma, V. (2022). Systematic literature review on predictive maintenance of vehicles and diagnosis of vehicle's health using machine learning techniques. *Computational Intelligence*, 38(6), 1990–2008.
6. Giannoulidis, A., & Gounaris, A. (2023). A context-aware unsupervised predictive maintenance solution for fleet management. *Journal of Intelligent Information Systems*, 60, 521–547.
7. Raghunath Loganathan. (2026). SaaS Entitlement Governance: A Reproducible Model for Detecting and Reclaiming Over-Provisioned Access at Enterprise Scale. *Journal of Intelligent Decision Making and Information Science*, 3(7s), 2519–2530. <https://doi.org/10.59543/jidmis.v3.1957>
8. Hiwase, S., & Jagtap, P. (2022). Predictive maintenance of automotive component using digital twin model. *SAE International*.
9. Barragán-Moreno, A., Schaltz, E., Gismero, A., & Stroe, D.-I. (2022). Capacity state-of-health estimation of electric vehicle batteries using machine learning and impedance measurements. *Electronics*, 11(9), 1414.
10. Yao, L., Wang, Y., Wang, Z., & others. (2022). A machine learning-based robust state of health (SOH) prediction model for electric vehicle batteries. *Electronics*, 11(8), 1216.
11. Banoth, S., Santoshi Kumari, M., Lalitha, P., Deepthi, P., Kumar Peddi, R., & Kavitha, P. (2026). An Efficient Hybrid K-Means and Random Forest-Based Approach for Cloud Malware Detection and Privacy Protection. In 2026 6th International Conference on Intelligent Technologies (CONIT) (pp. 1–6). IEEE. 2026 6th International Conference on Intelligent Technologies (CONIT). <https://doi.org/10.1109/conit69683.2026.11621822>
12. Hu, X., Jiang, J., Cao, D., & Egardt, B. (2022). Battery health prognosis for electric vehicles using machine learning approaches. *Renewable and Sustainable Energy Reviews*, 156, 111903.
13. Li, P., Zhang, Z., Yang, X., & others. (2022). An end-to-end neural network framework for state-of-health estimation and remaining useful life prediction of electric vehicle lithium batteries. *Renewable and Sustainable Energy Reviews*, 156, 111843.
14. Kulkarni, V., Jyothsna, P., Musku, K., Mattaparthi, R., & Nagaraj, S. S. (2026, July). A Multi-Objective Metaheuristic Framework for Demand-Side Management in Isolated Tropical Photovoltaic Microgrids: Performance Bounds and Battery Trade-off Analysis. In 2026 14th International Conference on Smart Grid (icSmartGrid) (pp. 331-337). IEEE.
15. van Wyk, B. J., et al. (2021). On fault classification in connected autonomous vehicles using supervised machine learning. *IEEE conference publication*.
16. Zhao, J., Ling, H., Liu, J., Wang, J., Burke, A. F., & Lian, Y. (2023). Machine learning for predicting battery capacity for electric vehicles. *eTransportation*, 15, 100214.
17. Movva, V. R., & Pareek, P. K. (2026). Multi-Agent AI Architecture for Autonomous Retail Operations: Coordinating Intelligent Agents Across Cloud, DevOps, and Enterprise Platform. *International Journal of Computer Information Systems and Industrial Management Applications*, 18(23s), 925-932.
18. Eaty, N. D. K. M., & Bagade, P. (2023). Digital twin for electric vehicle battery management with incremental learning. *Expert Systems with Applications*, 229, 120444.
19. Zeng, J., & Liang, Z. (2023). A dynamic predictive maintenance approach using probabilistic deep learning for a fleet of multi-component systems. *Reliability Engineering & System Safety*, 238, 109456.
20. Crespo del Castillo, A., Marcos, J. A., & Parlikad, A. K. (2023). Dynamic fleet maintenance management model applied to rolling stock. *Reliability Engineering & System Safety*, 240, 109607.
21. Piyush Kumar Pareek. (2026). Self-Evolving Analytics Pipelines for Reliable AI-Augmented Software Systems. *Journal of Intelligent Decision Making and Information Science*, 3(5s), 1558–1578. <https://doi.org/10.59543/jidmis.v3.1286>
22. Yuan, L., Brinton, C. G., Zak, S. H., & Wang, Z. (2024). Federated learning for connected and automated vehicles: A survey of existing approaches and challenges. *IEEE Transactions on Intelligent Vehicles*, 9(1), 119–137.
23. Chellapandi, V. P., Yuan, L., Brinton, C. G., Zak, S. H., & Wang, Z. (2024). Federated learning for connected and automated vehicles: A survey of existing approaches and challenges. *IEEE Transactions on Intelligent Vehicles*, 9(1), 119–137.
24. Haraz, A., Abualsaud, K., & Massoud, A. (2024). State-of-health and state-of-charge estimation in electric vehicles batteries: A survey on machine learning approaches. *IEEE Access*, 12, 158110–158139.
25. Eddy, C. W., Castanier, M. P., & Wagner, J. R. (2025). Predictive maintenance of a ground vehicle using digital twin technology. *SAE International Journal of Advances and Current Practices in Mobility*, 7(2), 865–876.
26. Loganathan, R., Vakkalagadda, T., & Potturi, P. (2026). Quantifying Cost Reduction from IT Service Management Automation in Fortune 500 Enterprises. *International Journal of Artificial Intelligence and Machine Learning*, 6(7s), 1093-1101.
27. Rahim, M. A., Rahman, M. M., Islam, M. S., Muzahid, A. J. M., Rahman, M. A., & Ramasamy, D. (2024). Deep learning-based vehicular engine health monitoring system utilising a hybrid convolutional neural network/bidirectional gated recurrent unit. *Expert Systems with Applications*, 251, 125080.
28. Hossain, M. N., Rahman, M. M., & Ramasamy, D. (2025). Advances in intelligent vehicular health monitoring and fault diagnosis: Techniques, technologies, and future directions. *Measurement*, 253, 117618.
29. Hossain, M. N., Rahman, M. M., & Ramasamy, D. (2025). Optimised decision-making model for vehicle health monitoring system leveraging deep learning algorithm. *Transportation Research? [Publication details should be checked against the final journal record before submission.]*

30. Ellenki, R. R., & Venkatesh, P. (2026). Collaborative AI Agent Architecture for Autonomous Retail Inventory and Allocation Management. *International Journal of Computer Information Systems and Industrial Management Applications*, 18(23s), 933-940.
31. Haraz, A., Abualsaud, K., & Massoud, A. (2024). State-of-health and state-of-charge estimation in electric vehicles batteries: A survey on machine learning approaches. *IEEE Access*, 12, 158110–158139.
32. Eaty, N. D. K. M., & Bagade, P. (2023). Digital twin for electric vehicle battery management with incremental learning. *Expert Systems with Applications*, 229, 120444.
33. Giannoulidis, A., & Gounaris, A. (2023). A context-aware unsupervised predictive maintenance solution for fleet management. *Journal of Intelligent Information Systems*, 60, 521–547.
34. IoV-TwinChain authors. (2025). IoV-TwinChain: Predictive maintenance of vehicles in internet of vehicles through digital twin and blockchain. *Internet of Things*, 30, 101514.
35. Madhavi, B., Kolla, S. K., & Gari, V. A. K. R. R. (2026). Comment on “Artificial intelligence in clinical nutrition: A narrative review”. *Clinical Nutrition ESPEN*, 74.
36. Karkaria, V., Chen, J., Luey, C., Siuta, C., Lim, D., Radulescu, R., & Chen, W. (2024). A digital twin framework utilizing machine learning for robust predictive maintenance: Enhancing tire health monitoring. *arXiv*.
37. Zhao, J., Ling, H., Liu, J., Wang, J., Burke, A. F., & Lian, Y. (2023). Machine learning for predicting battery capacity for electric vehicles. *eTransportation*, 15, 100214.
38. Theissler, A., Pérez-Velázquez, J., Kettelgerdes, M., & Elger, G. (2021). Predictive maintenance enabled by machine learning: Use cases and challenges in the automotive industry. *Reliability Engineering & System Safety*, 215, 107864.
39. A state-of-the-art on federated learning for vehicular communications. (2024). *Vehicular Communications*, 45, 100709.
40. Penaka, B. (2026). AUTONOMOUS MULTI-AGENT AI FRAMEWORK FOR END-TO-END CLINICAL DECISION SUPPORT AND CARE COORDINATION. *Genetics and Molecular Research*.