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SYNERGISING FINITE ELEMENT METHODS WITH AI-DRIVEN PREDICTIVE RISK MODELS IN MANUFACTURING: A SYSTEMATIC REVIEW

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ABSTRACT

Today's manufacturing industry is increasingly turning to simulation, sensing, and data-driven decisions, but these often do not converge into a single workflow. While the Finite Element Method (FEM) can give physically-based predictions of stress, strain, deformation and temperature, models with the high fidelity are slow and expensive to run repeatedly. By comparison, artificial intelligence (AI) absorbs intricacies from computer-simulated and measured data, and upon training, can be programmed to make predictions nearly instantaneously. In this systematic review, following the PRISMA 2020 guidelines, the two approaches are compared in their behaviour when their strengths are combined in the context of predictive risk management in manufacturing. The literature on FEM surrogates and physics-informed learning, AI-enhanced failure mode and effects analysis (FMEA), predictive maintenance, predictive quality and digital twins was synthesised into a 4-category, function-based taxonomy. The evidence demonstrates that the benefits of hybridisation do not lie in replacing simulation with AI, but rather in ensuring predictions are more relevant and reliable using physics-based knowledge, and in minimising the computation time required and making decisions rapidly using AI. Common constraints are: limited data sets, poor cross-domain validation, lack of quantification of uncertainty at the extremes of the training set, poor integration with live production systems; for industrial economies, these are further exacerbated by infrastructure issues, skills issues, and costs. The review thus highlights the gap between the success of lab demonstrations and strong plant-scale deployment. Further research and development is needed in the areas of establishing common benchmarks, risk-aware and explainable hybrid models, multi-fidelity data sets, low-cost deployment routes, and digital-twin models that properly connect simulation, sensing, risk assessment, and operational control.

Keywords: Finite element method; Artificial intelligence; Surrogate modelling; Physics-informed neural networks; Predictive maintenance; FMEA; Digital twin; Smart manufacturing

1 INTRODUCTION

The manufacturing is moving towards connected manufacturing and physical equipment, simulation models and information systems exchange data continuously throughout the manufacturing process (Tiwari, 2023; Soori, Arezoo

and Dasres, 2023). This transformation can be seen in smart manufacturing, predictive quality, condition monitoring and digital-twin applications. Machine learning (ML) has played an important part in the transition, since process and condition data that are generated by modern equipment is too vast to be processed just using fixed rules (Shang and You, 2019). Predictive maintenance and predictive quality have been reviewed and it was observed that the application of ML in these fields is expanding (Carvalho et al., 2019; Tercan and Meisen, 2022).

However, the rate of adoption is not uniform. The adoption of Industry 4.0 technologies in developing industrial economies like Zimbabwe is still hampered by inadequate infrastructure, lack of skills, and lack of organisational commitment (Muhla et al., 2025a), while industrial firms in a volatile market need to be agile in order to stay competitive (Muhla et al., 2023). The Finite Element Method has a different function in this ecosystem. It is derived from solving physical equations numerically and is extensively used to predict structural, thermal and mechanical responses.

The main drawback of it is its high computational expense, especially in cases of fine meshes, nonlinear material response, contact, transients and large design spaces. In recent years, then, the investigation of the reproduction of selected FEM responses, at much lower inference costs, has been studied by means of ML models (Badarinath, Chierichetti and Davoudi Kakhki, 2021; Hashemi, Jang and Beheshti, 2023). Therefore, a combination of the two is a tempting option, however, it is not a straightforward replacement of one technology with another. FEM can provide high fidelity training data or physical constraints to an AI model, while an AI model can be a surrogate, feature extractor, optimisation layer, or risk-classification mechanism for FEM. The physics-informed neural network (PINN) is a typical example of this approach, as governing equations and boundary conditions are not only used in the training of a model but also included into it (Haghighat and Juanes, 2021a; Karniadakis et al., 2021).

Other solutions involve graph-based representations of the mesh, finite element neural networks or hybrid simulation-learning loops (Pfaff et al., 2021; Black and Najafi, 2022; Quan et al., 2026). In manufacturing, the scope of predictive risk is also much wider than just structural failure. Defective products, excessive energy use, process instability, unsafe working conditions and unexpected downtime can be a problem in a production system.

Experimental research on energy consumption and product quality in the manufacturing processes of cutting, forming, injection moulding and additive manufacturing has revealed that the quality of the manufactured product and the energy consumed are sensitive to the process-parameter settings (Tayisepi et al., 2023); (Mapindu et al., 2026a); (Mapindu et al., 2026c). Human-factor failures are among the top causes of workplace accidents (Muhla et al., 2025b). The performance of ML models is deteriorating in case of changes in operating conditions (Aghahadi et al., 2025; Madhumitha et al., 2026), which is why their use for fault detection and prediction is increasing. Digital twins further enhance this by simulating and predicting the operation of the physical asset and incorporating that information into a virtual version of the asset (Soori, Arezoo and Dastres, 2023).

The identified gap in this review is the lack of integration of these strands into one manufacturing risk workflow. In comparison to stand-alone predictive quality, maintenance or optimisation studies, the integration of direct FEM–AI is less developed. The intent of this review is thus to look at the areas of strongest evidence and what is needed to progress from proof-of-concept models to reliable manufacturing systems. To this end the review (i) suggests a taxonomy of FEM–AI integration based on functionality, (ii) critically analyzes evidence encountered in the various application areas of simulations, quality, maintenance and risk-assessment, and (iii) outlines the gaps in research, which includes the specific gaps in the resource-constrained manufacturing environment.

2 BACKGROUND AND THEORETICAL FOUNDATION

2.1 The Finite Element Method

The FEM is a method that transforms a physical problem with infinite length into a finite number of elements linked together at nodes (Liu, Li and Park, 2022). Field variables are approximated within each element by interpolation (shape) functions and the resulting elemental relationships are assembled into a global system of equations (Zienkiewicz, Taylor and Zhu, 2013). This can be simplified in the case of a linear static structural problem to:

$$K u = F \quad (1)$$

In this equation, K is the global stiffness matrix, u is the vector of node displacement and F is the vector of nodal loading. After the displacement solution is found, the strain and stress fields are obtained using strain–displacement and constitutive relationships (Koutromanos, 2018). Thermal and fluid or coupled multiphysics problems can be solved using the same numerical principle. In manufacturing engineering, it is used to calculate quantities that would be difficult or expensive to measure directly, like stress concentrations, deformation, temperature fields, fatigue-related quantities and failure indicators.

For the design of a passive upper-limb exoskeleton, for example, three design concepts for two candidate materials were modelled and evaluated in SolidWorks and ANSYS using maximum deformation, stress and factor of safety before a final design was chosen (Tandi et al., 2025). Likewise, the load analysis and computational fluid dynamics (CFD) approaches were used to evaluate a vertical-axis wind turbine (VAWT) for capturing highway slipstream energy (Muyambo et al., 2025).

These studies are typical examples of the utility and the limitation of simulation: a new geometry, material or load case will need a new solve and for many combinations of design and process parameters, the cost becomes prohibitive. That's where surrogate modelling comes in handy. The relationship between the selected inputs and outputs is not solved in full every time, but rather an AI model is trained to approximate the relationship (Badarinath, Chierichetti and Davoudi Kakhki, 2021).

2.2 AI-Driven Predictive Risk Modelling

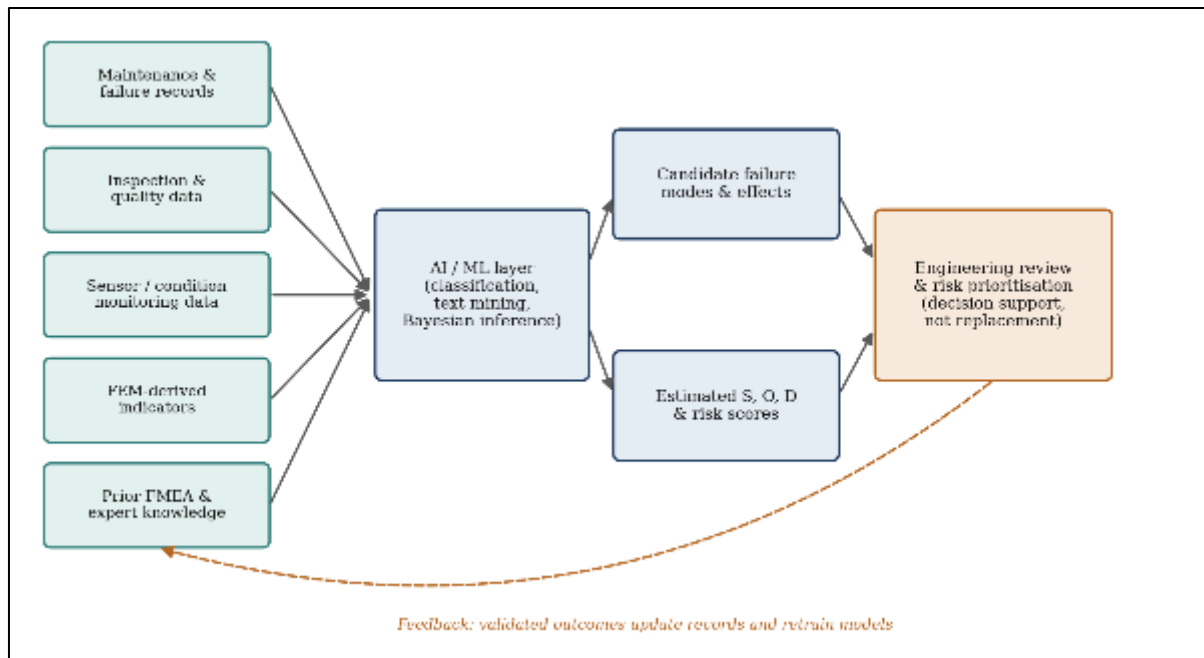


Figure 1: Conceptual workflow of AI-assisted FMEA and risk prioritisation.

Source: Authors' own construction, synthesised from Liu, Liu and Liu (2013) and Younus et al. (2026).

Predictive risk modelling are models used to estimate the probability or magnitude of an undesirable manufacturing event before it happens. The result can be a defect, machine failure, degradation, an unstable process condition, safety incident or any other risk to the process. Classical approaches include decision trees, random forests, support vector machines and Bayesian models, while deep-learning approaches include convolutional, recurrent and graph-based networks (Carvalho et al., 2019; Zonta et al., 2020). The results of predictive-maintenance reviews indicate that there is no single algorithm that works best in all industrial conditions for predictive-maintenance, because the suitability of any model depends on the nature of the data, the type of failure, and the predictive-maintenance evaluation protocol (Carvalho et al., 2019). This is supported in practice as follows: When comparing the performance of several classifiers on an operational data set of 13 years from a coal-based power plant in Zimbabwe, the random forest was chosen for the model of the preventive maintenance decision because of its high performance on non-linear operating data (Senda et al., 2026).

FMEA is a helpful tool to help connect prediction and engineering risk management. Traditional FMEA is heavily dependent on structured expert judgement and the traditional risk priority number has been widely criticized for being subjective and assigning the same weight to the three elements of severity, occurrence and detection (Liu, Liu and Liu, 2013). Additionally, human factors make risk assessments a complex process, as operator errors, ergonomic design, and safety culture all play a role in the number of accidents that occur on the shop floor (Muhla et al., 2025b). Recent work has investigated the use of AI-assisted methods to take advantage of historical records and structured data to help identify and prioritise failure modes, as outlined in Figure 1. The use of such systems should be seen as a decision support tool and not as a replacement for engineering judgement, especially with critical failure consequences (Younus et al., 2026).

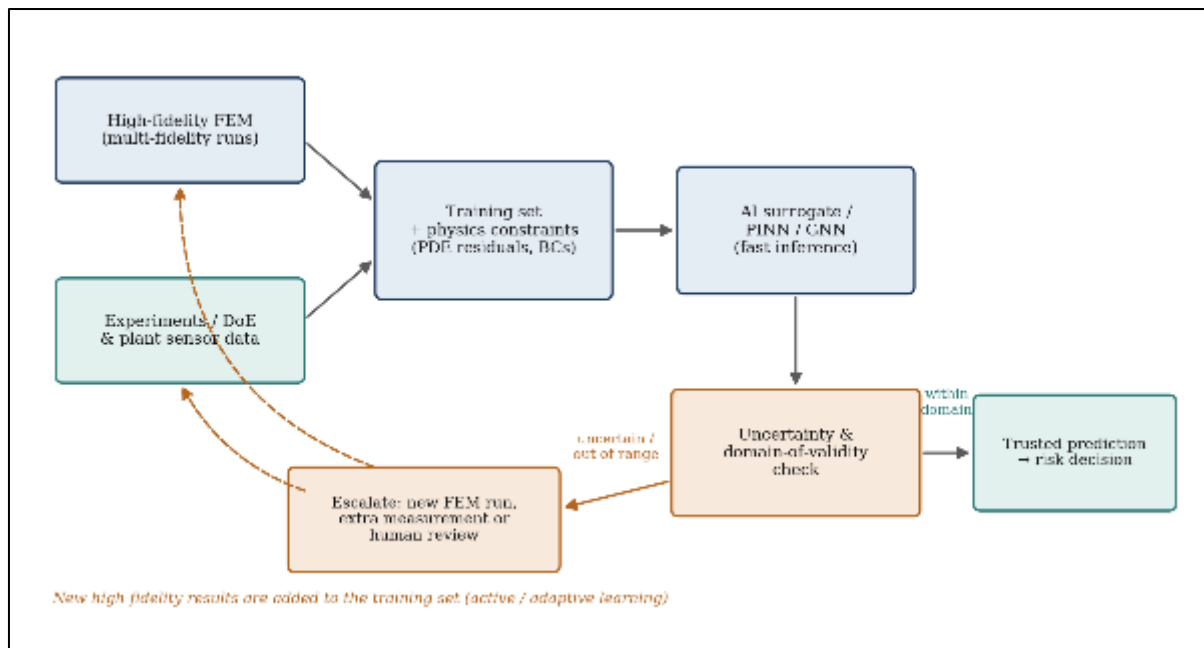


Figure 2: Uncertainty-gated hybrid FEM–AI workflow with escalation to high-fidelity analysis.

Source: Authors' own construction, informed by Karniadakis et al. (2021) and Haghighat et al. (2021b).

The two approaches are complementary; the theoretical basis of their complementarity is based on their weaknesses. Compared to other methods, FEM is relatively robust in terms of physical consistency, but may require long simulation times and rely on modeling parameters and boundary conditions (Santana et al., 2026). Once trained, AI inference is quick, but may fail if the input is not in the distribution that was used to train the AI. It is possible to then achieve a division of labour that, when combined, provides a FEM that delivers trusted physical information, an AI that learns useful approximations or risk relationships, and a further FEM or experimental check that is activated when a prediction is uncertain or beyond the range of the predictions the AI has made before (Figure 2). This is in line with recent efforts in physics-informed learning. Haghighat et al. (2021b) proposed neural-network models for multi-faceted inversion and surrogate modeling in solid mechanics. Xiong (2024) applied data-driven and physics-assisted learning to classify warpage and optimise process parameters. Meanwhile, Henkes, Wessels, and Mahnen (2022) established that physics-informed learning continues to have challenges with very localized effects and high nonlinearity. The evidence thus indicates that physics-aware learning is a potentially fruitful path, one that does not necessarily be a panacea for the traditional numerical simulation.

3 METHODOLOGY AND SEARCH STRATEGY

This paper uses a systematic literature review method to examine the use of finite element methods in conjunction with AI-based predictive risk models in manufacturing. Systematic review was an appropriate approach as the topic covered multiple related fields like finite element analysis, machine learning, predictive maintenance, failure prediction, defect detection, and optimisation of manufacturing process. The goals were not only to identify the previous studies, but to also compare the approaches, common findings and gaps to the integration of physics based simulation, failure-effects analysis and AI in manufacturing.

The review was guided by three research questions:

- RQ1: How are FEM and AI integrated in manufacturing prediction and risk-assessment workflows?
- RQ2: What benefits and limitations are reported for each form of integration?
- RQ3: What is required to move FEM–AI systems from laboratory demonstration to industrial deployment?

The review was conducted according to the general guidelines of the PRISMA 2020 statement (Page et al., 2021) that guides the identification, screening and selection of relevant studies. The process included identifying the records from the selected databases, eliminating the duplicate records, examining the remaining records by title and abstract, screening the eligible papers and then selecting the studies that fulfilled the eligibility criteria of the review (Figure 3).

3.1 Literature Search Strategy

The research targeted the publications that are concurrent with four concept groups: finite element method, artificial intelligence, predictive risk modelling and manufacturing. The databases searched were Google scholar, IEEE Xplore, Science Direct and the searches were done in the month and year of last searching. Boolean search strings used the OR operator together with synonyms within each concept group and used the AND operator to connect groups of concepts that were searched to broaden the search and to include the different terminologies used by researchers. One example string was: The primary sources of evidence were peer reviewed journal articles, and conference papers were considered, if they offered useful findings. Key reviews were used for backward citation searching to identify additional relevant studies.

3.2 Inclusion and Exclusion of Studies

Studies related to FEA/FEM, artificial intelligence, machine learning or hybrid physics-based simulation and data-driven approaches were emphasized. Studies that provided adequate details of methodology and results were preferred as this would make comparison of approaches meaningful. Studies that did not have a meaningful FEM/AI contribution, were not related to manufacturing, or did not include any prediction, risk, failure, maintenance, quality, or optimisation were excluded. These criteria are summarised in Table 1.

Table 1: Inclusion and exclusion criteria

Inclusion criteria	Exclusion criteria
Peer-reviewed journal articles and substantive conference papers	Non-peer-reviewed sources, opinion pieces, blogs and grey literature
Manufacturing or production-system context	No manufacturing or engineering-production context
Meaningful FEM/FEA, AI/ML or hybrid physics-data component	No substantive FEM or AI component
Addresses prediction, risk, failure, maintenance, quality or optimisation	Does not address any prediction or risk-related outcome
Published within the review period and in English	Outside the review period; duplicate records

3.3 Data Extraction and Analysis

Data derived from each included study concerned with the manufacturing process/assets, the type of AI method, the role of FEM, the data sources, the validation method, and the performance reported. The relationship between FEM and AI was given special consideration. The studies were then categorized into seven themes of integration: 1) FEM-generated data to train AI models, 2) AI surrogate models, 3) physics-informed models or hybrid models, 4) optimisation of manufacturing processes, 5) prediction of defects and quality, 6) predictive maintenance, and 7) applications of digital twins. The themes were then consolidated into the four-category taxonomy outlined in Section 4.

The studies were contrasted in terms of predictive performance, computational speed, required data, model validation, model interpretability and applicability in manufacturing. Overall, the methodology was designed to provide a structured and reproducible way of identifying literature on FEM–AI integration in manufacturing.

The search and screening process has been used to classify existing approaches, and the comparison of the selected studies has been employed to reveal common findings, limitations and research gaps. The results of these findings were then discussed on how physics-based engineering simulations can be integrated with AI-based predictive risk models in manufacturing in the future.

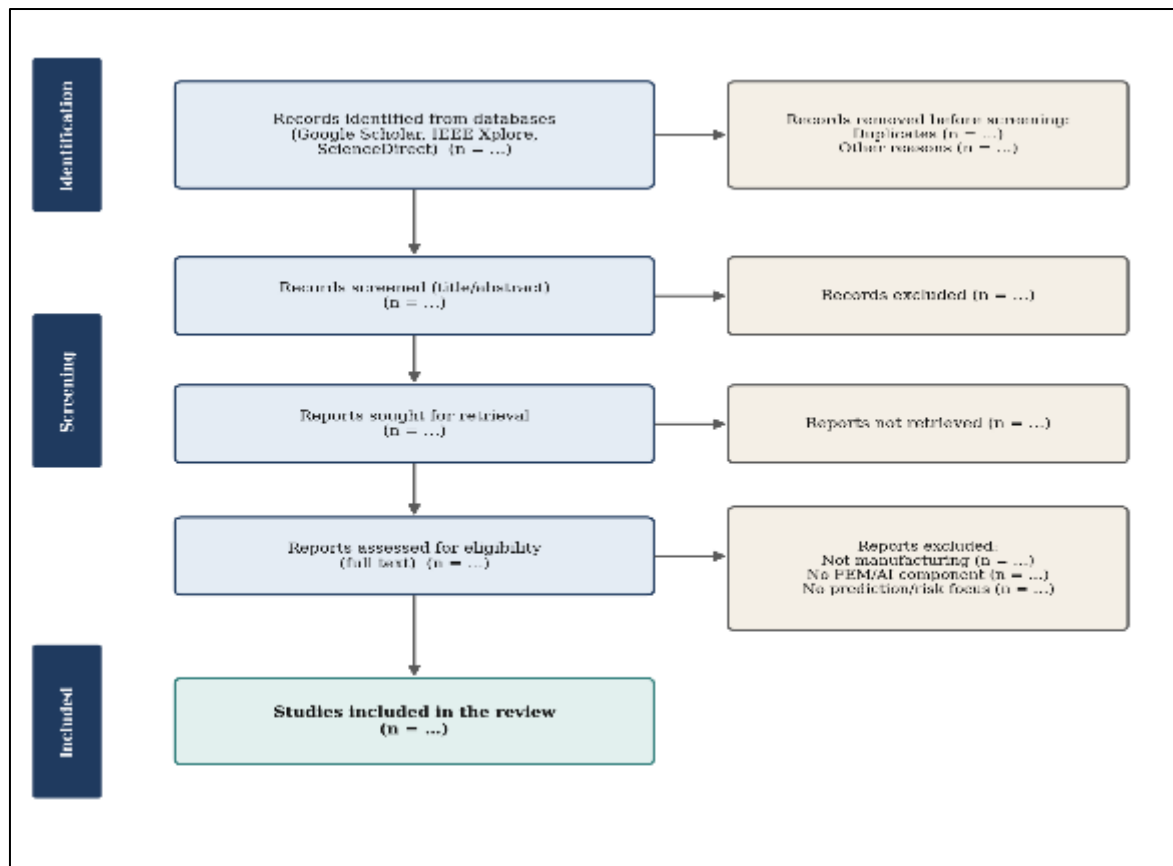


Figure 3: PRISMA 2020 flow diagram of study identification, screening and inclusion.

Source: Adapted from Page et al. (2021). Record counts (n) to be completed by the authors from the screening log.

4 CLASSIFICATION AND TAXONOMY

The included literature can be divided into four overlapping groups based on the function that is being fulfilled by the AI model and where FEM fits into the workflow (Table 2). These categories are not mutually exclusive, and one system could employ FEM for training purposes, surrogate for rapid simulation and another for estimating maintenance risk.

Table 2: Taxonomy of FEM–AI integration approaches in manufacturing

Category	Core role	Typical methods	Manufacturing purpose	Representative studies
I. AI as FEM surrogate	Approximate FEM outputs without repeated full solves	ANN, PINN, graph neural network, Gaussian process	Fast design and process simulation	Kohar et al. (2021); Black and Najafi (2022); Hashemi, Jang and Beheshti (2023)
II. AI-enhanced risk / FMEA	Support failure identification and prioritisation	Decision trees, Bayesian models, rule-based and multi-agent reasoning	Risk ranking and engineering decision support	Liu, Liu and Liu (2013); Mashava et al. (2026); Younus et al. (2026)
III. Hybrid FEM–AI optimisation	Couple simulation or experiments with learning in an iterative design/process loop	ANN, regression, Taguchi/DoE, grey relational analysis, metaheuristics	Parameter selection and process optimisation	Kasilingam et al. (2024); Mapindu et al. (2026a; 2026b; 2026c); Tayisepi et al. (2024)
IV. FEM-informed predictive maintenance	Combine condition data with physics-derived indicators	Random forest, regression, hybrid and digital-twin models	Failure prediction and remaining useful life	van Dinter, Tekinerdogan and Catal (2022); Senda et al. (2026)

4.1 AI as an FEM Surrogate

Surrogate modelling is the most obvious solution to the computational expense of FEM. The model is trained using the results of the simulations and then applied to estimate the response for new input conditions. For instance, Kohar et al. (2021) designed an ML framework using the data generated through CAE simulations to help speed up the process of designing structures for crashworthiness, and Yoo et al. (2021) applied deep learning to a CAD/CAE system for conceptualizing and assessing three-dimensional wheel designs. Black and Najafi (2022) proposed multi-fidelity graph neural networks for the learning of finite-element convergence, while Amiri-Hezaveh (2026) introduced a physics-augmented neural network to be embedded in a differentiable finite-element (FE) formulation to enable gradient-enhanced damage.

These studies are examples of various degrees of integration, ranging from external responses to prediction to neural components within the numerical method itself. The manufacturing relevance is that a surrogate can be used for parameter sweeps and a fast screening which otherwise would involve numerous costly solver runs (Bilal et al., 2026). Design studies in which candidate geometries and materials are compared by multiple runs of finite element analysis, such as Tandi et al. 2025, are obvious candidates for this sort of acceleration. But in the case of risk sensitive applications, it is not just about speed. If a surrogate fails to yield a physically implausible result outside of its training range, it might give rise to false confidence. That is why uncertainty estimation, checks on the domain of validity and selective re-evaluation with high fidelity FEM are not just added-on features, but essential design characteristics of the systems.

4.2 AI-Enhanced FMEA and Risk Prioritisation

The second type is more akin to the traditional approach to industrial risk management. AI can complement FMEA by analysing maintenance logs, inspection findings, sensor data and past risk assessments to aid in identifying and prioritising failure modes (Aluvihara, 2025). Recent studies on AI-enhanced FMECA (Pestano-Gupta, 2025) suggest that AI/ML can provide support to the analysts to help them identify potential failure modes and effects, which can help to lessen some of the manual work. There is a complementary approach of rule-based reasoning and agent-based reasoning.

A multi-agent system was developed for the induction furnace equipment and was successfully implemented with JESS rule inference that was able to diagnose anomaly in overheating refraction, degradation of cooling water flow, water conductivity, and deviations from inductor power, and automatically alert maintenance personnel (Mashava et al., 2026). A problem with this category is that the strength of the risk is often not tied to the components physical condition. A model can recognize that a machine is likely to fail even if it does not explicitly show why a stress concentration, temperature excursion or deformation pattern increases the likelihood of failure. One way to fill this gap would be to couple risk-prioritisation models with FEM-derived indicators.

4.3 Hybrid FEM-AI Process Optimisation

In hybrid optimization, the relationship between the controllable parameters and the engineering response is explored using FEM, which is then learned by AI. The trained model can then be combined with an optimisation algorithm to find some more appropriate operating conditions quicker. In the field of manufacturing processes, hybrid physics-based and data-driven modelling has been studied in a variety of processes (Kasilingam et al., 2024), and FEM-based simulation has also been employed to predict errors in the parts caused by milling of thin-walled parts (Xirouchakis, 2016).

However, in many manufacturing operations, the data for process optimisation are still obtained from designed experiments and not simulation. Shrinkage and warpage have proved to be most sensitive to injection pressure and melt temperature in injection moulding (Mapindu et al., 2026a); surface roughness and tool wear in CNC milling to feed rate and spindle speed (Mapindu et al., 2026b); and tensile strength and print time in fused deposition modelling to infill density and layer height (Mapindu et al., 2026c).

For wood machining, surface quality and energy consumption have been optimized in a joint effort (Tayisepi et al., 2023); in cast iron cylinder relining sleeves, surface quality optimization and experimental analysis were combined with predictive modelling in Minitab to design a vacuum bleaching system to improve edible-oil quality (Jansen et al., 2025). These studies provide statistically sound optima with a small number of trials, however each response curve fitted is only valid in the experimental range. They are thus already a logical starting point for FEM-AI hybridisation: validated simulations can be used to explore the design space at low cost and experimental results provide ground truth for a surrogate to be calibrated and validated.

A good surrogate provides the engineer an opportunity to explore a greater design space and to investigate trade-offs between conflicting goals. However, if the surrogate is only a little bit erroneous, an optimiser might be attracted to exactly those areas where the error is largest. It is recommended to run the confirmation experiments prior to the

predicted optimum for production, since validation with the original FEM model or physical test is necessary (Mapindu et al., 2026b).

4.4 FEM-Informed Predictive Maintenance

Predictive maintenance is a more advanced use case of AI in industrial production and there is a significant amount of literature on fault detection, prognosis and remaining useful life in this area (Zonta et al., 2020). While ML methods have been growing rapidly, the quality of the data is still a problem, and the practice of evaluation and the operating conditions are still evolving (Carvalho et al., 2019; Boddupally, 2020). This picture is borne out by case evidence from the developing world. In Zimbabwe, corrective maintenance took up approximately 72% of the maintenance strategy mix, and an optimal reliability point was identified, and a model for preventive-maintenance was built using ML to minimize failures in the boiler (Senda et al., 2026).

Real-time architectures are also emerging: Mashava et al. (2026) used infrared temperature, flow, conductivity and level sensors to connect up to a PLC, OPC server and multi-agent platform based on the FIPA standard for autonomous fault detection, diagnosis and notification. A second way to fuse simulation and operational data is via digital twins, and van Dinter, Tekinerdogan and Catal (2022) reviewed 42 studies and found that a significant issue is the computational size.

FEM can enhance the predictive maintenance by providing features that are hard to measure, like concentrations of stress, fatigue indicators, thermal exposure or expected deformation. This leads to a model that is able to associate an observable signal with a physically meaningful degradation state. This is especially helpful where there is limited real failure data, as simulation provides supplemental labelled failures, but the simulated data needs to be verified for consistency with the real production behaviour.

5 CRITICAL ANALYSIS AND SYNTHESIS

5.1 Areas of Agreement

There are three general conclusions that can be drawn from the overall picture of evidence. The first is that AI works best when it is not seen as a standalone predictor, but as a part of the engineering process. It has been shown that algorithm selection is not the only important factor for predictive maintenance and predictive quality review, data pipelines, sensors and operational context are just as crucial (Carvalho et al., 2019; Tercan and Meisen, 2022).

This same lesson is learned from implementation studies, where the usefulness of a diagnostic system is as much an issue of integration with PLCs, databases and notification channels, as it is of the inference engine (Mashava et al., 2026) and from the wider review, evaluating the value of integrated cyber-physical architectures over stand-alone models (Gao et al., 2024). Secondly, it is always mentioned that computational acceleration is a crucial advantage provided by surrogate modelling. AI offers fast inference in repeated evaluation, and FEM offers the costly high fidelity calculations in model development. Kohar et al. (2021) and other recent studies that integrate FEM with ML show the viability of this approach, and emerging research includes graph-based and physics-informed architectures (Pfaff et al., 2021; Black and Najafi, 2022). The take-home message is that simulation can get closer to the operational time-scales needed for smart manufacturing.

Thirdly, there is still the question of generalisation. Model accuracy can be high on training data but low on test data because of a change in geometry, material, load or process (Nash, Drummond and Biribilis, 2018). Concept drift and lack of real-world validation are additional issues mentioned in reviews of industrial predictive maintenance (Paolanti et al., 2018; Zonta et al., 2020). For FEM surrogates it is of special importance as manufacturing processes are frequently used in several products and parameter ranges.

5.2 Areas of Tension

The straightforward idea that one should always prefer physics-informed models over purely data-informed models (Karniadakis et al., 2021; Donnelly, Daneshkhah and Abolfathi, 2024; Kasilingam et al., 2024; Meng et al., 2025) is not necessarily true. They benefit from high-quality physics models, training data, formulation of a problem, and relative weighting of data vs physics loss terms, and comparative studies can yield a variety of results depending on the task. There are also challenges reported in the research of PINNs with strong nonlinearities and localised solution features (Cuomo et al., 2022; Wessels and P, 2026).

There is also some difference between computational performance and manufacturing readiness. A model which is fast and accurate in a controlled experiment may not perform well when deployed on a plant, if it doesn't include uncertainty estimates, connect with existing systems, have cybersecurity controls or procedures to handle abnormal operating conditions (Chowdhury, 2023). Even in the context of the developing economies, these barriers are compounded with

deficits in infrastructure and lack of trustworthiness in power supply and also lack of skilled workforce in simulation, quality and maintenance studies (Muhla et al., 2025a), which makes the deployment gap in the context of these economies may be greater in these studies.

5.3 Evidence from Manufacturing Applications

The application evidence points to a more immediate market that is not a standalone FEM–AI factory. Layered is a more realistic progression (Figure 4). The first layer is the layer of acceleration of simulation or prediction of quality variables using AI (Hashemi, Jang and Beheshti, 2023). At the second, a combination of predictions with sensor information and engineering rules. At the third, an action is recommended or a higher fidelity FEM analysis is triggered. Once these stages have been validated, closed-loop control should be considered. This is a staged view as per the investigated corpus where the individual parts of the architecture are more mature than the complete closed loop.

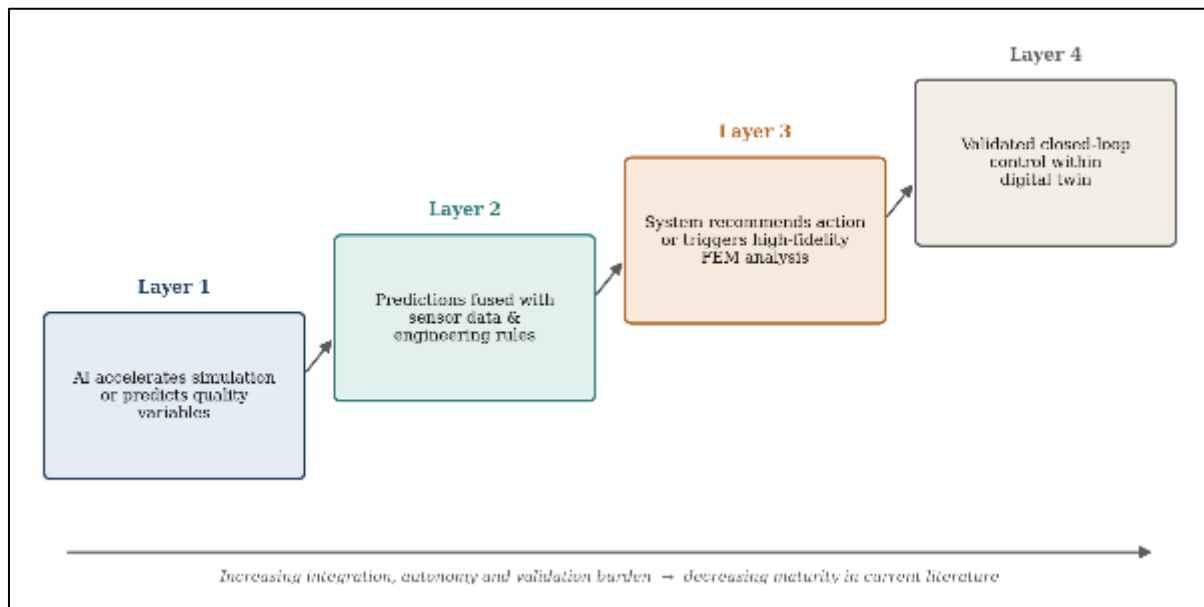


Figure 4: Layered pathway for deploying FEM–AI predictive risk systems in manufacturing.

Source: Authors' own construction based on the synthesis in Section 5.

An example of this is the quality of the predictions. Tercan and Meisen (2022) analyzed 81 publications and concluded that there was a wide range of application of process and sensor data to estimate product quality, but the application was not even distributed in manufacturing process groups, and few work has been proposed for monitoring multistage processes with minimal-sensing frameworks, which reduces the number of required instruments (Davari Ardakani and Lee, 2018). The opportunity is best exemplified by injection moulding. Experimental results have been obtained to illustrate the dominating factors of shrinkage and warpage, injection pressure and melt temperature (Mapindu et al., 2026a), and a physics-assisted classifier as proposed by Xiong (2024) may take advantage of both shrinkage and warpage. In a more general context, physical information derived from the FEM could be added to enhance the interpretability of the model in applications where the final quality measure is related to the stress, thermal history, deformation or residual effects.

6 RESEARCH GAPS AND FUTURE DIRECTIONS

6.1 Uncertainty quantification and safe escalation

Future systems need to be able to differentiate between a confident prediction and a prediction outside the model's domain. If an uncertainty threshold is hit, a high fidelity FEM run may be triggered, an additional sensor measurement or a human engineering review may be conducted (Figure 2) and the resulting high fidelity results can be used to supplement the training set using active learning.

6.2 Explainability and traceability

Decisions made in manufacturing with safety or quality implications must have more than a prediction value. Users must be aware of the variables that formed a prediction and whether or not that result is in line with known engineering

behaviour. Traceable reasoning is also crucial for the incorporation of AI-generated outputs into FMEA records, as well as for the human-factor aspects of workplace risk (Muhla et al., 2025).

6.3 Digital-twin integration

FEM, sensors, AI and operational history (Stavroulakis, Charalambidi and Koutsianitis, 2022) can be integrated into digital twins, to provide a natural environment for such integration. Nevertheless, continuous lifecycle integration (Mihai et al., 2022) is still underrepresented in the literature, and computational complexity, data complexity and lacking reference architectures are among the challenges identified in the digital-twin predictive maintenance reviews (Aivaliotis, Georgoulas and Chrysosolouris, 2019; Chen et al., 2023). The agent-based architectures that have already been coupled with sensing, rule inference, databases and notification (Mashava et al., 2026) could provide a very practical basis to which FEM surrogates can be attached.

6.4 Benchmarks and multi-fidelity datasets

There are no shared datasets and evaluation protocols between studies, making comparisons difficult. Benchmarks that combine coarse and fine FEM results with experimental measurements in the open form would enable the comparison of surrogate, physics-informed and purely data-driven models on equal footing. Experiments that are well-documented like the Taguchi studies reviewed here, in the study of minimizing injection molding defects (Mapindu et al., 2026a), optimizing cutting parameters in milling (Mapindu et al., 2026b), and optimizing welding parameters for weld strength (Mapindu et al., 2026d) could be one of those experiment tiers in a set of benchmarks.

6.5 Transferability to different products and SMEs

Most of the experimental literature is based on a specific geometry, material and/or research data set (Gao et al., 2024). The potential for transfer learning, modular models, and low-cost deployment methods that are suitable for manufacturers that are unable to maintain a large computing and data-science team would be interesting for future research. This is particularly important in developing economies, where the adoption of Industry 4.0 is limited by Infrastructure (Muhla et al., 2025a) and Skills (Muhla et al., 2023) and agility is reliant on the ability to reconfigure rapidly for new products. The use of low-cost embedded platforms, like the system developed for a smart wheelchair (Munotyaani et al., 2026), highlights that effective sensing and control can be achieved at a not too high cost.

6.6 Skills development and experimental testbeds

Engineers who can competently use those tools need to have a strong understanding of both numerical simulation and data science in order to be able to use the hybrid tools effectively. Learning factories provide realistic environments where these competencies can be developed, and FEM–AI digital twins can be tested prior to industrial deployment, and have been suggested as a pathway for skills development and innovation within Southern Africa's engineering education (Ndiyamba et al., 2026).

7 CONCLUSIONS

This review explored the role of FEM and AI-based predictive risk models in manufacturing. Together, FEM and AI can offer a more comprehensive understanding of structural, thermal and process behavior, and can greatly assist in making predictions, classifications and optimizations quickly. Four paths of integration were identified: AI as an FEM surrogate (Badarinath, Chierichetti and Davoudi Kakhki, 2021), AI-enhanced risk and FMEA analysis, hybrid FEM–AI optimisation, and predictive maintenance with features derived from the FEM.

Evidence for complete systems continuously integrating high fidelity simulation, live sensor data, uncertainty estimation and operational risk decisions (S.) is less mature. R and Riffat, 2025). What is not an easy technical hurdle, then, are the main limitations. These include validation and generalisation, data availability and interpretability, interoperability as well as model uncertainty management (Garg, Sharma and Zheng, 2025; Wendland, 2025) and in the context of developing industrial economies, these include infrastructure, skills, and cost (Muhla et al., 2025a).

The main takeaway message for manufacturing engineering is that FEM and AI are not mutually exclusive, but rather complementary tools. A more functional architecture involves distributing these roles across the three: FEM runs a physics-based reference, AI runs a rapid approximation and pattern recognition, and the production system runs a validation and escalation rules to control when prediction can be trusted (Shahin et al., 2025). The most important next step identified by this review is to advance this concept into the development of robust digital twins and real manufacturing environments, with the requisite skills development.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

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Disclosure of conflict of interest

There is no conflict of interest.

REFERENCES

- [1] Aghahadi, M. et al. (2025) 'Predicting faults in power distribution grids during heatwaves: A comparative study of machine learning models applied to Milan', *Sustainable Energy, Grids and Networks*.
- [2] Aivaliotis, P., Georgoulis, K. and Chryssolouris, G. (2019) 'The use of Digital Twin for predictive maintenance in manufacturing', *International Journal of Computer Integrated Manufacturing*, 32(11), pp. 1067–1080. Available at: <https://doi.org/10.1080/0951192X.2019.1686173>.
- [3] Aluvihara, S. (2025) 'The importance of artificial intelligence (AI) tools in the modern science, engineering and technological research and innovations: A review', *American Journal of Artificial Intelligence*.
- [4] Amiri-Hezaveh, W. (2026) 'A differentiable framework for gradient-enhanced damage with physics-augmented neural networks in JAX-FEM', *Mechanics Research Communications*.
- [5] Badarinath, P.V., Chierichetti, M. and Davoudi Kakhki, F. (2021) 'A machine learning approach as a surrogate for a finite element analysis: Status of research and application to one dimensional systems', *Sensors*, 21(5), 1654. Available at: <https://doi.org/10.3390/s21051654>.
- [6] Bilal, M. et al. (2026) 'Integrating first-principles modeling with explainable machine learning for non-isothermal chromatography', *ACS Omega*.
- [7] Black, N. and Najafi, A.R. (2022) 'Learning finite element convergence with the multi-fidelity graph neural network', *Computer Methods in Applied Mechanics and Engineering*, 397, 115120. Available at: <https://doi.org/10.1016/j.cma.2022.115120>.
- [8] Boddupally, H. (2020) 'Enterprise-scale data quality improvement using machine learning: Frameworks, validation strategies, and operational insights', *European Journal of Advances in Engineering and Technology*.
- [9] Carvalho, T.P., Soares, F.A.A.M.N., Vita, R., Francisco, R.d.P., Basto, J.P. and Alcalá, S.G.S. (2019) 'A systematic literature review of machine learning methods applied to predictive maintenance', *Computers & Industrial Engineering*, 137, 106024. Available at: <https://doi.org/10.1016/j.cie.2019.106024>.
- [10] Chen, C., Fu, H., Zheng, Y., Tao, F. and Liu, Y. (2023) 'The advance of digital twin for predictive maintenance: The role and function of machine learning', *Journal of Manufacturing Systems*, 71, pp. 581–594. Available at: <https://doi.org/10.1016/j.jmsy.2023.10.010>.
- [11] Chowdhury, A. (2023) 'Design, testing and troubleshooting of industrial equipment: A systematic review of integration techniques for US manufacturing plants', *Review of Applied Science and Technology*.
- [12] Cuomo, S., Di Cola, V.S., Giampaolo, F., Rozza, G., Raissi, M. and Piccialli, F. (2022) 'Scientific machine learning through physics-informed neural networks: Where we are and what's next', *Journal of Scientific Computing*, 92(3), 88. Available at: <https://doi.org/10.1007/s10915-022-01939-z>.
- [13] Davari Ardakani, H. and Lee, J. (2018) 'A minimal-sensing framework for monitoring multistage manufacturing processes using product quality measurements', *Machines*.
- [14] Donnelly, J., Daneshkhah, A. and Abolfathi, S. (2024) 'Physics-informed neural networks as surrogate models of hydrodynamic simulators', *Science of the Total Environment*, 912, 168814. Available at: <https://doi.org/10.1016/j.scitotenv.2023.168814>.
- [15] Gao, R.X., Krüger, J., Merklein, M., Möhring, H.-C. and Váncza, J. (2024) 'Artificial intelligence in manufacturing: State of the art, perspectives, and future directions', *CIRP Annals*, 73(2), pp. 723–749.
- [16] Garg, A., Sharma, A. and Zheng, W. (2025) 'A review on artificial intelligence-enabled mechanical analysis of 3D printed and FEM-modelled auxetic metamaterials', *Virtual and Physical Prototyping*.

- [17] Haghighat, E. and Juanes, R. (2021a) 'SciANN: A Keras/TensorFlow wrapper for scientific computations and physics-informed deep learning using artificial neural networks', *Computer Methods in Applied Mechanics and Engineering*, 373, 113552. Available at: <https://doi.org/10.1016/j.cma.2020.113552>.
- [18] Haghighat, E., Raissi, M., Moure, A., Gomez, H. and Juanes, R. (2021b) 'A physics-informed deep learning framework for inversion and surrogate modeling in solid mechanics', *Computer Methods in Applied Mechanics and Engineering*, 379, 113741. Available at: <https://doi.org/10.1016/j.cma.2021.113741>.
- [19] Hashemi, A., Jang, J. and Beheshti, J. (2023) 'A machine learning-based surrogate finite element model for estimating dynamic response of mechanical systems', *IEEE Access*, 11.
- [20] Henkes, A., Wessels, H. and Mahnken, R. (2022) 'Physics informed neural networks for continuum micromechanics', *Computer Methods in Applied Mechanics and Engineering*, 393, 114790. Available at: <https://doi.org/10.1016/j.cma.2022.114790>.
- [21] Jansen, K.C., Mapindu, I., Muhla, T.M., Kanyemba, G. and Mashava, D. (2025) 'Optimization of edible oil quality through vacuum bleaching: An experimental design and analysis study', *Open Access Research Journal of Science and Technology*, 13(2), pp. 68–78. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0051>.
- [22] Karniadakis, G.E., Kevrekidis, I.G., Lu, L., Perdikaris, P., Wang, S. and Yang, L. (2021) 'Physics-informed machine learning', *Nature Reviews Physics*, 3(6), pp. 422–440. Available at: <https://doi.org/10.1038/s42254-021-00314-5>.
- [23] Kasilingam, S., Yang, R., Singh, S.K., Farahani, M.A., Rai, R. and Wuest, T. (2024) 'Physics-based and data-driven hybrid modeling in manufacturing: A review', *Production & Manufacturing Research*, 12(1), 2305358. Available at: <https://doi.org/10.1080/21693277.2024.2305358>.
- [24] Kohar, C.P., Greve, L., Eller, T.K., Connolly, D.S. and Inal, K. (2021) 'A machine learning framework for accelerating the design process using CAE simulations: An application to finite element analysis in structural crashworthiness', *Computer Methods in Applied Mechanics and Engineering*, 385, 114008. Available at: <https://doi.org/10.1016/j.cma.2021.114008>.
- [25] Koutromanos, I. (2018) *Fundamentals of finite element analysis: Linear finite element analysis*. Hoboken, NJ: John Wiley & Sons.
- [26] Liu, H.-C., Liu, L. and Liu, N. (2013) 'Risk evaluation approaches in failure mode and effects analysis: A literature review', *Expert Systems with Applications*, 40(2), pp. 828–838. Available at: <https://doi.org/10.1016/j.eswa.2012.08.010>.
- [27] Liu, W.K., Li, S. and Park, H.S. (2022) 'Eighty years of the finite element method: Birth, evolution, and future', *Archives of Computational Methods in Engineering*, 29(6), pp. 4431–4453. Available at: <https://doi.org/10.1007/s11831-022-09740-9>.
- [28] Madhumitha, K. et al. (2026) 'A hybrid machine learning framework for image-based bearing fault diagnosis advancing SDG Goal 9: Sustainable industry and innovation', *Array*.
- [29] Mapindu, I., Foya, A., Muhla, T.M., Chinguwo, K.N. and Kanyemba, G. (2026a) 'Minimizing defects in injection molding using the Taguchi method', *World Journal of Advanced Engineering Technology and Sciences*, 20(2), pp. 240–252. Available at: <https://doi.org/10.30574/wjaets.2026.20.2.0419>.
- [30] Mapindu, I., Munhuwamambo, G., Mashava, D. and Ngwenya, L. (2026b) 'Optimization of cutting parameters in CNC milling using the Taguchi method', *Global Journal of Engineering and Technology Advances*, 28(2), pp. 149–162. Available at: <https://doi.org/10.30574/gjeta.2026.28.2.0223>.
- [31] Mapindu, I., Muhla, T.M., Chinguwo, K.N. and Foya, A. (2026c) 'Process parameter optimization for 3D printing using the Taguchi method', *Open Access Research Journal of Science and Technology*, 18(1), pp. 34–45. Available at: <https://doi.org/10.53022/oarjst.2026.18.1.0082>.
- [32] Mapindu, I., Mashava D., Shangwa, V., Chigavazira-Gwara, T.T., Munhuwamambo, G (2026d) 'Taguchi-based optimization of GMAW welding parameters for joint strength', *World Journal of Advanced Engineering Technology and Sciences*, 20(3), pp. 206–219. Available at: <https://doi.org/10.30574/wjaets.2026.20.3.0448>
- [33] Mashava, D., Muhla, T.M., Munhuwamambo, G., Mapindu, I., Chinguwo, K.N. and Wachenuka, T. (2026) 'A multi-agent system framework for real-time self-diagnostic condition monitoring of induction furnace equipment in developing industrial economies', *Open Access Research Journal of Science and Technology*, 17(2), pp. 28–43. Available at: <https://doi.org/10.53022/oarjst.2026.17.2.0071>.
- [34] Meng, C., Seo, S., Cao, D., Griesemer, S. and Liu, Y. (2025) 'When physics meets machine learning: A survey of physics-informed machine learning', *Machine Learning for Computational Science and Engineering*.

- [35] Mihai, S., Yaqoob, M., Hung, D.V., Davis, W., Towakel, P., Raza, M. et al. (2022) 'Digital twins: A survey on enabling technologies, challenges, trends and future prospects', *IEEE Communications Surveys & Tutorials*, 24(4), pp. 2255–2291.
- [36] Muhla, T., Mapindu, I., Munyau, M., Mashava, D., Mhlanga, S. and Goriwondo, W. (2023) 'Agility as a strategy in Zimbabwean manufacturing industries', *Zimbabwe Journal of Science and Technology*, 18(1), pp. 1–11. Available at: <https://www.ajol.info/index.php/zjst/article/view/271920> (Accessed: 24 September 2026).
- [37] Muhla, T.M., Mashava, D., Kanyemba, G., Mapindu, I. and Goriwondo, W.M. (2025a) 'An assessment of the implementation of Industry 4.0 in Zimbabwean manufacturing industries', *World Journal of Advanced Engineering Technology and Sciences*, 15(2), pp. 970–984. Available at: <https://doi.org/10.30574/wjaets.2025.15.2.0653>.
- [38] Muhla, T., Kanyemba, G., Mapindu, I., Chinguwo, N., Mashava, D. and Goriwondo, W. (2025b) 'Enhancing safety in Zimbabwean manufacturing industry: The role of human factors engineering in reducing workplace accidents', *Open Access Research Journal of Science and Technology*, 13(2), pp. 19–30. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0037>.
- [39] Munotyaani, S., Bawono, N.M.H., Tayisepi, N., Mapindu, I., Anggoro, P.W., Bawono, B., Pamosoaji, A.K. and Adi, A.Y.N.M.P. (2026) 'Design and development of a dual-mode smart wheelchair prototype with obstacle detection for Zimbabwe', *Jurnal Rekayasa Mesin*, 21(1), pp. 51–66. Available at: <https://doi.org/10.32497/jrm.v21i1.6954>.
- [40] Muyambo, R.D., Muhla, T., Kanyemba, G., Mashava, D., Munhuwamambo, G. and Mapindu, I. (2025) 'Design and development of a vertical axis wind turbine for slip stream energy harvesting', *Global Journal of Engineering and Technology Advances*, 23(3), pp. 10–20. Available at: <https://doi.org/10.30574/gjeta.2025.23.3.0166>.
- [41] Nash, W., Drummond, T. and Birbilis, N. (2018) 'A review of deep learning in the study of materials degradation', *npj Materials Degradation*, 2, 37. Available at: <https://doi.org/10.1038/s41529-018-0058-x>.
- [42] Ndiyamba, D., Murena, E., Kasukusa, S., Mafuratidze, F., Nenzhelele, T., Mpofu, K. and Mapindu, I. (2026) 'Learning factories as a catalyst for innovation in Southern African engineering education', in *CLF 2026 Book of Short Papers on Learning Factories: Proceedings of the 16th Conference on Learning Factories*, Bolzano, Italy, 5–7 May 2026. Bolzano: Free University of Bozen-Bolzano, pp. 93–95. Available at: <https://doi.org/10.5281/zenodo.20780648>.
- [43] Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D. et al. (2021) 'The PRISMA 2020 statement: An updated guideline for reporting systematic reviews', *BMJ*, 372, n71. Available at: <https://doi.org/10.1136/bmj.n71>.
- [44] Paolanti, M., Romeo, L., Felicetti, A., Mancini, A., Frontoni, E. and Loncarski, J. (2018) 'Machine learning approach for predictive maintenance in Industry 4.0', in *2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA)*. Oulu: IEEE, pp. 1–6. Available at: <https://doi.org/10.1109/MESA.2018.8449150>.
- [45] Pestano-Gupta, F. (2025) 'Artificial intelligence (AI) tools in the modern science: Technological research and innovations: A review', *American Journal of Artificial Intelligence*.
- [46] Pfaff, T., Fortunato, M., Sanchez-Gonzalez, A. and Battaglia, P.W. (2021) 'Learning mesh-based simulation with graph networks', in *International Conference on Learning Representations (ICLR 2021)*.
- [47] Quan et al. (2026) 'An explicit physical-state neural network method for constitutive modeling', *Computer-Aided Civil and Infrastructure Engineering*.
- [48] S.R, S. and Riffat, J. (2025) 'Intelligent structural health monitoring of jack-up platform legs using high-density sensor networks, real-time digital twins, and machine learning-based damage detection', *Future Cities and Environment*.
- [49] Santana, P. et al. (2026) 'Uncertainty in composite damage modeling and finite element model updating: A survey', *Archives of Computational Methods in Engineering*.
- [50] Senda, S., Muhla, T.M., Mapindu, I., Ngwenya, L., Mushangure, R.O. and Mashava, D. (2026) 'Machine learning enabled preventive maintenance strategy for improving boiler reliability of a thermal power station', *Open Access Research Journal of Science and Technology*, 17(2), pp. 18–27. Available at: <https://doi.org/10.53022/oarjst.2026.17.2.0070>.
- [51] Shahin, M. et al. (2025) 'Generative artificial intelligence in manufacturing: Applications, case studies, and future directions for next-generation intelligent production systems', *The International Journal of Advanced Manufacturing Technology*.

- [52] Shang, C. and You, F. (2019) 'Data analytics and machine learning for smart process manufacturing: Recent advances and perspectives in the big data era', *Engineering*, 5(6), pp. 1010–1016. Available at: <https://doi.org/10.1016/j.eng.2019.01.019>.
- [53] Soori, M., Arezoo, B. and Dastres, R. (2023) 'Digital twin for smart manufacturing, A review', *Sustainable Manufacturing and Service Economics*, 2, 100017. Available at: <https://doi.org/10.1016/j.smse.2023.100017>.
- [54] Stavroulakis, G.E., Charalambidi, B.G. and Koutsianitis, P. (2022) 'Review of computational mechanics, optimization, and machine learning tools for digital twins applied to infrastructures', *Applied Sciences*, 12(23).
- [55] Tandi, O., Mapindu, I., Muhla, T.M., Chinguwo, N.K. and Tayisepi, N. (2025) 'Design and analysis of a passive upper limb exoskeleton for augmented construction worker strength', *Open Access Research Journal of Science and Technology*, 13(2), pp. 79–88. Available at: <https://doi.org/10.53022/oarjst.2025.13.2.0050>.
- [56] Tayisepi, N., Svosve, R., Tigere, G., Mnkandla, A.N. and Mapindu, I. (2023) 'Comparative optimisation of the cutting parameters for surface quality and energy efficiency during the machining manufacturing of teak, saligna and pine wood materials', *Journal of Engineering Research and Reports*, 25(11), pp. 73–87. Available at: <https://doi.org/10.9734/JERR/2023/v25i1111023>.
- [57] Tayisepi, N., Mugwagwa, L., Mnkandla, A.N., Mapindu, I. and Muhla, T.M. (2024) 'Experimental investigation and simultaneous optimisation of honing parameters of dry cast iron cylinder relining sleeves of motor vehicle engine blocks for surface finish and energy use', *Computational Engineering and Physical Modeling*, 7(4), pp. 88–103. Available at: <https://doi.org/10.22115/cepm.2024.473138.1324>.
- [58] Tercan, H. and Meisen, T. (2022) 'Machine learning and deep learning based predictive quality in manufacturing: A systematic review', *Journal of Intelligent Manufacturing*, 33(7), pp. 1879–1905. Available at: <https://doi.org/10.1007/s10845-022-01963-8>.
- [59] Tiwari, S. (2023) 'Smart warehouse: A bibliometric analysis and future research direction', *Sustainable Manufacturing and Service Economics*, 2.
- [60] van Dinter, R., Tekinerdogan, B. and Catal, C. (2022) 'Predictive maintenance using digital twins: A systematic literature review', *Information and Software Technology*, 151, 107008. Available at: <https://doi.org/10.1016/j.infsof.2022.107008>.
- [61] Wendland, M. (2025) 'Exploring the potentials and limitations of AI-based CAD design for mechanical engineering', *Education and New Developments*.
- [62] Wessels and P, M. (2026) 'Physics-informed neural networks (PINNs) as intelligent computing technique for solving partial differential equations: Limitation and future prospects', *SCIENCE CHINA Physics, Mechanics & Astronomy*.
- [63] Xiong (2024) 'Data-driven and physics-assisted machine learning approach for warpage classification and process parameter optimization', *Transactions on Computational Social Systems*.
- [64] Xirouchakis (2016) 'Finite element method based machining simulation environment for analyzing part errors induced during milling of thin-walled components', *International Journal of Machine Tools and Manufacture*.
- [65] Yoo, S., Lee, S., Kim, S., Hwang, K.H., Park, J.H. and Kang, N. (2021) 'Integrating deep learning into CAD/CAE system: Generative design and evaluation of 3D conceptual wheel', *Structural and Multidisciplinary Optimization*, 64(4), pp. 2725–2747. Available at: <https://doi.org/10.1007/s00158-021-02953-9>.
- [66] Younus, H. et al. (2026) 'AI- and ontology-based enhancements to FMEA for advanced systems engineering: Current developments and future directions', *Applied Sciences*.
- [67] Zienkiewicz, O.C., Taylor, R.L. and Zhu, J.Z. (2013) *The finite element method: Its basis and fundamentals*. 7th edn. Oxford: Butterworth-Heinemann.
- [68] Zonta, T., da Costa, C.A., Righi, R.d.R., de Lima, M.J., da Trindade, E.S. and Li, G.P. (2020) 'Predictive maintenance in the Industry 4.0: A systematic literature review', *Computers & Industrial Engineering*, 150, 106889. Available at: <https://doi.org/10.1016/j.cie.2020.106889>.