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Research Article

AI-Augmented DFMEA Framework for Predictive Failure Prevention in Heavy-Duty Automotive Lift Systems Using Simulation-Driven Design Validation

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Abstract:

Heavy-duty automotive lift systems are subject to coupled structural, hydraulic, tribological, control, and human–machine interaction constraints where failure prevention requires more than just a conventional design review approach based on a checklist. The review explores the potential for enhancing design failure mode and effects analysis (DFMEA) using artificial intelligence, prognostics, digital-twin concepts and simulation-based validation for predictive failure prevention (PFP) of vehicle lifting devices. The review compares the state-of-the-art research literature regarding FMEA enhancement, machine prognostics, assessment of fatigue and welded joints, hydraulic-system modelling, surrogate-based simulation, Bayesian calibration, and digital engineering. The findings suggest that traditional DFMEA is relevant to organizing the causal thinking process, but ordinal risk prioritization does not adequately represent safety-critical risk for lift systems where rare structural or hydraulic failures may account for a disproportionate share of the overall safety risk. When combined with validated finite-element, multibody and hydraulic simulations, the remaining useful life (RUL) and occurrence estimates can be enhanced using AI-based anomaly detection and model updating. However, few public datasets are available, model transferability between lift architectures remains weak, and uncertainty propagation from model assumptions to DFMEA rankings is not yet well formalized. A technically defensible framework must thus have a clear line of sight between failure modes, simulation observables, sensor signals, risk controls and validation evidence. Future research should focus on benchmark datasets, physics-informed prognostics, uncertainty-aware DFMEA scoring and standardization of validation protocols for lifting applications with safety implications.

1. Introduction

The load paths, hydraulic functions, synchronization controls, locking mechanisms, anchorage conditions, wear surfaces, and operator-dependent use conditions interact over repeated lifting cycles of a heavy-duty automotive lift system, making these systems safety-critical electromechanical assets. As opposed to many automotive systems that are validated predominantly as a component of mobile platforms, the ability of the workshop lift system to withstand high static and cyclic loads and provide positional stability and fail-safe holding capability during inspection, repair and maintenance operations is a key requirement. The engineering challenge is not only to achieve strength to meet rated capacity, but also to ensure that the welded and bolted structure is fatigue resistant, hydraulic seals and hoses are not degraded, pins and sliding guides are not worn, synchronization drift does not occur, the locks can be engaged reliably, and incipient problems can be identified before they create a risk of uncontrolled descent, vehicle tilting, or structural failure.

Failure Mode and Effects Analysis (FMEA) has been applied to safety-critical engineering systems for many years to structure failure causes, prioritize risks, and record design controls and corrective actions for potential failures [1, 2]. However, traditional DFMEA relies heavily on expert input, ordinal scoring and review at the end of the process. These well-documented limitations of conventional risk-priority-number ranking include different severity–occurrence–detection combinations yield the same number, ordinal scales are frequently used as interval scales, and uncertainty in the expert rating is rarely passed on to the prioritization [3]. When occurrence evidence is limited and detection capability is unknown, some of these weaknesses can have a significant impact on heavy-duty lift systems, as a low-frequency, high-consequence failure, such as a weld crack propagation, a cylinder leakage under load, anchor pull-out, chain elongation, or lock-pawl non-engagement, can be underestimated.

The paradigm in research has now undergone a change towards predictive failure prevention by prognostics and health management, machine learning, digital twins and simulation-based engineering. In machinery prognostics, monitoring has evolved from signal-feature tracking to remaining useful life (RUL) estimation and decision support based on vibration, acoustic, current, pressure, temperature, and operational-load signals [4]. Digital-twin research has also highlighted the two-way communication between the physical asset and the numerical model, allowing updates to the model, tracking of anomalies, and evaluation of scenarios for the design and operation of the asset [5,6]. In the case of heavy duty lifts, these improvements mean that DFMEA must not be considered a static document. Rather, it can be an evidence-managed risk model that can be refined based on finite element fatigue analysis, hydraulic simulation, durability testing, and field-sensor data, and explainable learning models.

The technical basis for this integration is multidisciplinary. Fatigue crack initiation, stress concentration, welded-joint detail, residual stress and load-spectrum uncertainty are factors that need to be considered in structural risk assessment [7]. When performing a hydraulic risk assessment, the fluid compressibility, leakage, valve dynamics, friction, seal wear, and actuator instability must all be taken into account [8]. However, AI-based condition monitoring requires further criteria, such as representative training data, robustness against distribution shift, physical interpretability, and validation against degradation mechanisms rather than reliance solely on isolated classification accuracy [9]. Only if model assumptions, mesh sensitivity, boundary conditions, material scatter, load histories and calibration data can be traced back to the DFMEA failure mode being assessed is simulation-driven design validation valuable.

The challenge is therefore not only computational but also methodological. There are mature tools available in the literature for improving FMEA, fatigue simulation, prognostics, surrogate modelling, Bayesian calibration, and digital twins, but these tools are seldom integrated into a lift-specific DFMEA framework that connects safety-critical design failure modes to predictive indicators and/or validation evidence. This review aims to assess the evidence required to support the use of an AI-augmented DFMEA framework for heavy-duty automotive lift systems, determine which integrations are most technically defensible and outline the research objectives for predictive failure prevention through simulation-driven design validation.

2. Literature Review

Current FMEA research has focused primarily on the mathematical limitations of ordinal risk ranking rather than on the engineering problem of tracing risk estimates to physical evidence. The relationships among failure mode, effect, cause, control and corrective action are structured in classical DFMEA, but the severity, occurrence and detection ratings are often combined into one product, leading to unstable rankings when ordinal scales are used as numerical variables [1,2]. Liu et al. conducted a review of the risk-evaluation approaches in FMEA and demonstrated that fuzzy logic, grey theory, evidential reasoning and multi-criteria decision making techniques were used primarily to address uncertainty, the weighting and disagreement among experts in the field [3]. Expert judgement cannot be avoided in the early design phase, and these methods are applicable to lift systems, but the resulting fuzzy or multicriteria DFMEA score may still be physically misleading. If the occurrence estimate associated with a weld crack, seal leak, or lock failure does not relate to load spectrum, material scatter, degradation (wear) mechanism, or inspection capability, the fuzzy or multicriteria DFMEA score is still low.

One major alternative to hard-coded RPN ranking is found in fuzzy-FMEA studies. Bowles and Peláez were the first to apply fuzzy logic to prioritize failure modes when the linguistic assessment was more realistic than numerical scores [10]. Pillay and Wang applied approximate reasoning to marine-system FMEA and showed that fuzzy inference is useful for prioritizing risks in the presence of expert uncertainty [11]. In a critique of the conventional RPN approach, Franceschini and Galetto argued that multiplication of ordinal values can mask the sense of risk equivalence and weighting [12]. Braglia's multi-attribute failure mode analysis, and later the fuzzy weighted geometric mean, added more flexibility in the weighting of the risk dimensions [13,14]. To better represent expert disagreement, Chin et al. used a new approach called group-based FMEA, which is based on evidential reasoning [15]. These studies provide support for AI-augmented DFMEA for uncertainty-aware prioritization over the use of simple RPN multiplication. Their principal limitation is that they are predominantly decision-analytic, with few studies focusing on physics-based validation or sensor-based updating.

The missing operational evidence layer is provided by the prognostics and health management literature. Jardine et al. reviewed condition based maintenance and highlighted the importance of the quality of degradation features, historical data, and failure labels for diagnostics, prognostics, and maintenance decision-making [16]. Sikorska et al. compared the options of prognostic modelling and pointed out the difference between physics-based, data-driven and knowledge-based remaining-life approaches [17]. Lee et al. related the design of PHM to intelligent maintenance systems and demonstrated that the design of monitoring architectures should depend on the failure mechanisms and operation context of the system, rather than on general data collection [18]. Later, Lei et al. identified the complete machinery prognostics pipeline starting from the data acquisition to the construction of health indicators and the modelling of RUL [4]. Zhao et al. summarized the research on deep learning for machine health monitoring, highlighting the advantage of better feature learning but also the need for a large amount of data, high-quality labels, and consistency of the machine domain [9]. In PHM, Fink et al. pointed out limitations of deep learning, such as transferability, uncertainty quantification and validation in rare failure regimes [19]. In the case of lift systems, these findings suggest that AI should be deployed alongside DFMEA only when there is a link between the degradation observables and the failure mode, such as pressure-hold decay for hydraulic leakage, strain-range accumulation for welded-frame fatigue, motor-current asymmetry for synchronization resistance and displacement mismatch for column imbalance.

Simulation-driven validation is necessary because full-scale lift-system failures are infrequent, costly to reproduce, and potentially hazardous, costly to reproduce, and potentially hazardous. The digital-twin and simulation literature offers ways to tie computational models to operational data. Tao et al. summarized the digital-twin applications in industry and focused on geometry, physics, behaviour and rule models associated with physical entities [5]. Tuegel et al. [6] presented the concept of digital-twin structural life prediction as an example of a safety-critical application in which the load history and damage evolution are required to update a life estimate. Schleich et al. related digital twins to design and production engineering, emphasising that digital twins should not be limited to just geometry in order to support the decision-making process [20]. Wagg et al. reviewed the application of digital twins in engineering dynamics and emphasized the importance of uncertainty-aware model updating, stress hot spots identified through finite element analysis [21]. This is directly transferable to heavy-duty lifts at the methodological level: DFMEA occurrence ranking can be based on the stress hot spots generated by Finite Element Analysis, probabilistic fatigue damage, hydraulic circuit response, and updated degradation states, and not just on expert judgement.

Structural durability evidence is key because automotive lifts experience high repeated loads and eccentric loading of welded, bolted, pinned, and sliding parts. Local stress concentration, crack-like defects, surface condition, residual stress, and loading sequence influence fatigue life [7]. Fatemi and Yang [22] summarized the results of cumulative fatigue damage and demonstrated that linear damage rules are still prevalent but may be incorrect in the case of variable amplitude loading. According to Schijve [23], fatigue performance is governed not only by nominal stress but also by local geometry, manufacturing quality, and load spectra. Radaj, Sonsino and Fricke developed local-approach solutions for welded-joint fatigue, such as notch stress solutions for lift arms, runways, crossbeams and column welds [24]. Sonsino proved the importance of selecting the S–N curve in the field of high-cycle fatigue for various materials, joint details, and component designs [25]. Murakami's defect-based fatigue model also explains why small inclusions, weld imperfections and surface defects can dominate fatigue strength [26]. From these works, it can be concluded that the severity of a DFMEA may be high for a structural fracture, but occurrence needs to be estimated based on stress-range distributions, weld detail class, fabrication quality, and the inspection interval.

The second major failure domain is tribology and hydraulic degradation. The Archard wear relation remains a fundamental basis for relating wear volume to normal load, sliding distance, and material hardness [27]. Holmberg and Erdemir clearly showed the significance of friction and wear in mechanical energy losses and degradation of components at a system level [28]. Seal integrity, valve response, cylinder friction, and fluid behaviour are also crucial to hydraulic lift systems. Nikas examined reciprocating hydraulic seals and demonstrated that the sealing performance depends on contact pressure, film formation, surface finish, thermal effects, and material behaviour [29].

Merritt's hydraulic-control theory and Watton's fluid-power modelling provide a dynamic relationship between flow, pressure, compressibility, valve characteristics and actuator motion [8,30]. Edge pointed out control problems in fluid-power systems such as nonlinearities and dynamic response [31]. For the synchronization and motion-control validation, Jelali and Kroll presented modelling, identification, and control methods for hydraulic servo-systems that are relevant to synchronization and motion-control validation [32]. However, for DFMEA, these studies provide a basis for a failure-mode mapping, where the failure of a seal, internal leakage, valve sticking, cavitation, hose degradation, and actuator friction are considered as measurable failure modes instead of generic hydraulic failures.

Surrogate modelling and uncertainty quantification are enabling methods for practical simulation-driven DFMEA. Exhaustive exploration of load cases, tolerances, material scatter and misuse scenarios is too costly using high fidelity finite element and hydraulic simulations. Simpson et al. analysed metamodels for engineering problems and suggested the experimental design and validation of response surfaces and kriging be done with care [33]. The method of surrogate-based analysis and optimization was reviewed by Queipo et al., where they demonstrated that approximate models would help explore engineering designs when it is too costly to simulate the process directly [34]. Forrester, Sóbester and Keane developed surrogate modelling for design optimization, including sampling and validation, and expected-improvement strategies [35]. The influential parameters of the nonlinear simulation models can be ranked using global sensitivity indices by Sobol and Saltelli's global sensitivity analysis methods [36,37]. The Bayesian calibration framework of Kennedy and O'Hagan is especially relevant because it explicitly represents parameter uncertainty, observation error, and model discrepancy [38]. These techniques can help measure the extent to which these design variables contribute to stress hot spots, pressure spikes, synchronization error or lock engagement margin during simulation, and provide evidence for risk-control.

As summarized in Table 1, no single research stream provides all of the capabilities required for an integrated framework. Structured risk reasoning is provided by enhanced FMEA; predictive evidence is provided by PHM; Mechanism fidelity is provided by fatigue and hydraulic modelling, whereas computational tractability and uncertainty management are supported by surrogate modelling and calibration. The main unanswered question remains about the failure mode level integration. To maintain the traceability of DFMEA, a lift-system framework should incorporate evidence-based estimates of occurrence and detection derived from simulation, testing and field monitoring in place of static occurrence and detection scores.

3. Methodology

The review has focused on the peer-reviewed journal papers and academic books related to four interconnected domains: risk prioritization of DFMEA, degradation mechanisms of structural–hydraulic lifting systems, simulation-based engineering validation, and prognostics of machinery. The search terms were optimized for various bibliographic databases that are frequently used by engineering researchers such as Scopus, Web of Science, ScienceDirect, IEEE Xplore, Springerlink, Wiley Online Library, Taylor & Francis, and ASME journal collections. Representative terms were "design FMEA", "failure mode effects analysis", "fuzzy FMEA", "evidential reasoning FMEA", "risk priority number limitations", "machinery prognostics", "remaining useful life", "digital twin structural health", "simulation driven design", "finite element fatigue", "welded joint fatigue", "hydraulic seal leakage", "fluid power control", "surrogate modelling", "Bayesian calibration", and "global sensitivity analysis". Since there are relatively few peer-reviewed datasets that are specific to lifts, the review focused on methods that can be applied to heavy-duty automotive lift systems as well as studies that were not specifically identified as automotive lifts but were applicable.

The literature time frame included the basic works which are still methodologically central and PHM studies used time-series sensor data. Only if they provided an analytical basis that is still in use today were older sources kept. These include fuzzy FMEA, wear modelling, fatigue theory, hydraulic-control modelling, and Bayesian calibration. Recent sources were selected for AI-based prognostics, deep-learning-based health monitoring and digital twins due to the rapid evolution in these fields. Non-peer-reviewed reports, industry handbooks, standards, websites, preprints and generic trade materials were not cited. Theoretical foundations in reliability, fatigue, hydraulic systems, surrogate modelling or statistical reliability analysis, provided by academic books, were used.

There was a wide variation in the methodological approaches found in the literature reviewed. The FMEA studies reviewed were mostly based on expert elicitation [3], linguistic ratings [10–12], fuzzy membership functions [13–14], evidential reasoning [15], multicriteria weighting [11–13], and ranking comparisons [13–17]. These studies typically used ordinal expert ratings and preferences rather than physical degradation measures. They had used time-series sensor data, engineered health indicators, statistical degradation models, neural networks, support vector methods, ensemble learning, and hybrid physics–data models [4,9,16-19] in PHM studies. Validation commonly relied on run-to-failure datasets, case-specific industrial datasets, cross-validation procedures, or prognostic-horizon metrics. Stress-life, strain-life, fracture mechanics, notch stress, local fatigue approaches and defect-based assessment [7,22-26] were used for structural durability studies. Analytical modelling, experimental seal tests, wear laws, fluid-dynamic equations, system identification and nonlinear control models were employed for hydraulic and tribological studies [8,27-32]. Design of experiments, response surfaces, kriging, Gaussian processes, sensitivity indices, Monte Carlo and Bayesian calibration [33–38] were used in surrogate and uncertainty studies.

In this topic, the evidence was analysed by connecting the failure modes. A study was deemed to be extremely relevant if the methods used would directly impact a DFMEA field: failure cause, occurrence evidence, detection control, prevention control, validation method, or residual risk. For instance, the occurrence evidence for weld fracture was only considered to be fatigue simulation when it was possible to represent load spectra, local stress concentration, material scatter, and weld quality. AI-driven anomaly detection was considered detection evidence only when measurable signals were causally related to a failure mode. Surrogate models were deemed useful when predictions remained grounded in physical constraints and there was a reduction in the cost of the simulations.

Only data extracted manually from the reviewed literature, or transparently calculated from the classification of that literature, were used for quantitative interpretation in the Results and Discussion. This means that the figures are based on review-corpus counts and categorical method mappings, and are clearly labelled by their illustrative framework scores, rather than verified field-failure statistics. This decision was made due to the lack of publicly available and peer-reviewed datasets that are specific to heavy-duty automotive lift failures. Therefore, this review does not attempt to establish empirical failure rates for lift systems. Rather, it considers the feasibility of a scientifically defensible DFMEA structure that can be combined from available scientific techniques and determines where there is an empirical validation gap for lift systems.

4. Discussion

The reviewed evidence confirms a staged AI-augmented DFMEA architecture that not only provides a list of failure modes but also establishes a connection with the observables through the simulation, sensors and uncertainty models, and controls for validation. This traceability structure is shown in Table 2. The key distinction is between automating risk ranking and augmenting DFMEA with physical risk evidence. The limitations of the traditional RPN table could not be addressed by automating the table using ML. In contrast, augmentation of DFMEA is based upon physically relevant data, such as stress-range histograms, weld hot-spot factors, hydraulic pressure decay, cylinder drift, motor-current imbalance, lock engagement displacement, chain elongation, thermal rise, leakage rate, and vibration features. The validity of this interpretation is supported by FMEA studies, which have led to the questioning of the correctness of aggregation of simple RPNs [3,10–15] as well as PHM studies, which have led to the arguments for failure-mechanism alignment when predicting failure data [4,16–19].

The first key finding is that the lift-system DFMEA requires the separation of severity assessment from occurrence uncertainty. The severity associated with catastrophic structural collapse, uncontrolled descent, or vehicle instability is inherently high, and cannot be mitigated by improved prediction. The engineering community will find most value in the ways that AI and simulation help them to try to avoid the events from happening or to make them more visible before they pose a risk. Many AI-FMEA proposals do not differentiate between the two. In the case of heavy duty lifts, severity should be held firmly to the physical consequences, and occurrence to validated fatigue, wear, leakage or control-instability models. Detection should be associated with signals and diagnostic coverage that can be measured. Table 3 shows the mapping of model classes and their functions to these DFMEA functions.

Simulations are most useful in cases of structural failure modes. Finite element models can be used to identify areas of stress concentration at arm pivots, column base welds, runway crossbeams, carriage plates, locking rack joints, and scissor link joints. These stress margins alone are insufficient as a basis for predictive failure prevention. The literature on fatigue has shown that the small defects, local notch geometry, residual stress, weld imperfections and variable amplitude loading can play an important role in influencing life prediction [22-26]. So, the occurrence of fatigue in an AI-augmented DFMEA should be considered a statistical probability function of these factors: load spectrum, local stress range, weld detail, manufacturing variability, corrosion state and inspection interval. Surrogate models [33-35] can be used to approximate high fidelity stress or fatigue outputs over thousands of loading cycles and design combinations. Sensitivity indices can indicate which parameters most strongly influence the predicted risk metrics and therefore merit priority in design-control studies [36,37]. This is more informative than a score given based on the expert judgement only.

The second big result is that there is an interplay needed between coupled dynamic and tribological evidence for hydraulic failure modes. Relevant hydraulic failure modes include external or internal leakage, seal wear, valve sticking, pressure transients, hose degradation, cavitation, thermal sensitivity, and actuator drift. The nonlinear flow-pressure relations, compressibility, friction, leakage and dynamics of the valves have been demonstrated to influence the motion of the actuators in the hydraulic-control literature [8,30–32]. In the literature, the effects of the contact mechanics, lubrication film, surface finish, temperature and material behaviour on the reciprocating seal behaviour are also noted [29]. These mechanisms indicate that pressure and position measurements should be interpreted with the support of a validated hydraulic model. If a low threshold for pressure decay is used, then normal load-dependent pressure decay may be mistaken for slow leakage. Using a simple pressure threshold can result in a pressure decay being interpreted as a slow leak caused by temperature changes. Results obtained from the hydraulic simulation should then be used to constrain AI models trained from data of pressure, displacement, temperature and motor-current or to calibrate with results of controlled leakage and drift tests.

The third major finding concerns the choice of AI models. In machinery health monitoring, deep learning has come up with greater advancement in representation learning, but there is still limited practical evidence for heavy-duty automotive lift systems compared with rotating machinery, bearings, and gears, and benchmark datasets remain scarce [9,19]. Lift systems have shorter operating cycles, strong load dependency, fewer documented failure examples, and limited public run-to-failure data. In these cases, data driven classifiers may not be as defensible as classifiers that rely on physics-based features, probabilistic inference and conservative uncertainty bounds. Random forests and gradient-boosting models can be used in cases where tabular evidence exists, because these models can learn the nonlinear interactions and mixed features in tabular data; Recurrent neural networks can be used in cases where a large number of labelled time series exist for the pressure–position case to learn time series patterns[39 – 40]. One possible way to incorporate governing equations into learning is provided by physics-informed neural networks, which still have some validation requirements that need to be met [41]. The implication is that the complexity of the model should be supported by the failure mode observability and available information of failure degradation and not by algorithmic novelty alone.

The fourth finding is that digital twins do not replace DFMEA; rather, they can provide validation and evidence-management infrastructure. The literature on digital twins emphasizes the importance of combining the physical resources with the computational models, the operational data and decision models [5,6,20,21]. In the lift system, the responsibility of the twin can be specified in the DFMEA. Each high-risk failure mode should have a digital-twin requirement, which consists of a simulation model, an observable signal, a calibration parameter, an alert logic, and a design-control action. For example, during overload and eccentric-load tests, a hot-spot in a weld in a carriage plate might have to be strain-gauged; during a representative duty cycle, a hot-spot might have to be subjected to fatigue-damage accumulation tests; and a hot-spot may have to be inspected at specified intervals with varying rules for inspection. A hydraulic cylinder drift mode can be a test for pressure-hold, a test for displacement decay, an estimation of leakage parameters, or a test for diagnostic separation of valve- and seal-related faults. The flow of evidence from design intent to predictive DFMEA updating is shown in Figure 1.

The imbalance among evidence domains was examined through a qualitative classification of the reviewed corpus. To illustrate this, Figure 2 is included, indicating that all of these FMEA enhancement, PHM, simulation/digital twin, structural fatigue, hydraulic/tribological modelling and surrogate/uncertainty methods are represented across different domains but rarely integrated within a lift-specific DFMEA framework. This distribution does not represent the breadth of literature but instead is reflective of the characteristics of the evidence base upon which this review has been built. Current methods are technically well-developed; however, they are poorly developed as a system for performing DFMEA on a lift system. Table 1 also indicates that previous research is well equipped to deal with uncertainty handling, monitoring and modelling, but most of the previous works do not consider traceability from DFMEA controls to simulated failure mechanism.

The fifth finding is that uncertainty propagation is the weakest link in terms of implementation. These uncertainties result from the tolerances of the geometry, the properties of the materials, the quality of the welds, the boundary conditions, the load spectra, friction coefficients, leakage parameters, or sensor noise in the simulation models. The AI model introduces uncertainty in the form of bias in the training set, class imbalance, and rare events/distribution shift. If there is ample validation data, separating out parameter uncertainty with observation noise and model discrepancy can be performed using Bayesian calibration [38]. Various statistical reliability methods and accelerated testing can be used to aid in estimation of life distributions, censoring, confidence bounds and degradation trajectories [42,43]. The Monte Carlo reliability analysis can be performed using a structural model or a hydraulic model to estimate ranges of failure probability [44]. These methods are not often included in a traditional DFMEA and are necessary when the ranking of rare, high consequence failures is a design decision.

The following is an example of the risk-evidence heat map for six lift-system failure domains (Figure 3). The scores are not field failure rates; they represent qualitative assessments of mechanism-model maturity, simulation observability, sensor observability, AI suitability, and validation feasibility. Structural fatigue is given a high score for modelling and simulation of the mechanisms, and a moderately high score for continuous sensing, except if strain or acoustic sensing are added to the mix. Hydraulic leakage has a high sensor observability rating as the pressure and displacement decay can be measured while the separation between seal wear and thermal effects and valve leakage is still a challenge. There is high safety relevance, and targeted validation, because the routine sensor data cannot be expected to show the local engagement margin and/or the substrate degradation due to engagement failure and/or anchorage failure. This is the reason why, as a pattern, we require evidence that is specific to that failure mode instead of just one universal AI layer.

The proposed framework also changes the planning of the design validation. Conventional validation generally determines whether a design satisfies predefined acceptance tests. The simulation, diagnostic models, and evidence-updating procedures used within the AI-augmented DFMEA framework require validation. Load cases should therefore be chosen to be both severe and sensitive to parameters which are uncertain. The control tests to be performed are leakage tests, temperature variation tests, load asymmetry tests, valve response tests and valve drift condition tests. Examples of structural testing are strain mapping at finite element hot spots, eccentric loading of the vehicle, repeated cycling, or the review of the weld details. The control-system tests should include synchronization disturbances, sensor faults, emergency stop conditions and lock engagement timing. These needs are then translated to a research and a validation matrix in Table 4.

The sixth finding is that explainability must be treated as a design traceability to the extent that it is an engineering traceability rather than a post-factum visualization. A model is useful for DFMEA only if its outputs can be traced to a plausible failure cause, a detectable state, and an associated preventive or corrective action. For example, if a hazard occurs an anomaly score should identify precursor behaviour or abnormal operating states associated with hydraulic leakage, mechanical binding, synchronization drift, or load imbalance. When performance is equivalent, Rudin proposed that interpretable models are better, as compared to opaque ones, in high stakes decisions [45]. Restricting the features to quantities that are physically meaningful, adding monotonic constraints when appropriate, providing uncertainty intervals, and connecting the alerts to validated failure mode evidence are all ways to achieve interpretability in lift-system DFMEA. Another application of black-box models is feature learning, but the models must be well validated before they can be used for design risk ranking.

A final issue concerns the distinction between prevention and detection. The majority of the literature on predictive maintenance is based on detecting degradation during the system operation. DFMEA is design-oriented, however. One of the biggest benefits AI could provide before field deployment is handling the analysis of the outcome of simulation, durability testing, and past service logs to identify design variables that lead to low detection coverage or high occurrence sensitivity. It is used to help with prevention, ranking a set of design alternatives, checking load cases, showing simulation sensitivities and even creating combinations of tolerances that increase risk. The classification of the method contribution by DFMEA function is shown in Figure 4 based on review-corpus. Fatigue simulation, hydraulic modelling, surrogate optimization and sensitivity analysis are particularly suitable techniques that can be used for prevention. PHM, sensor analytics and updating with digital twins are the most effective ways of detection. Uncertainty-aware FMEA and Bayesian evidence updating are the best approaches for risk prioritizing. The three functions need to be integrated into a full range of activities.

5. Future Directions

Future work should be done to generate evidence for a specific lift instead of generic AI-FMEA automation. The highest priority is an open, peer-reviewed benchmark set of data for heavy duty automotive lift systems. The synchronized pressure data, displacement data, motor-current, strain, temperature, vibration, lock-position and load-condition signals under normal operation and controlled fault insertion should be included in such a dataset. Fault classes that are relevant should contain hydraulic leakage, seal degradation, valve sticking, chain/cable elongation, synchronization drift, structural looseness, weld-crack proxies, mechanical binding and lock-engagement faults. Otherwise, model comparisons will continue to rely on unrelated machinery benchmarks whose findings may not transfer reliably to slow-cycle, high-load lifting equipment.

Physics-informed prognostics is the second priority. It is revealed in the current literature on PHM that only data-driven models are prone to failure in the case of low frequency of failure labels and varying operating conditions [4,9,17,19]. This challenging regime is a good match for lift systems. Future models should be developed that include hydraulic governing equations, finite-element derived stress indicators, friction and wear relations, and fatigue-damage constraints. While physics-informed neural networks and hybrid Bayesian models are promising, calibration quality and uncertainty bounds must be considered alongside failure-mode separability in judging the models' worth, rather than nominal prediction accuracy [38,41]. Potential contributors to apparent synchronization drift including hydraulic leakage, asymmetric loading, sensor bias, mechanical binding, and thermally induced pressure changes should be modelled and distinguished explicitly.

The third priority is the uncertainty-aware DFMEA scoring. Distributions, confidence intervals or evidence grades should supplant or supplement conventional severity–occurrence–detection scoring. Where possible, use simulation ensembles, accelerated testing and field monitoring to derive occurrence estimates, and also, reliability models [42–44]. Detection estimates should give a quantitative value for diagnostic coverage, false alarm probability, missed alarm probability, and time margin between detection and hazardous state. Bayesian updating can offer a formal method for updating DFMEA ratings as test and field evidence is observed [38]. This would make DFMEA a controlled evidence model and not be a static design review.

The fourth priority is related to the development of a validation protocol. The reliable finite element, hydraulic, multibody, and control models are the foundation of simulation-driven DFMEA. For validation, one should consider mesh convergence, material and weld detail uncertainty, boundary condition justification, representativeness of the load spectrum, calibration against sensor measurements and cross-validation against independent physical tests. The sampling design, error metrics, extrapolation limits and sensitivity stability of surrogate models should be reported [33-37]. Digital-twin implementations should document: the management of model discrepancy; how the risk estimates of the design change as the operational data are updated; the linkage of the alert to the design controls [5,6,20,21].

Human- machine integration is the fifth priority. Vehicle placement, pad contact, overload, asymmetric loading, maintenance quality and inspection practices have an impact on lift-system safety. Operational misuse scenarios should thus be added to the DFMEA, alongside component degradation, for AI-augmented DFMEA. Further research is needed on the effect of sensor feedback, lock-state indication, load-asymmetry alerts and maintenance decision support on real-world failure prevention. This research should not include applying too many conclusions from rotating machinery or mobile vehicles to workshop lifts.

Last but not least, research should explain the nature of evidence that is acceptable for certification. In safety-critical lifting tasks, opaque prediction models may face substantial barriers to acceptance unless they provide traceable evidence and conservative uncertainty handling. Interpretable models, physics-based features and auditable validation records are therefore key design requirements. The most robust future framework will bring together DFMEA, simulation, testing, field monitoring, and AI in one evidence-management process, instead of as a series of engineering tools.

Table 1. *Literature comparison of peer-reviewed studies relevant to AI-augmented DFMEA and simulation-driven validation*

Ref.	Study focus	Model used	Key findings	Limitations or research gap	Relevance to lift-system DFMEA
[3]	FMEA risk-	Review of fuzzy,	Conventional	Limited	Supports

	evaluation review	grey, evidential, and multicriteria FMEA	RPN limitations are recurrent; uncertainty methods improve ranking logic	mechanism-specific validation	replacing static RPN with evidence-conditioned risk evaluation
[10]	Fuzzy FMEA	Fuzzy logic for linguistic severity, occurrence, detection	Improved handling of imprecise expert judgement	Does not link scores to physical degradation	Useful for early DFMEA uncertainty
[11]	Approximate-reasoning FMEA	Fuzzy inference applied to marine systems	Demonstrated flexible risk prioritization under uncertainty	Domain transfer requires mechanism mapping	Applicable to sparse lift failure knowledge
[12]	RPN critique	Mathematical analysis of risk-priority evaluation	Showed ranking ambiguity in conventional RPN	Does not provide physical validation workflow	Justifies avoiding simple multiplicative scoring
[13]	Multi-attribute FMEA	Multicriteria failure-mode ranking	Allows weighted comparison across risk attributes	Expert weights remain subjective	Supports risk weighting for safety-critical lift modes
[14]	Fuzzy weighted geometric FMEA	Fuzzy weighted geometric mean	Improved prioritization consistency compared with simple RPN	Still dependent on expert input	Can rank lift failure modes under uncertainty
[15]	Group-based FMEA	Evidential reasoning with multiple experts	Represents disagreement and incomplete evidence	Limited integration with test or simulation data	Useful for design reviews involving structural, hydraulic, and controls experts
[4]	Machinery prognostics	Review of data acquisition, health indicators, RUL models	PHM requires high-quality degradation features and validation	Lift-specific data not addressed	Guides predictive detection layer
[9]	Deep learning for health monitoring	CNN, RNN, autoencoder, deep architectures	Deep models can learn features from signals	Data volume, domain shift, interpretability issues	Warns against unvalidated black-box lift diagnostics
[19]	Deep learning in PHM	Review of opportunities and barriers	Transferability and uncertainty remain major challenges	Rare-failure validation remains difficult	Supports hybrid and uncertainty-aware AI
[5]	Digital twins in industry	Review of digital twin models and applications	Digital twins require physical–virtual data linkage	Implementation maturity varies by domain	Provides architecture for updating DFMEA evidence
[6]	Structural digital twin	Structural life prediction with load history	Demonstrated model-updating concept for life prediction	Aerospace focus, not lift systems	Transferable to lift structural fatigue monitoring
[21]	Digital twins for engineering dynamics	Review of modelling, updating, and uncertainty	Emphasized uncertainty and decision integration	Validation remains application-specific	Supports dynamic DFMEA evidence management
[34]	Surrogate-based design	Surrogate modelling and optimization	Enables expensive simulation exploration	Surrogate error must be controlled	Useful for exploring lift load cases and tolerances

Table 2. *Failure-mode traceability matrix for AI-augmented DFMEA in heavy-duty automotive lift systems*

Failure domain	Representative failure mode	Simulation observable	Sensor or test observable	AI/analytics role	DFMEA field strengthened	Principal validation risk
Structural frame	Weld crack at arm, carriage, runway, or column joint	Hot-spot stress, stress range, fatigue damage	Strain, acoustic emission, crack inspection, load-cycle count	Fatigue-damage updating, anomaly detection	Occurrence, prevention control	Load-spectrum and weld-quality uncertainty
Pinned/sliding joints	Pin wear, bushing clearance, guide wear	Contact pressure, sliding distance, local deformation	Clearance, vibration, displacement hysteresis	Wear-state classification, drift trend detection	Occurrence, detection	Wear mechanisms may be mixed
Hydraulic actuation	Seal wear, internal leakage, cylinder drift	Pressure decay, leakage coefficient, actuator displacement	Pressure, position, temperature, drift rate	Leakage estimation, fault separation	Occurrence, detection	Thermal and load effects confound leakage
Synchronization/control	Column speed mismatch, sensor bias, valve lag	Motion error, control response, flow imbalance	Position mismatch, motor current, valve command	Time-series anomaly detection	Detection, corrective action	Fault labels may be sparse
Load support/locking	Lock-pawl non-engagement, rack wear	Engagement margin, contact stress, impact load	Lock-position sensor, displacement after stop	Engagement-state verification	Detection, prevention control	Local contact not easily inferred remotely
Anchorage/interface	Anchor loosening, floor-interface degradation	Base reaction, uplift, bolt stress	Torque checks, strain, displacement, inspection	Risk flagging from load and installation variables	Prevention control	Installation variability outside design model

Table 3. *Model classes and their DFMEA contribution*

Model class	Main inputs	Outputs	Best-suited DFMEA function	Strength	Limitation
Finite-element fatigue model	Geometry, material, weld detail, load spectrum	Stress range, hot spots, fatigue damage	Occurrence and prevention	Mechanism-specific structural evidence	Sensitive to boundary conditions and weld assumptions
Hydraulic dynamic model	Flow, pressure, valve data, leakage, friction	Pressure response, drift, stability	Occurrence and detection	Captures coupled actuator behaviour	Parameter identification can be difficult
Multibody model	Link geometry, mass, joints, load placement	Kinematics, load transfer, synchronization demand	Prevention	Captures eccentric and transient loading	Requires accurate joint and friction parameters
Surrogate model	Simulation design points, parameters	Fast approximation of high-fidelity outputs	Prevention and prioritization	Enables large design exploration	Extrapolation can be unsafe

Bayesian calibration	Test data, simulation output, prior distributions	Updated parameters and uncertainty	Occurrence and validation confidence	Separates parameter uncertainty and discrepancy	Requires adequate validation data
Machine-learning classifier	Sensor features, labelled states	Fault class, anomaly score	Detection	Detects multivariate patterns	Domain shift and rare labels reduce reliability
RUL model	Health indicators, cycle history, degradation labels	Remaining life estimate	Detection and maintenance planning	Supports predictive intervention	Requires degradation trajectories
Sensitivity analysis	Parameter distributions, model outputs	Importance ranking	Prevention	Identifies dominant design variables	Requires representative input ranges

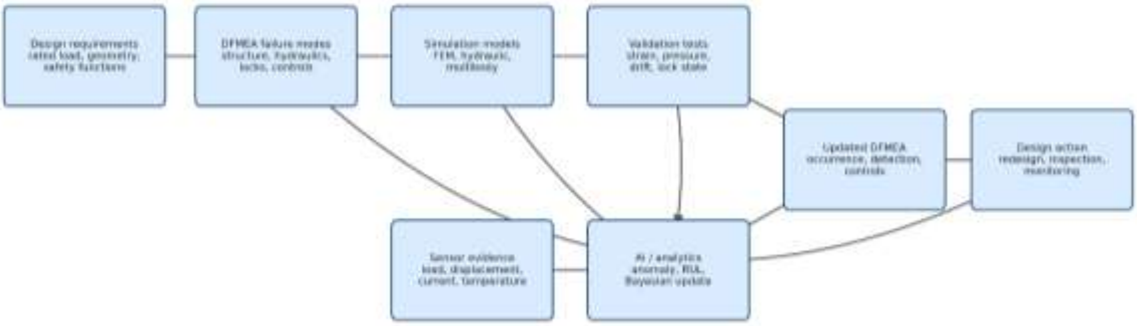

Figure 1. *Proposed evidence flow for AI-augmented DFMEA*

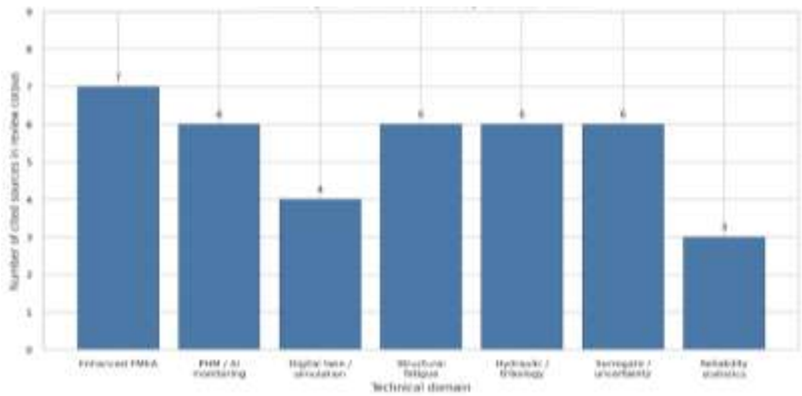

Figure 2. *Distribution of reviewed peer-reviewed sources by technical domain*

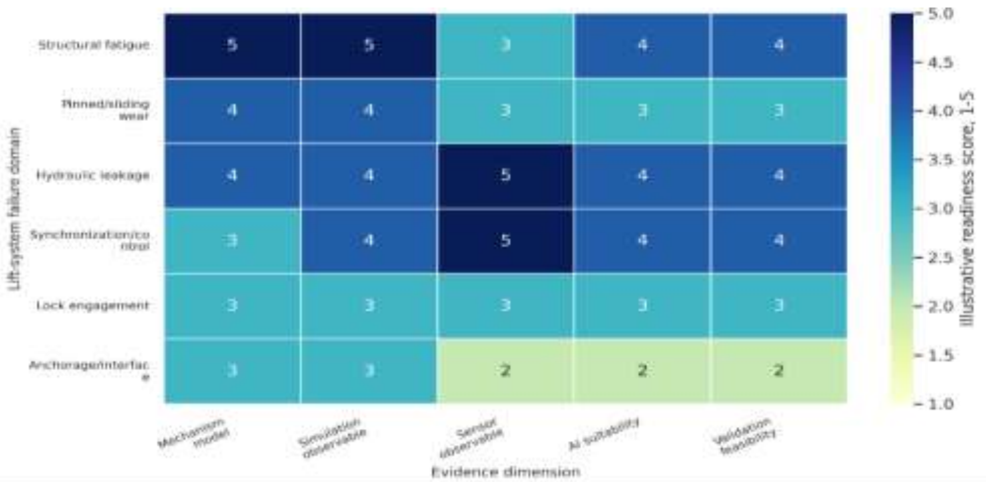

Figure 3. *Failure-domain readiness heatmap for AI-augmented lift-system DFMEA*

***Table 4**. Research gap and validation matrix for future AI-augmented DFMEA*

Gap	Technical consequence	Required research pathway	Suitable evidence type	Priority
Lack of public lift-system degradation datasets	AI models cannot be benchmarked reliably	Instrumented lift testbeds with controlled faults	Time-series pressure, strain, current, displacement, lock-state data	High
Weak integration between DFMEA and simulation	Risk scores remain subjective	Failure-mode-to-observable traceability models	Linked DFMEA tables, FEM, hydraulic simulation, validation records	High
Limited uncertainty propagation	Risk rankings may be overconfident	Bayesian and Monte Carlo DFMEA updating	Parameter distributions, calibration data, confidence intervals	High
Sparse rare-failure labels	Black-box classifiers may overfit normal data	Hybrid physics-informed anomaly detection	Controlled degradation tests and mechanism-based features	High
Poor validation of surrogate models	Design exploration may misrank risk	Error-bounded surrogate modelling	Holdout simulations, sensitivity stability, extrapolation checks	Medium
Limited lock and anchorage monitoring	Local safety-critical states may be missed	Sensorized lock and base-interface validation	Engagement displacement, contact strain, anchor response	High
Human misuse not integrated	Risk controls may ignore real operating variability	Operational scenario modelling	Load-placement, overload, pad-contact, operator-action data	Medium

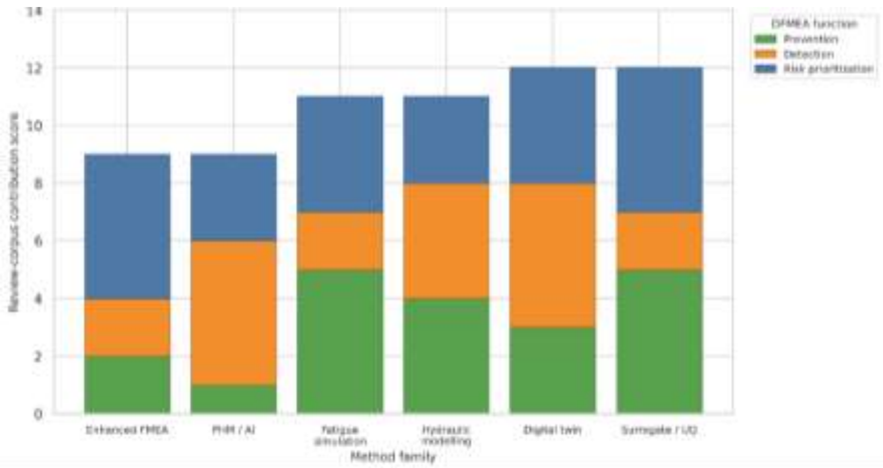

***Figure 4**. Contribution of method families to DFMEA functions*

6. Conclusions

If used as an evidence-based engineering process, AI-augmented DFMEA can provide a technically defensible route toward predictive failure prevention for heavy-duty automotive lift systems, instead of being treated as a risk-scoring algorithm. Conventional DFMEA remains valuable because it captures causal failure structure, design accountability, and traceability to control actions. It has the disadvantage that it relies on ordinal expert ratings which are not sufficient to capture uncertainty, rare high-consequence events, or dynamics of degradation.

The reviewed literature indicates that simulation validation can be used to complement the DFMEA in that it can be used to correlate the various failure modes (structural, hydraulic, tribological and control) with measurable physical quantities. Finite-element fatigue analysis, hydraulic system modelling, surrogate simulation, sensitivity analysis, Bayesian calibration, and prognostics provide more support for the occurrence and detection of the events than does static judgement. AI techniques are most useful for analysing physically meaningful features, using models calibrated against test data, and using constraints based on the knowledge of the mechanisms. They should be utilized to enhance early detection, to give updated risk assessments, to detect design vulnerabilities and to help in planning validation.

The primary unaddressed constraint is the absence of validated and peer-reviewed datasets and protocols for use with specific lifts. If an AI model is developed from unrelated machinery systems, it cannot be assumed to be relevant to slow-cycle, high-load lifting systems. Going forward, the addition of instrumented testing, simulation uncertainty, field monitoring and models that are interpretable into the DFMEA process will be important to future progress.

Therefore, each high-risk lift-system failure mode should be represented as a traceable evidence object linked to a mechanism, simulation output, sensor signal, validation test, uncertainty model, and corrective action. The change would move DFMEA from a paper documentation process to a design assurance process, thereby supporting improved safety and reliability in heavy-duty lift systems.

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