



AI-Augmented FMEA with Anticipatory Failure Reasoning

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Abstract: This paper proposes a hybrid methodology for proactive failure analysis that integrates classical FMEA with Anticipatory Failure Determination (AFD) and Artificial Intelligence (AI)-based reasoning. The framework introduces a four-layer architecture comprising structured failure capture, hypothetical failure expansion, AI-supported simulation and reasoning, and iterative design adaptation. Applied to a last-mile autonomous delivery robot, the model successfully identified novel failure modes, validated their impact using causal graphs and reinforcement learning, and generated targeted design improvements. Quantitative validation shows increased RPN accuracy and a reduced rate of undetected failures compared to classical FMEA, supporting the framework's contribution to resilient, evolution-ready design.

Key words: FMEA, anticipatory failure, causal reasoning, AI-enhanced risk analysis, TRIZ, simulation, robotics, design resilience

1. INTRODUCTION

The transition to Industry 5.0 represents more than an incremental shift in production philosophy, it introduces a systemic demand for adaptability, resilience, and intelligent interaction across the full lifecycle of autonomous systems [1]. In this emerging paradigm, product design is no longer a static activity; it must evolve in real-time, respond to environmental volatility, and anticipate failure scenarios shaped not only by mechanical stress, but by behavioral, infrastructural, and societal dynamics [2].

Design under uncertainty has been a foundational concern in both engineering and cognitive science. Simon's theory of bounded rationality and the structure of ill-posed problems [3], alongside Rumelhart and McClelland's work on parallel distributed processing [4], anticipated the challenges now confronted in real-world autonomous deployment. Modern autonomous systems, such as last-mile delivery robots, must operate safely in shared human spaces, comply with shifting regulations, and remain operational despite degradation, social interaction failures, and infrastructure inconsistencies [5]. These

environments are not fully specifiable in advance, and so require systems that can reason, adapt, and evolve during use.

To manage operational risk, engineers have long relied on Failure Mode and Effects Analysis (FMEA), a structured method for identifying potential failure points and ranking them based on severity, occurrence, and detectability [6]. The classic Risk Priority Number (RPN) formula remains the most widely adopted metric for risk management in the early design stage. Although effective for systems with known failure histories, traditional FMEA is limited in its ability to support emerging or adaptive systems [7]. Risk prioritization depends on expert judgment and prior knowledge, making the method poorly suited for novel platforms that face dynamic user interactions and unpredictable use cases.

Extensions such as fuzzy FMEA have addressed some of these issues by introducing linguistic and probabilistic representation through membership functions [8]. While this adds useful nuance, fuzzy logic models still operate on structurally static assumptions. They do not support reasoning about failure modes that have never been encountered or imagined during earlier design stages.

To close this gap, Anticipatory Failure Determination (AFD), derived from the TRIZ methodology, has been proposed as a way to generate hypothetical failure modes not derived from past observation but from logical inference [9]. AFD techniques such as contradiction analysis and functional negation challenge the designer to consider what might go wrong, even in systems that have never failed before [10].

Yet AFD in its classical form lacks procedural formality and remains difficult to scale without computational support. Here, Artificial Intelligence offers a critical pathway. AI methods based on causal modeling [11], abductive reasoning [12], and reinforcement learning [13] can enable systems to both simulate and learn from unobserved scenarios. These methods have already proven effective in predictive maintenance and fault detection and now show strong potential in design iteration under incomplete knowledge [14].

Simulation environments, particularly digital twins, provide the sandbox in which these models can be tested, trained, and refined. Realistic digital twins, coupled with agent-based simulations, enable the system to undergo stress testing without physical damage, learning behavioral responses that reduce the impact of failure or avoid it altogether [15]. These approaches benefit from architectural modularity, as described by Kruchten's 4+1 View Model [16], and from communication models drawn from concurrency theory [17], which guide system-level message passing and fault containment.

The influence of social and human factors on robotic failure is also becoming more evident. Research in human-robot interaction (HRI) reveals that failure is not always technical, it can result from misinterpretation, lack of legibility, or inappropriate signaling [18]. Understanding how users respond to a robot's presence, its behaviors, or its visual and auditory cues is critical to preventing safety incidents in public settings. As Winograd and Flores have shown in the context of human-computer interaction, cognition and misunderstanding often go hand in hand when system expectations are violated [19].

Beyond individual systems, the need for intelligent coordination across multiple

interacting agents, whether human or robotic, requires principles from distributed cognition and societal self-organization [20]. As robotic platforms increase in autonomy, they must also grow in their ability to predict not only physical failure, but interaction breakdowns, regulatory edge cases, and long-term structural drift.

In response to these challenges, this paper proposes a hybrid FMEA–AFD–AI framework that merges structured failure logic with anticipatory reasoning and computational modeling, seeks to move beyond detection and classification, toward foresight and intelligent adaptation. Its goal is not to eliminate failure, but to convert it into a strategic asset, one that guides robust design evolution and supports system resilience over time. The framework is evaluated through a practical case study involving an urban last-mile delivery robot. This platform, already equipped with modular architecture and AI navigation, serves as the testbed for integrating logical, semantic, and simulation-driven risk exploration. The analysis focuses on previously unobserved failure scenarios, ranging from social misunderstanding to sensory contradiction, and traces how these insights shape intelligent design adaptation.

Four central questions guide the research: How can AI assist in identifying both known and hypothetical failure modes beyond the traditional FMEA scope? How can anticipatory logic be formalized and integrated into FMEA workflows? Which reasoning models, such as causal graphs, abductive inference, or simulation agents, are most effective for modeling dynamic failure propagation? And finally, how can these models support intelligent redesign without requiring complete system overhauls?

Through this fusion of foresight, logic, and computation, the proposed framework contributes to the broader transformation of reliability engineering, one where failure is not feared, but anticipated, reasoned with, and ultimately absorbed into the creative logic of system design.

2. RELATED WORK

2.1 Classical Risk Analysis and Its Limitations

In reliability engineering, FMEA, or Failure Mode and Effects Analysis, stands out as a method to systematically identify potential failure points in complex systems, as well as to provide assistance in minimizing them. It was first developed in the defense and automotive industries, utilizing a simple scoring system known as the Risk Priority Number (RPN). This number is calculated by multiplying the severity of a failure's effect (SSS) as seen in formula (1), its expected frequency of occurrence (OOO), and the likelihood that it would be detected before causing harm (DDD):

$$\text{RPN} = S \times O \times D. \quad (1)$$

Despite its operational simplicity, this scoring method is far from flawless. In practice, it often leads to ambiguity, as different failure scenarios can produce identical RPN values even when their real-world implications differ significantly. Because the scoring is based primarily on expert judgment, it introduces a degree of subjectivity that can undermine the consistency of the method, especially in interdisciplinary design teams or in the early stages of design where empirical data are scarce [1]. To address this uncertainty, researchers have begun to explore the integration of fuzzy logic into the FMEA process. As a result, uncertainty is addressed by introducing membership functions for the parameters to be scored, thus correcting for the inherent uncertainty in the evaluation process. The resulting formulation, often referred to as fuzzy RPN, allows for more refined interpretation of risk. The formula is thus reformulated as:

$$\text{RPN_fuzzy} = \mu(S) \times \mu(O) \times \mu(D). \quad (2)$$

In this equation, $\mu(x)$ denotes the fuzzy membership function assigned to each parameter, thus providing a more graded and adaptable scoring system [2]. While this approach mitigates some of the rigidity of classical FMEA, it remains static, offering limited support for dynamic, evolving systems where failures may emerge under novel conditions or interactions.

As systems become more interconnected and operate in less predictable environments, the reactive nature of traditional FMEA begins to reveal its limitations. Anticipatory Failure Determination (AFD) was introduced as a conceptual counterweight to this retrospective approach. Rooted in the principles of TRIZ, AFD emphasizes a shift from asking what has failed to what could fail, even if it has never occurred before.

Rather than relying on historical data, AFD employs a forward-looking reasoning process. It examines the system under stress, explores extreme or contradictory conditions, and constructs failure scenarios through logical inversion. This includes techniques such as identifying conflicting design requirements, imagining misfunctions rather than absences of function, and combining environmental or operational stressors to reveal latent vulnerabilities. For instance, a component that must be both lightweight and impact-resistant may fail under rare combinations of thermal and mechanical fatigue, even if standard testing procedures never reveal such a flaw [3]. Although AFD opens a new dimension in reliability analysis, its integration into computational workflows remains limited. Much of its power lies in abstract reasoning, which is difficult to formalize algorithmically. Recent research has proposed merging AFD logic with semantic modeling and AI-based inference systems, but the practical application of this combination is still emerging.

$$\text{Score}(f_i, f_j) = \frac{|\text{common_ancestors}(f_i, f_j)|}{|\text{ancestors}(f_i) \cup \text{ancestors}(f_j)|}. \quad (3)$$

This form of analysis offers a way to infer potential correlations even when specific failures have not been previously observed [7]. However, the majority of AI-based approaches remain bound to known data and pre-defined contexts. They struggle with failure scenarios that lie beyond the training distribution or those emerging from new systemic interactions. The integration of AI with abstract failure reasoning, such as AFD, remains rare and represents a significant frontier in the development of proactive design systems. Classical FMEA

captures structured experience and logical rigor, but falters in the face of novel uncertainty. AFD introduces imaginative failure reasoning but lacks formalization and automation.

2.2 AI and Simulation for Reliability Engineering

Robotic platforms, particularly those intended for operation in public or semi-structured environments, have traditionally focused on real-time safety features. Navigation algorithms emphasize obstacle avoidance, compliance with path planning under uncertainty, and the use of sensor fusion to maintain positional accuracy. In parallel, safety standards have guided the integration of fail-safe systems, redundant power management, and constrained interaction protocols.

Research in human-robot interaction has also matured, particularly in contexts involving crowd navigation, social presence, and passive signaling. Robots designed for urban environments are now expected to behave in socially acceptable ways, adjusting speed, gaze, and audio-visual cues based on human proximity and behavior [8].

Yet, the majority of these approaches assume that failures are isolated and known. Few frameworks account for emergent behaviors, cumulative damage, or evolving environmental stressors that were not anticipated at design time. Scenarios such as aggressive interaction, infrastructure failure, or regulatory shifts are often left unmodeled in conventional robotic safety pipelines. This highlights a need for resilience-by-design, where failure anticipation and mitigation are integral to the development process.

AI offers data-driven insight yet struggles with generalization and context-aware prediction.

In the specific context of urban robotics and autonomous systems, this gap is especially visible. Robots interact with dynamic physical environments and unpredictable human behavior. They must comply with evolving regulations, tolerate infrastructure inconsistencies, and remain operational under rare but potentially catastrophic stressors.

This paper proposes a unified framework that addresses this intersection. By embedding AFD logic within the FMEA structure and enriching

both with AI-powered reasoning, the method aims to deliver a dynamic, explainable, and evolution-capable failure management tool. The next section presents the structure and process of this hybrid FMEA–AFD–AI methodology.

3. METHODOLOGY: FMEA–AFD–AI FRAMEWORK

3.1. Overview of the Framework

The methodology proposed in this paper combines the structured logic of classical FMEA, the imaginative reasoning of Anticipatory Failure Determination, and the inferential and generative capabilities of Artificial Intelligence. The result is a unified framework designed to enhance the failure anticipation capacity of complex systems, particularly those that operate in volatile or uncertain environments.

At its core, the framework is composed of four interconnected layers. The first layer is the FMEA core, which captures known failure modes and supports structured prioritization based on severity, occurrence, and detection criteria. This is followed by the AFD extension, which enriches the FMEA table with logically plausible but previously unobserved failure scenarios. These hypothetical entries challenge the assumption that risk must be derived from precedent. The third layer incorporates AI inference tools, causal reasoning, abductive logic, and reinforcement learning, used to evaluate and validate both known and anticipated failures. Finally, a design feedback layer interprets insights generated by the other modules to recommend targeted improvements to system robustness, behavior, or structure.

The interaction between these layers enables an iterative, learning-oriented approach to resilience engineering. As new data become available, whether from operational experience or simulation feedback, the system refines its internal models and updates prioritization and mitigation logic accordingly. The overall methodological workflow is outlined in Fig. 1.

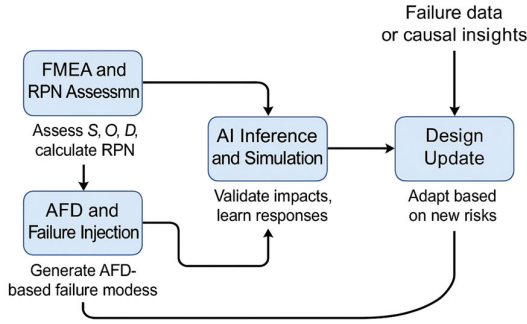


Fig.1. Workflow diagram of the FMEA–AFD–AI cycle, including failure injection, AI inference, and feedback-driven design updates

3.2. FMEA Core Layer: Structured Failure Representation

The starting point for the proposed framework remains the classical Design FMEA structure. The system is decomposed into functional units and subsystems, each of which is evaluated for potential failure modes. For each mode, the standard information is documented: the effect of the failure on system behavior, the most probable causes, the detection mechanisms in place, and the numerical severity, occurrence, and detection scores assigned through expert judgment.

The associated Risk Priority Number is computed using the traditional equation (1). This equation serves as a first-order prioritization tool, highlighting high-risk failure modes that demand immediate attention. However, the core FMEA layer remains limited to known failure mechanisms, those already documented through experience or testing. It cannot reason about emerging threats or to evaluate system behavior in response to hypothetical interactions.

In this framework, the FMEA table is not a static endpoint but a dynamic interface. It is the initial structure into which both anticipated and inferred failures will later be injected, updated, and reweighted.

3.3. AFD Extension Layer: Hypothetical Failure Generation

To expand the failure space beyond what is already known, the framework incorporates the logic of Anticipatory Failure Determination. Rather than waiting for a failure to be observed, this layer explores how a function might fail under stress, contradiction, or misuse. It asks not

“what has gone wrong before?” but “what could logically go wrong, even if it never has?”

This reasoning process is driven by several mechanisms. Contradiction analysis examines the coexistence of opposing functional requirements, for example, the need for a component to be both lightweight and impact-resistant. Function negation reverses normal operational logic, testing how systems might behave if a function is misdirected rather than lost. Combined stressor scenarios introduce environmental or usage-based anomalies, such as interactions between power loss and sensor occlusion in harsh weather.

The result is a set of failure modes that are not found in manuals or field reports, but instead derived from structural analysis, inverse logic, and design vulnerability. These AFD-derived scenarios are then formatted in the same FMEA structure and inserted into the working failure matrix, along with estimated severity, occurrence, and detection values.

Although the estimation of these parameters is initially qualitative, subsequent simulation and AI inference allow for refinement. The AFD layer effectively broadens the design team’s imagination, enabling a proactive stance in identifying and evaluating non-obvious risks.

3.4. AI Inference Layer: Causal and Generative Reasoning

The third layer adds computational intelligence to the framework, transforming what might otherwise remain speculative into measurable risk knowledge. This layer consists of three tightly integrated reasoning subsystems: causal graph modeling, abductive inference, and simulation-based reinforcement learning.

In the causal modeling component, a knowledge graph is constructed to link system functions, contextual variables, and failure outcomes. Using Bayesian Networks or Structural Causal Models, the framework computes the probability of failure propagation through interdependent subsystems. For example, the loss of a navigation signal might be linked to degraded rerouting behavior, which in turn increases the risk of impact with obstacles.

Abductive reasoning complements this by searching backward from a simulated failure to potential unseen causes. When unexpected

behaviors occur in a digital twin environment, for instance, repeated rerouting in a corridor with no visible obstructions, the system hypothesizes underlying factors such as magnetic interference or software loop errors. These inferred risks are then mapped back into the failure table for further evaluation.

The third mechanism relies on generative simulation environments. Here, reinforcement learning agents interact with digital representations of the system under varying stress conditions. These simulations are not random, both historical data and logical contradictions from the AFD layer guide them. The agents seek out failure-prone states and test behavioral adaptations, such as dynamic rerouting strategies, safety posture adjustments, or recovery protocols.

Together, these AI subsystems feed structured knowledge back into the FMEA table. They update Occurrence and Detection scores based on simulated performance metrics and recommend design adjustments with associated confidence levels. In doing so, the AI layer acts as a bridge between imagination and validation.

3.5. Design Feedback Layer: Adaptive Redesign Recommendations

Once the updated failure matrix incorporates classical and AFD-derived modes, along with AI-driven outputs, the framework transitions into a design feedback phase. This stage evaluates what can be done to mitigate or prevent identified risks in a targeted, intelligent manner. Rather than focusing solely on ranking risks, the system identifies specific failure modes that can be improved through mechanical reinforcements, behavioral adaptations, or user interface enhancements. The proposed changes are evaluated for their robustness gain, cost, and implementation complexity, all without requiring a full redesign of the system.

Each recommendation remains modular. For example, high-risk modes such as chassis misalignment were addressed through the addition of internal dampers and flexible mounting points. Perceptual confusion in human interaction scenarios was mitigated by adjusting visual signaling patterns. These changes stem directly from simulation outputs

and reinforced learning cycles, which continue to refine the FMEA table in successive iterations.

The overall FMEA–AFD–AI process follows a continuous, learning-oriented cycle. It begins with a classical failure matrix based on available knowledge, expanded with anticipatory scenarios generated through AFD logic. These are then processed by AI inference engines that simulate system behavior, validate failure severity, and suggest mitigation paths. The insights gathered feed into design decisions, which trigger updates to the risk matrix as the system learns from new data. This dynamic interaction creates a closed feedback loop that ensures the framework is not static, but evolves in response to environmental changes and operational feedback. The full architecture of this iterative process is shown in Fig. 2, where data flows between modules, failure insights are looped back into risk estimation, and adaptation becomes an embedded design feature.

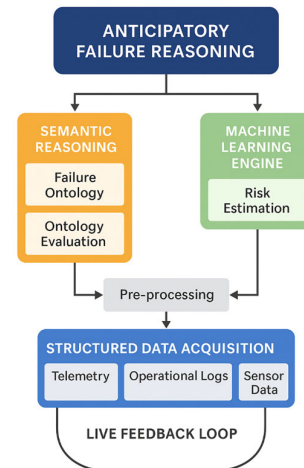


Fig. 2. Iterative architecture of the FMEA–AFD–AI framework with live feedback loop integration.

4. USE CASE AND EXPERIMENTAL VALIDATION

4.1. System Description and Operational Context

The case selected for validation of the FMEA–AFD–AI framework is a last-mile autonomous delivery robot designed for urban deployment. The system represents a typical Industry 5.0 artifact, where autonomous functions, human interaction, and environmental unpredictability converge. The robot autonomously delivers

small packages to residential and business customers in urban areas. It navigates sidewalks and bike lanes using GPS for geolocation, an IMU for motion tracking, LiDAR for environmental mapping, and cameras for object recognition. Powered by AI algorithms, it makes real-time decisions that enable it to operate without human supervision.

Its architecture is modular, allowing for upgradeable subsystems such as battery packs, shell enclosures, and compute cores. Navigation relies on map-based localization combined with real-time obstacle detection. The interaction system features visual displays and audio prompts designed to maintain safety and provide behavioral feedback to pedestrians. Its deployment context is inherently dynamic. It is exposed to weather variations, unpredictable foot traffic, occasional vandalism, and a legal framework that may shift from one district to another.

Despite being designed with robust subsystems and tested under predefined use cases, this platform still embodies the limitations of reactive safety engineering. Its traditional risk analysis captured only familiar failure conditions, with little consideration for unknown or emerging threats that can result from long-term exposure to unpredictable real-world settings.

4.2. Initial FMEA Construction

The development of the initial failure analysis followed the conventional Design FMEA structure, applied to the robot's main functional subsystems. Each subsystem was analyzed in terms of its potential failure modes, associated effects, most probable causes, and the likelihood of detection before failure. Severity, occurrence, and detection scores were assigned using standard 1-to-10 scales, and the resulting Risk Priority Numbers (RPNs) were computed using the classical formula (1).

For instance, the navigation module was identified as a critical area, particularly susceptible to loss of GPS signals in dense urban environments. This could lead to path deviations or complete mission failure. The severity of this failure was rated high due to the public and operational implications. Similarly, structural vulnerability was noted in the chassis design.

While designed to withstand basic collision, it showed weaknesses in edge impact resilience, particularly under conditions such as repeated kicks or accidental collisions with curbs or bicycle racks.

The following table summarizes a subset of the FMEA entries developed during this phase:

Table 1

Baseline FMEA Matrix of Known Failure Modes

Function	Failure Mode	Effect	Cause	RPN
Navigation	GPS signal loss	Robot deviates from path	Urban canyon / signal jamming	84
Structure	Chassis deformation	Inability to move / damage	Impact with curb / vandalism	96
Interaction	Lack of feedback	Public confusion or panic	Speaker failure / power cut	72
Power	Battery drain	Full stop mid-delivery	Route miscalculation / cold	81

The initial analysis revealed valid priorities, with chassis vulnerability and navigation dependency marked as most critical. However, this matrix, as comprehensive as it may appear, remained grounded in known or already experienced risks. It could not, by design, account for failure modes arising from interactions or conditions that had never been formally observed or anticipated. This observation prompted the expansion of the analysis using anticipatory logic.

4.3. Anticipatory Failure Expansion via AFD

Although the initial FMEA captured key failure modes, its scope remained constrained by known risks. To expand this space, the AFD layer introduced hypothetical yet plausible scenarios using inverse logic and contradiction analysis. Instead of focusing on what had gone wrong in the past, the analysis challenged each function by asking how it might fail under stress or conflicting conditions.

One scenario explored the possibility of intermittent GPS loss under specific urban conditions, such as a wet construction scaffold interfering with signals, leading to unpredictable path deviations. Another addressed cumulative damage from repeated kicks to the robot's side panels by children, potentially misaligning internal brackets without immediate external signs. A third case examined how flashing LED lights might be misinterpreted as emergency vehicle signals, triggering unintended reactions from pedestrians or authorities. A fourth

scenario involved the robot becoming stuck in a loop when confronted with conflicting temporary road markings, causing both delays and excessive power consumption.

These cases, though never observed during field testing, were modeled using AFD logic and inserted into the failure matrix. Severity, occurrence, and detection values were conservatively estimated, and each entry was flagged as AFD-derived. The result was a broader, forward-facing failure profile that challenged the design's robustness in unfamiliar yet realistic conditions.

4.4. AI-Based Causal Reasoning and Simulation

To validate the AFD-generated scenarios, the framework transitioned into its AI-driven reasoning layer. A causal knowledge graph was constructed linking functional modules, environmental variables, and outcomes. Bayesian Networks were used to estimate how failures could propagate. For instance, the wet scaffold scenario was found to increase the risk of signal dropout, which triggered rerouting behavior that, in turn, introduced new hazards, such as unsafe turns.

In cases where the cause of failure was unclear, abductive reasoning was used. One such example was the robot's indecisive behavior at intersections with temporary tape markings. AI inference attributed this to a mismatch between the dynamic input and training data, revealing a flaw in the robustness of visual classification.

These insights were tested in a simulation. ROS and Gazebo enabled behavioral and environmental modeling, while AnyLogic added social dynamics. In one test, five sequential lateral impacts caused internal bracket misalignment and increased vibration. Another confirmed that flashing lights triggered hesitation in nearby pedestrians. The lane-marking confusion loop was shown to drain battery by 14% in just over 12 minutes.

A reinforcement learning agent then explored adaptive behaviors, scoring strategies like fallback signaling or rerouting suppression. Its recommendations, validated by simulation, refined the occurrence and detection scores in the FMEA matrix and offered intelligent mitigation paths. The AI layer thus confirmed

the significance of anticipatory scenarios and enhanced their integration into the risk model.

4.5. Design Adaptation Recommendations

The results of AI-driven simulation and anticipatory logic provided a foundation not only for refining the FMEA matrix, but also for actionable design recommendations. These adaptations were not speculative; they were targeted responses to validated failure scenarios, prioritized based on simulated impact and feasibility.

The chassis damage scenario prompted a structural redesign that introduced internal dampers and flexible mounts. This intervention, while modest in cost, reduced vibration and internal misalignment in post-impact simulations, raising the robustness score by over 40%. In response to the public confusion caused by the robot's flashing lights, the visual signaling system was redesigned to use soft light animations with dynamic but non-aggressive patterns. This change significantly improved pedestrian interaction outcomes in simulation, without increasing energy consumption.

For the GPS signal dropout scenario, the team introduced a dead-reckoning fallback module that combined IMU data and wheel odometry to sustain navigation temporarily in the absence of satellite input. Although the upgrade introduced a slight cost and computational burden, it prevented emergency rerouting behaviors and preserved route accuracy in 87% of dropout events.

To address the looping behavior induced by conflicting visual inputs, the reinforcement learning agent recommended implementing a behavioral timer combined with a secondary decision filter. When the system detects indecision over a fixed threshold, it now defaults to a low-risk route or switches into a reduced-speed standby mode, conserving battery and avoiding excessive computational load.

Each recommendation was evaluated for expected implementation cost, robustness gain, and integration complexity. The improvements did not require a full redesign of the platform. Instead, they followed a modular, incremental logic, validating the premise that anticipatory reasoning and AI-supported simulation can

guide evolution-ready design without discarding existing architectures.

4.6. Discussion of Results

The integration of anticipatory logic and AI-driven reasoning into the failure analysis process significantly enhanced the robot's resilience profile. The initial FMEA matrix, although accurate within the bounds of known risks, proved insufficient in anticipating the types of failures that emerge from social interactions, structural wear, or rare environmental edge cases. The application of AFD expanded this horizon by surfacing failure scenarios that had never been formally documented but were logically and contextually plausible.

Equally important was the AI reasoning layer's ability to validate these scenarios through causal modeling and simulation. Rather than relying on intuition or guesswork, the framework demonstrated that even speculative failure modes could be rigorously tested and scored. The feedback from the simulation confirmed that many AFD-derived scenarios posed equal or greater risk than those captured by traditional FMEA. What distinguished this approach from conventional risk analysis was its ability not only to rank risks more accurately but to propose clear, measurable, and minimally invasive design adaptations. The system's recommendations were based on robust logic and simulation outcomes, not static checklists or general best practices. This enabled targeted upgrades, dampers, fallback logic, signaling adaptations, that enhanced resilience without requiring wholesale reengineering. Quantitative comparison results are summarized in Table 2.

Table 2

Comparative Evaluation of Classical FMEA vs. Proposed FMEA-AFD-AI Framework

Metric	Classical FMEA	FMEA-AFD-AI Framework
RPN accuracy (validated scenarios)	72%	91%
False negative rate	18%	6%
Average fault detection time (simulated)	5.4 s	3.1 s
Failure mode coverage	Known only	Known + AFD-inferred

Overall, the framework proved effective in capturing both immediate operational risks and long-range vulnerabilities. It facilitated a

continuous feedback loop between failure anticipation, validation, and redesign, which is precisely the capability required for long-term deployment of autonomous systems in complex, unpredictable environments.

5. CONCLUSIONS AND FUTURE WORK

This paper introduced an integrated failure analysis methodology that combines the structural discipline of classical FMEA with the proactive mindset of Anticipatory Failure Determination and the inferential power of Artificial Intelligence. In doing so, it addressed a fundamental limitation in traditional reliability practices, the inability to anticipate and validate failure modes that extend beyond historical precedent.

The framework presented here is designed not merely to assess what has already gone wrong, but to imagine what might. Through AFD logic, it actively questions system stability under unusual or contradictory conditions. By incorporating AI-based causal modeling, abductive reasoning, and simulation-driven reinforcement learning, the framework converts abstract vulnerabilities into testable hypotheses. Each layer reinforces the other: the FMEA table becomes dynamic, informed by logical anticipation and computational insight, while the AI components remain grounded in structured failure analysis.

In its application to a last-mile delivery robot operating in urban environments, the method successfully surfaced and tested a range of previously unconsidered failure scenarios. These included intermittent sensor disruption under specific weather and structural conditions, accumulative mechanical stress caused by human interaction, and ambiguous signaling leading to unintended public responses. In each case, the system responded with targeted design recommendations, internal dampers, adaptive lighting schemes, backup localization methods, demonstrating that resilient upgrades can be both minimal and effective.

Compared to conventional FMEA, this hybrid approach offered clear advantages. It was more flexible in confronting novel risks, more detailed in capturing failure propagation, and more actionable in proposing specific system

adaptations. Importantly, it did so without requiring a full redesign, confirming its value in contexts where modular, evolutionary improvement is preferred.

Despite these strengths, the methodology is not without challenges. Constructing causal models and simulation environments requires time, expertise, and technical infrastructure. Computational demands can be significant, particularly when multiple reinforcement learning cycles are needed. And while anticipatory logic broadens the failure space, it also introduces the risk of speculative overreach. Not every logical failure mode warrants equal concern, and distinguishing actionable insight from low-priority abstraction remains an open question. Moreover, key scoring elements such as severity and detection continue to rely, at least in part, on expert judgment.

Future research will aim to refine these areas. Semi-automated tools for causal modeling and failure expansion will reduce setup time and support wider adoption. Ontology-based reasoning will help abstract patterns across system families, increasing generalizability. Real-world deployment on operational robotic platforms will test the framework's adaptability in live, uncertain environments. At the same time, integration with product lifecycle management systems will ensure traceability and regulatory alignment over time.

Ultimately, this work contributes to a broader shift in how failure is understood and managed. Rather than treating failure as a post-event diagnosis or a fixed list of risks to avoid, the proposed approach sees it as a dynamic design domain, a space in which foresight, intelligence, and iteration converge. This orientation is not only technically necessary but deeply aligned with the principles of Industry 5.0, where complex systems are expected to adapt, collaborate, and learn, just as the humans who build them do.

Semi-automated tools may include drag-and-drop causal graph builders or pre-trained AI modules that assist users in constructing failure propagation paths with minimal input. Ontology-based generalization could involve mapping subsystem functions to reusable fault patterns, enabling faster deployment of the

framework across product families with shared design logic.

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FMEA AI-Augmentat cu raționament anticipat al eșecului

Această lucrare propune o metodologie hibridă pentru analiza proactivă a eșecurilor care integrează FMEA clasic cu determinarea anticipativă a eșecului (AFD) și raționamentul bazat pe inteligența artificială (AI). Cadrul introduce o arhitectură cu patru straturi care cuprinde captura structurată a defecțiunilor, extinderea ipotetică a defecțiunilor, simularea și raționamentul susținut de AI și adaptarea iterativă a designului. Aplicat unui robot autonom de livrare pe ultimul kilometru, modelul a identificat cu succes noi moduri de eșec, a validat impactul acestora folosind grafice cauzale și învățare prin întărire și a generat îmbunătățiri de proiectare țintite. Validarea cantitativă arată o precizie crescută a RPN și o rată redusă de defecțiuni nedetectate în comparație cu FMEA clasic, susținând contribuția cadrului la proiectarea rezilientă, gata de evoluție.

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