

# Dynamic Driver Risk Management: Integrating AFDD and FMEA

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## ABSTRACT

Driving accidents remain a major global safety concern, largely driven by human factors such as fatigue, distraction, and cognitive overload. Existing driver-assistance systems primarily address external risks and often fail to capture real-time changes in driver condition. This paper proposes an integrated framework combining Automatic Fatigue and Distraction Detection (AFDD) with a dynamic Failure Mode and Effects Analysis (FMEA) model. AFDD continuously monitors driver state using multimodal data, while dynamic FMEA updates risk parameters in real time to produce adaptive Risk Priority Numbers (RPN). Results indicate a 42–62% reduction in RPN across key failure modes. The framework enables predictive, human-centered safety interventions and improves overall road safety performance.

**Keywords:** Driver distraction, Driver distraction detection, Distracted driver classification, Vision-based driver monitoring, Failure mode effect analysis

## INTRODUCTION

Driving accidents remain a major global public health and economic burden (Soole et al., 2023), with human-factor impairments such as fatigue, distraction, cognitive overload, delayed reactions, and other behavioural or physiological limitations playing a leading role in traffic fatalities (Vecchiato et al., 2022). The World Health Organization reports that about 1.19 million people die each year due to road traffic accidents. Such impairments undermine hazard perception, lane keeping, braking performance, and overall vehicle control. Human behaviour is consistently recognized as a dominant contributor to crashes (Butt et al., 2020), particularly failures in attention, decision-making, and reaction timing, which further illustrates the importance of road-transport systems that proactively address human-factor risks and respond to changing driver conditions (Razzaghi et al., 2024).

This study aims to determine the effectiveness of integrating Automatic Fatigue and Distraction Detection (AFDD) with FMEA for a more responsive and comprehensive approach to managing and enhancing driver safety. We expect the combination of predictive risk analysis and real-time behavioural monitoring to reduce accident rates and enhance overall transport safety in the UAE.

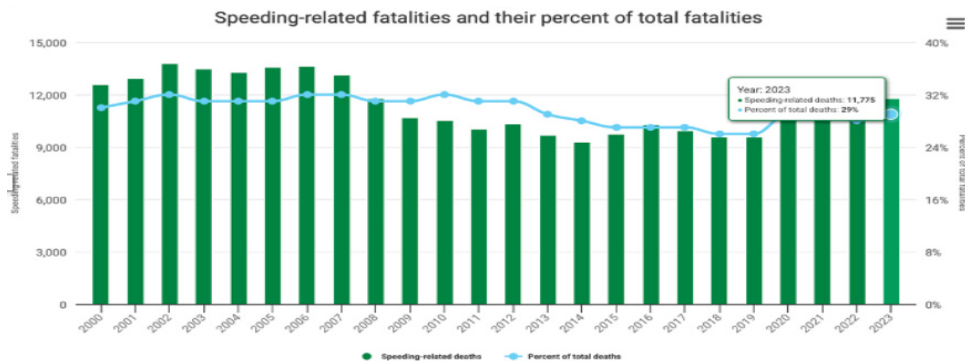


Figure 1: Speeding fatalities per year (The U.S. National Safety Council, 2023).

### METHODOLOGY

This study adopts a data-driven and analytical approach to develop a dynamic driver risk management framework by integrating Automatic Fatigue and Distraction Detection (AFDD) with Failure Mode and Effects Analysis (FMEA).

AFDD is an AI-based system that monitors driver condition using multimodal inputs, including facial features, steering behaviour, and environmental conditions. It operates through data acquisition, feature extraction, and real-time classification of driver state (Hu et al., 2024).

The system generates a fatigue/distraction score (AF) and a confidence score (C), which are used to determine driver risk levels and trigger appropriate interventions such as alerts, speed reduction, or lane assistance. A range of recent studies (Guptaa, 2024), global road safety reports, and published research on driver behaviour (Uddin et al., 2025) were reviewed to identify the primary human-factor causes of driving incidents. These include fatigue, distraction, cognitive overload, delayed reaction, aggressive driving, and impaired visibility.

Based on this review, the most critical failure modes contributing to road accidents were defined and categorized. These failure modes form the foundation for the FMEA model. A baseline FMEA was constructed by assigning Severity (S), Occurrence (O), and Detection (D) ratings to each identified failure mode using expert judgment supported by literature. The Risk Priority Number (RPN) was calculated as:  $RPN = S \times O \times D$

Table 1: Driving hazards FMEA.

Failure Mode	Failure Causes	“O” (1–10)	“D” (1–10)	“S” (1–10)	RPN
Dozed	Physical fatigue, sleep deprivation, long driving hours, circadian rhythm misalignment	8	6	10	480
Sleepy	Inadequate sleep, medication effects, illness	8	6	9	432

(Continued)

**Table 1:** Continued.

Failure Mode	Failure Causes	“O” (1–10)	“D” (1–10)	“S” (1–10)	RPN
Distracted	Visual distraction / cognitive distraction	7	4	8	224
Delayed Braking	Cognitive fatigue, high workload, medication	7	5	9	378
Aggressive	Risk-taking behaviour, emotional stress, fatigue	6	5	8	240
Lane Departure	Microsleeps, distraction, poor visibility, cognitive overload	7	5	8	280
Impaired Visibility Response	Night driving, glare, rain/fog, fatigue	6	6	7	252
Cognitive Overload	Navigation, infotainment, external distractions, mental stress	6	5	7	210
Fatigue	Incomplete rest, circadian misalignment, post-nap grogginess	5	5	8	200

To address the limitations of static FMEA, AFDD outputs were integrated into the risk evaluation process. The AFDD system continuously monitors driver state using multimodal inputs such as eye movement, head position, steering behaviour, and environmental conditions (Vecchiato et al., 2022). Based on these inputs, a fatigue/distraction risk score (AF) and a confidence level (C) are generated in real time. These values are used to dynamically adjust the Occurrence (O) and Detection (D) ratings in the FMEA model.

Using AFDD inputs, a new dynamic RPN is calculated continuously during driving. This enables risk levels to reflect actual driver conditions rather than static assumptions (Phan et al., 2023). Unlike traditional systems where safety actions are triggered only when a fixed threshold is exceeded, the proposed framework allows for continuous risk evaluation. This dynamic assessment enables more appropriate and proportional safety interventions, such as gradual alerts, adaptive speed control, or automated assistance, depending on the severity of the detected risk.

The dynamically updated RPN values are classified into risk levels (low, medium, high), which determine the type and intensity of intervention (Mangal et al., 2025). This ensures that safety responses are adaptive and context-aware, improving effectiveness compared to static, condition-based systems. The system consists of five layers: sensing, feature extraction, risk scoring, control response, and feedback learning. Multimodal sensors collect driver and environmental data, which are processed into risk indicators (Li et al., 2025). Dynamic FMEA updates risk levels, and the control layer executes interventions based on risk classification (low, medium, high). A feedback loop continuously improves system performance.

*Equation 1: O<sub>adj</sub>*

$$O_{\text{adj}} = O \times (1 - k_O \times AF \times C)$$

Equation 2:  $D_{adj}$

$$D_{adj} = D \times (1 - k_D \times AF \times C)$$

AF represents the AFDD fatigue/distraction risk score (0–1), C denotes the confidence score (0–1), and  $k_O$  and  $k_D$  determine how strongly AFDD inputs influence the Occurrence and Detection metrics. The dynamic Risk Priority Number is then calculated as:

Equation 3:  $RPN_{dynamic}$

$$RPN_{dynamic} = S \times O_{adj} \times D_{adj}$$

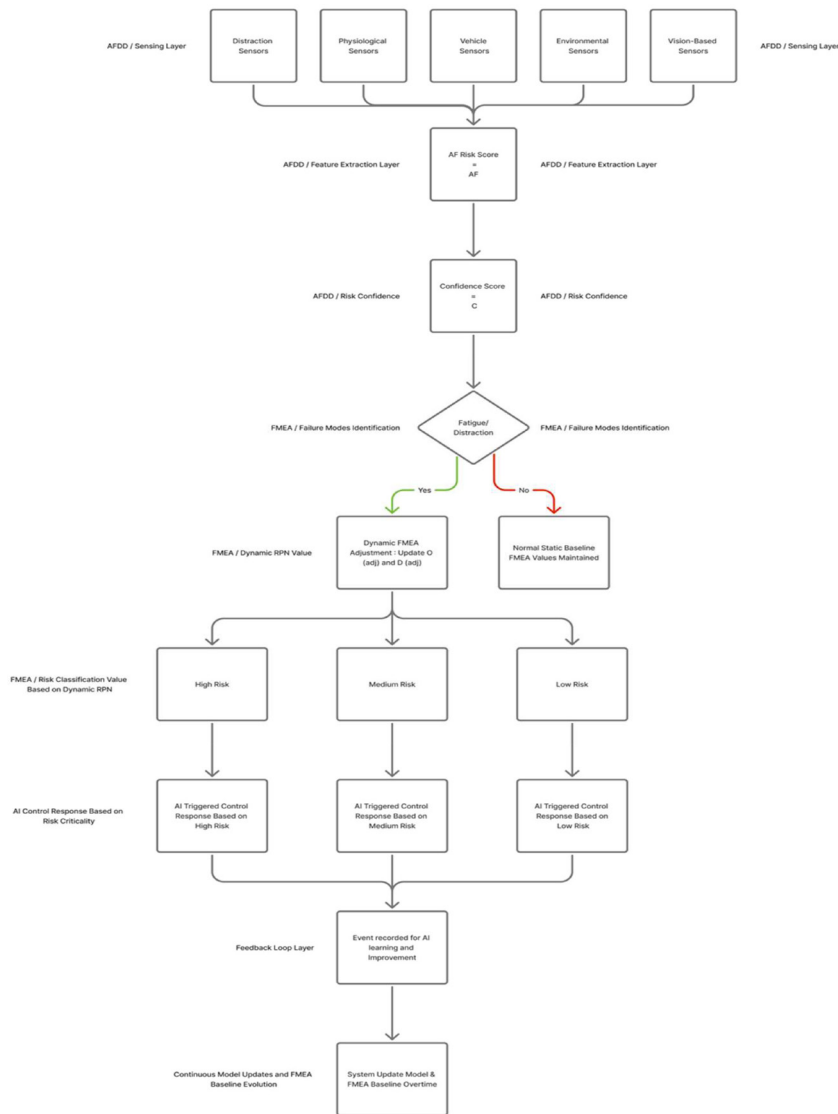
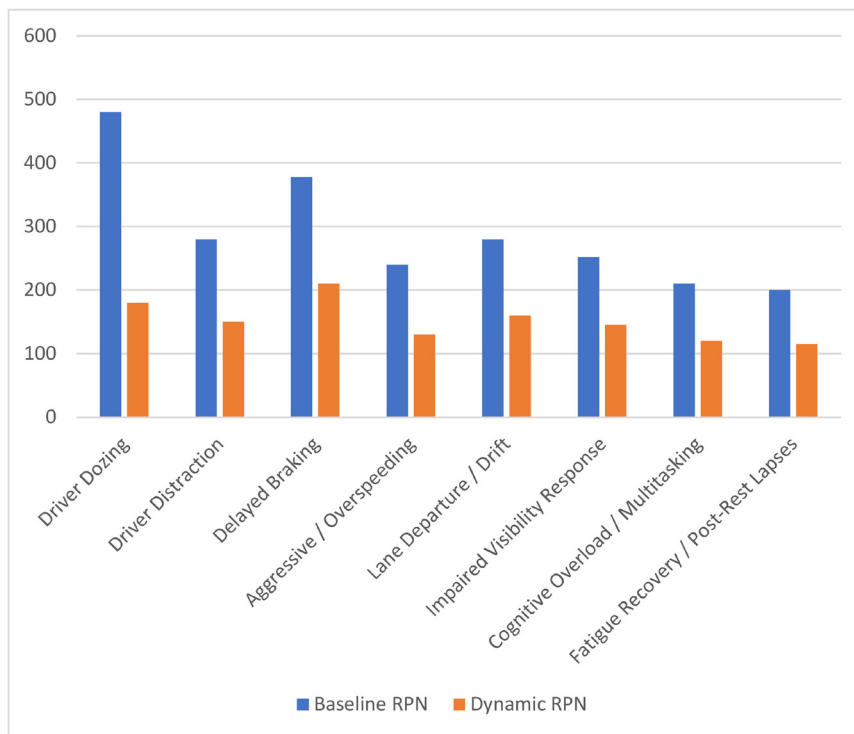


Figure 2: Framework process flow diagram.

## RESULTS

Upon simulating the integrated FMEA framework with AFDD systems, the data obtained from previous research are showcased for the purpose of validating the effectiveness of adding a dynamic detection to the cases presented.

Figure 3 depicts the baseline versus dynamic RPN values for each failure mode, highlighting the absolute reduction in risk levels. Driver dozing shows the largest improvement, with an RPN reduction of 62%, indicating the effectiveness of AFDD in real-time monitoring of severe fatigue events.



**Figure 3:** Effect of AFDD-dynamic FMEA integration on RPN reduction.

These results confirm that dynamically updating Occurrence and Detection scores based on AFDD outputs enables FMEA to represent real-time driver risk more accurately than traditional static scoring (Xu et al., 2024). By continuously adapting to driver state variations, this integrated approach not only reduces the RPN for high-risk failure modes but also enhances proactive risk mitigation strategies, thereby improving overall road safety outcomes. Table 2 showcases how the RPN is reduced during the simulated cases.

**Table 2:** Baseline vs. dynamic RPN values for driver-related failure modes.

Failure Mode	Baseline RPN	Dynamic RPN	Reduction (%)
Driver Dozing	480	180	62%
Driver Distraction	280	150	46%
Delayed Braking	378	210	44%
Aggressive / Overspeeding	240	130	46%
Lane Departure / Drift	280	160	43%
Impaired Visibility Response	252	145	42%
Cognitive Overload / Multitasking	210	120	43%
Fatigue Recovery / Post-Rest Lapses	200	115	42%

## FUTURE WORK

Despite the promising outcomes of the proposed AFDD–Dynamic FMEA framework, several limitations must be acknowledged. First, the accuracy and reliability of the system are highly dependent on sensor performance (Li et al., 2025). Vision-based and physiological sensors may be affected by poor lighting conditions, occlusions (e.g., sunglasses, masks), or hardware limitations, potentially reducing detection accuracy. This can lead to false positives, where normal driver behaviour is incorrectly classified as impaired, or false negatives, where actual fatigue or distraction is not detected. Such inaccuracies may result in either unnecessary interventions or missed critical warnings, both of which can impact user trust and system effectiveness (Mangal et al., 2025).

Second, the study relies on simulated data derived from existing case studies and literature rather than real-world experimental deployment. While this approach demonstrates the feasibility of the framework, it may not fully capture the complexity, variability, and unpredictability of real driving environments. Factors such as diverse driver behaviours, cultural differences, and varying road conditions could influence system performance (Lin and Zuo, 2024).

Additionally, the dynamic adjustment of FMEA parameters is based on predefined mappings between AFDD outputs and risk ratings, which may oversimplify the relationship between human behaviour and accident risk. Environmental constraints, such as extreme weather or sensor interference, may further limit system reliability.

Future work should focus on real-world validation, improved sensor fusion techniques, and adaptive calibration methods to enhance robustness, reduce false detections, and ensure broader applicability of the framework.

## CONCLUSION

Human Systems Integration (HSI) is becoming a critical piece of complex systems. This study demonstrates that integrating Automatic Fatigue and Distraction Detection (AFDD) with Dynamic Failure Mode and Effects

Analysis (FMEA) provides a proactive framework for improving driving safety. AFDD enables continuous monitoring of driver impairments such as fatigue, distraction, and cognitive overload, while FMEA offers a structured method for quantifying and prioritizing risks. By dynamically updating Occurrence and Detection scores using real-time AFDD data, the framework reduces Risk Priority Numbers (RPN) and enables timely interventions before hazards escalate.

This approach shifts safety management from reactive to predictive, allowing for adaptive interventions such as lane-keeping assistance, speed regulation, and multimodal alerts based on risk level. Continuous feedback and system learning further enhance detection accuracy and reduce unnecessary alerts over time.

Overall, the framework supports both immediate risk reduction and long-term system improvement, with strong potential for future integration of additional human-factor indicators and advanced connectivity solutions in next-generation driver safety systems.

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