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Integrating Artificial Intelligence with Failure Mode and Effects Analysis (AI-FMEA) in Event Management: A Hybrid Risk Framework for Intelligent, Predictive Event Reliability

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Abstract

Event management is increasingly complex, technology-driven, and data-rich. Integrating Artificial Intelligence (AI) into Failure Mode and Effects Analysis (FMEA) — hereafter AI-FMEA — can transform traditional, manual risk assessments into predictive, data-driven processes that detect hidden failure modes, prioritize interventions, and automate detection and mitigation workflows. This study proposes an AI-FMEA framework for event management and evaluates its impact through a mixed-methods pilot involving event professionals (n = 140) and three live events where an AI-FMEA prototype was deployed. Quantitative analysis showed that AI-FMEA competency (advisory + technical) was strongly associated with improved event reliability (R^2 =.58, p <.001). Qualitative feedback highlighted improvements in early failure detection (computer vision and anomaly detection), communication through NLP-driven alerts, and more effective contingency planning via digital twin simulations. The findings suggest that AI-FMEA enhances predictive risk control, reduces Risk Priority Numbers (RPNs) through targeted automation, and improves stakeholder satisfaction — but success depends on human–AI collaboration, data quality, and organizational readiness. The study concludes with practical guidelines for integrating AI into FMEA workflows and recommendations for training event teams in AI-enhanced risk management.

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Introduction

Events today are socio-technical systems where logistics, human behavior, technology platforms, vendors, and regulatory requirements interact dynamically (Getz & Page, 2020). Traditional FMEA provides a systematic way to list failure modes and prioritize corrective actions using Severity (S), Occurrence (O), and Detection (D) ratings (Stamatis, 2019). However, conventional FMEA is largely retrospective or based on expert judgment, limiting its ability to predict emergent risks in real time.

Artificial Intelligence (AI) — including machine learning (ML), computer vision (CV), natural language processing (NLP), and digital twin simulations — offers capabilities for predictive analytics, anomaly detection, and automated decision support (Russell & Norvig, 2016; Goodfellow *et al.,* 2016). Combining AI with FMEA (AI-FMEA) can shift event risk management from reactive to proactive by (a) mining historical and real-time data to estimate occurrence rates, (b) improving detectability using sensors and CV, and (c) recommending prioritized mitigations via decision-support algorithms (Davenport & Ronanki, 2018; Baryannis *et al.,* 2019).

This study develops and tests an AI-FMEA model tailored to event management, asking:

- How can AI techniques augment traditional FMEA tasks (identification, scoring, detection, mitigation)?
- What is the relationship between AI-FMEA competency and event reliability?
- What practical benefits and constraints emerge from deploying AI-FMEA in live events?

The objectives of this study are to design an AI-FMEA framework that integrates predictive analytics, computer vision, natural language processing, and digital twin simulations for comprehensive event risk assessment; to measure AI-FMEA competency among event teams and evaluate its relationship with event reliability outcomes; to pilot an AI-FMEA prototype across live events while documenting its effects on RPN reduction, failure-detection latency, and stakeholder satisfaction; and to develop implementation guidelines for effectively integrating AI into standard event management processes.

FMEA and Its Limitations in Dynamic Service Contexts

FMEA helps structure potential failures and prioritize corrective actions, but standard practice relies heavily on expert scoring that can be subjective and slow (Stamatis, 2019). In service sectors, contextual variability and human factors make occurrence and detection estimates uncertain (Chiozza & Ponzetti, 2009).

AI for Predictive Risk and Decision Support

AI algorithms enable prediction from historical and streaming data, improving estimation of occurrence probabilities and detectability metrics (Davenport & Ronanki, 2018). Supervised learning models can forecast equipment or vendor failures when sufficient labeled data exist (Goodfellow *et al.,* 2016). Unsupervised methods and anomaly detection identify atypical patterns without prior labels (Baryannis *et al.,* 2019).

Computer Vision and Crowd Monitoring

Computer vision systems can estimate crowd density, flow, and abnormal behavior in real time — enabling early detection of crowding, bottlenecks, or safety hazards (Zhang, Zhou, & Chen, 2016). CV improves the D (detectability) factor in FMEA by automating observation tasks that humans might miss.

Natural Language Processing for Communication and Vendor Management

NLP can parse vendor messages, social media signals, and attendee feedback to surface issues (e.g., complaints, logistic delays) and to automate alert generation (Liu, 2015). Automated summarization and intent detection reduce information overload and speed detection and response.

Digital Twins and Simulation for Scenario Testing

Digital twin technology models event systems to simulate failure propagation and test mitigation strategies before live deployment (Tao *et al.,* 2018). Simulation improves planning by revealing cascading effects and helping prioritize high-impact failure modes.

Human–AI Teaming, Ethics, and Data Quality

AI tools must operate in a human-centered framework; overreliance without transparency can create new risks (Russell & Norvig, 2016). Data quality, privacy, and explainability are essential for trustworthy AI in events (Davenport & Ronanki, 2018).

Research Methodology

Research Design

A mixed-methods design combined (a) a cross-sectional survey measuring AI-FMEA competency and perceived event reliability (quantitative), and (b) pilot deployments of an AI-FMEA prototype at three medium-scale events with post-event interviews (qualitative). This approach allows measurement of statistical associations and in-depth evaluation of implementation dynamics (Creswell & Creswell, 2018).

Population and Sample

Participants included 140 event professionals (planners, technical leads, safety officers) recruited via purposive sampling for the survey. The pilot involved three live events (educational conference, cultural festival, and corporate launch) where the AI-FMEA prototype was integrated into planning and operations.

Instruments

AI-FMEA Competency Scale (AIFCS)

A 25-item scale measuring skills and organizational readiness across: (a) Data integration and quality, (b) Predictive analytics proficiency, (c) CV/NLP tool usage, (d) Digital twin/simulation competency, and (e) Human–AI collaboration practices. Responses used a 5-point Likert scale.

Event Reliability Effectiveness Scale (ERES-AI)

Measured event outcomes: operational incidents, time-to-detect, mitigation speed, attendee / stakeholder satisfaction.

Combined self-reports and objective logs from the pilot events.

Qualitative Interview Protocol

Semi-structured interviews focused on experiences using AI tools, perceived benefits, limits, and human–AI coordination issues.

Prototype AI-FMEA System

The prototype included:

- A predictive occurrence module (supervised ML model trained on historical vendor delays, equipment faults).
- A detection layer: CV crowd monitoring, anomaly detection on sensor feeds, and NLP monitoring of vendor/attendee communications.
- A digital twin simulation engine to test mitigation sequences and estimate residual RPN.
- A dashboard that auto-generates recommended actions and updates S, O, D scores dynamically.

Data Collection Procedure

Survey data were collected online. Pilot events logged system alerts, detection times, and incident outcomes. Post-event interviews (n = 18) were recorded and transcribed.

Statistical Tools and Analysis

Descriptive statistics summarized competency levels. Pearson correlations and multiple regression tested relationships between AI-FMEA competency and event reliability. Thematic analysis (Braun & Clarke, 2006) analyzed interview transcripts for implementation themes.

Data Analysis and Interpretation

Quantitative Results

Descriptive results showed moderate AI readiness overall, with higher confidence in basic data collection and lower scores in simulation and ML model tuning. Pearson correlation analysis revealed a strong positive correlation between AI-FMEA competency and event reliability ($r \approx .76$, $p < .001$).

Multiple regression indicated that AI-FMEA competency explained 58% of variance in event reliability ($R^2 = .58$, $p < .001$), with the detection layer (CV + NLP) and simulation competency being the strongest predictors.

Pilot Event Outcomes

Across the three pilot events, the AI-FMEA prototype:

- Reduced median time-to-detect of critical incidents (e.g., A/V failures, vendor no-shows) compared to baseline logs.
- Flagged emerging crowding risks earlier via CV alerts, enabling staff re-routing.
- Allowed planners to test mitigation sequences in the digital twin, which improved resource allocation and reduced contingency response times.
- Automated routine communications (NLP templates) that decreased coordination delays.

Quantitative logs showed a measurable reduction in residual RPNs after AI-guided mitigation planning (teams reported lower estimated RPNs following simulation-based changes).

Qualitative Themes

Thematic analysis revealed key themes:

- Improved Situational Awareness: Teams valued continuous monitoring and early alerts.
- Trust & Explainability Needs: Operators needed transparent rationale for AI alerts to act confidently.
- Training Gaps: Users requested more training on model limitations and dashboard interpretation.
- Data and Infrastructure Constraints: Inadequate historical data limited predictive accuracy; sensor/network issues affected detection reliability.

- Human Oversight Essential: Staff emphasized that AI should support — not replace — human judgment.

Findings and Discussion

AI Enhances Occurrence and Detection Estimates

Predictive models improved estimates of occurrence probabilities by learning from historical patterns (Goodfellow *et al.,* 2016).

Detection improved via CV and NLP, increasing the detectability metric (D) in FMEA and thereby lowering effective RPNs when detection controls were implemented.

Digital Twin Enables Proactive Mitigation

Simulations helped planners explore "what-if" scenarios, surface cascading failures, and prioritize high-impact mitigations — improving the severity (S) management through contingency planning (Tao *et al.,* 2018).

Automation Reduces Response Latency

Automated alerting and template-driven communications reduced the time between detection and mitigation, decreasing the operational impact of failures (Davenport & Ronanki, 2018).

Human–AI Teaming is Central

AI systems provided value only when operators trusted outputs and could interpret recommendations.

Explainable AI and transparent dashboards were critical to adoption (Russell & Norvig, 2016).

Limitations and Risks

AI-FMEA introduces new dependencies: data quality issues can bias predictions, CV may raise privacy concerns, and overautomation can produce complacency. Ethical and legal considerations (privacy, bias) must be addressed before wide deployment.

Implications

Practical Implementation Roadmap

Data Foundation: Institutions must invest in structured historical logging (vendor SLAs, equipment maintenance, incident logs).

Pilot and Iterate: Start with non-mission-critical events to refine detection models and dashboards.

Human-Centered Design: Build explainable alerts and role-based dashboards for different stakeholders.

Privacy & Compliance: Ensure CV and NLP use comply with local privacy law and consent practices.

Training & Capacity Building: Offer training for planners on interpreting AI outputs and simulation results.

Curriculum and Professional Development

Event management programs should include modules on AI in risk management, data literacy, and digital twin simulation to prepare future professionals for AI-FMEA workflows.

Policy Recommendations

Organizations should codify AI-FMEA into SOPs, define human oversight levels, and set thresholds for automated actions to balance speed and safety.

In conclusion, AI-FMEA represents a promising evolution of risk management in event contexts, combining predictive analytics, CV, NLP, and digital twin simulations to make FMEA dynamic, data-driven, and actionable. The mixed-methods pilot provided empirical and experiential evidence that AI-FMEA improves detectability, reduces residual RPNs, enhances situational awareness, and shortens mitigation cycles — provided that teams invest in data quality, maintain human oversight, and implement explainable AI practices. Future research should examine scalability across large-scale events, longitudinal impacts, cost-benefit analyses, and ethical frameworks for privacy-preserving detection.

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