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The Implementation of Artificial Intelligence (AI) in Aviation Accident Investigations

Gustavo Sanchez, Dimitrios Ziakkas, and Debra Henneberry

Purdue University, School of Aviation and Transportation Technology, West Lafayette, IN 47907, USA

ABSTRACT

Accident investigation is fundamental to aviation safety, serving to identify causal factors and prevent the recurrence of accidents. Traditionally, such investigations have depended on systematic methodologies like the SHELL model and Fault Tree Analysis, drawing on data from flight data recorders, cockpit voice recorders, and eyewitness accounts. However, the rapid integration of digital technologies, the increasing complexity of modern systems, and the challenges posed by globalized operations have created an urgent need for more sophisticated investigative tools. Artificial intelligence offers capabilities such as pattern recognition, predictive modeling, and real-time data analysis, which can significantly augment the investigative process and improve outcomes. This research explores the application of AI in aviation accident investigations with a specific focus on several areas. First, the literature review examines the use of AI for human error analysis, investigating behavioral patterns, decision-making processes, and cognitive workload during incidents. It also evaluates the potential of AI tools to assess system reliability by detecting latent failures and interdependencies in avionics and mechanical systems. Furthermore, the research considers how AI-driven applications - simulations can be used for resilience modeling by reconstructing accidents and assessing system responses to cascading failures. In addition, the study evaluates how AI can enhance investigative efficiency through the automation of data sorting, analysis, and hypothesis testing. A multi-disciplinary approach was employed, integrating theoretical frameworks with AI-driven simulations and case study analyses. The methodology began with an extensive literature review of existing accident investigation methodologies, emphasizing the role of technology and data analytics. Building on this review, an AI-powered investigative framework was developed that incorporates machine learning algorithms for anomaly detection, natural language processing for analyzing cockpit communications and maintenance logs, and predictive analytics for modeling potential accident scenarios based on historical data. The framework was then tested through the “Aviation Human Factors Analyst” Open AI application simulations that replicated past aviation accidents to validate its ability to identify causal factors and suggest preventive measures. Finally, the framework was applied to real-world aviation accidents, such as controlled flight into terrain and loss of control in flight, to assess its effectiveness in uncovering human, technical, and environmental contributors. By augmenting traditional methodologies with advanced AI-driven tools, investigators can achieve greater accuracy and efficiency in uncovering causal factors, ultimately enhancing overall aviation safety. Future research should address cybersecurity considerations to protect AI systems from cyber threats, explore the transferability of AI frameworks to other transportation sectors such as rail and maritime, develop AI tools capable of real-time incident analysis to support immediate corrective actions, and advance methods in explainable AI to ensure transparency and accountability in AI-driven findings. Integrating AI into aviation accident investigations promises a more resilient and adaptive safety ecosystem, paving the way for safer skies.

Keywords: Aviation safety, Artificial intelligence (AI), Accident investigation, Human error, Reliability, Resilience, Performance

INTRODUCTION

In the aviation industry, accident investigations have long relied on systematic methodologies such as the SHELL model and Fault Tree Analysis (Reason, 1997). These traditional Safety I approaches focus on retrospectively identifying errors and failures by analyzing data from flight data recorders, cockpit voice recorders, and eyewitness testimonies (ICAO, 2020). Such methods have proven effective in isolating causal factors in many incidents. However, as modern aviation systems become increasingly complex—with digital technologies generating vast amounts of diverse data and intricate interdependencies emerging among technical components, human operators, and environmental conditions—the limitations of conventional approaches become more pronounced, merging safety paradigms distinguished between Safety I and Safety II approaches. While Safety I concerns itself with reducing adverse outcomes by scrutinizing past failures, Safety II shifts the focus toward understanding how systems succeed under varying conditions and enhancing their resilience (Hollnagel, 2017). This newer perspective does not simply seek to eliminate errors; it also strives to foster the system's capacity to adapt and continue functioning effectively even when deviations occur.

In aircraft accident investigations, integrating Safety II concepts involves understanding the conditions that enable successful operations, providing essential insights for preventing future mishaps. Recent advances in artificial intelligence (AI) present promising opportunities to bridge the gap between these two safety paradigms. AI systems can process vast amounts of data in real-time, identify subtle patterns that may escape human analysis, and simulate various operational scenarios. By incorporating machine learning algorithms, natural language processing, and advanced predictive analytics, an AI-powered investigative framework can enhance both the error-focused analysis typical of Safety I and the resilience-oriented insights emphasized by Safety II. For instance, AI-driven simulations can reconstruct accident sequences with high fidelity, uncovering not only the immediate failures but also the underlying conditions that allowed the system to operate successfully most of the time. This dual perspective—leveraging the strengths of both Safety I and Safety II—can ultimately lead to more proactive safety interventions and a more resilient aviation system ecosystem.

In summary, the aviation industry can achieve a more comprehensive understanding of accident causation by augmenting traditional investigation methods with AI-based tools that incorporate the principles of both Safety I and Safety II. This integrated approach not only improves the detection of latent failures and human errors but also supports the design of safety barriers using technological, regulatory, and training tools capable of adapting to the challenges of modern aviation.

LITERATURE REVIEW

In aviation, AI applications are not confined to operational optimization; they extend into critical safety domains such as predictive maintenance, air traffic management, and crew training (EASA, 2023). During aviation accident investigations, AI applications are not limited to operational optimization; they also encompass critical safety areas such as predictive maintenance, air traffic management, and crew training (EASA, 2023). While investigating aviation accidents, AI facilitates comprehensive analyses of data from Flight Data Recorders (FDR), Cockpit Voice Recorders (CVR), maintenance logs, and operational records. These advanced analytical capabilities allow investigators to identify patterns and anomalies that may go undetected by traditional investigative methods (Strauch et al., 2023).

In predictive maintenance, AI models forecast potential equipment failures before they occur, thereby significantly reducing the likelihood of accidents stemming from mechanical issues. In air traffic management, AI enhances traffic flow efficiency, mitigates congestion, and improves safety by predicting potential conflicts (Abdillah, 2024). Furthermore, in flight operations monitoring, AI continuously evaluates flight data to identify irregularities that could signal emerging safety risks, thus enabling proactive interventions (Malakis et al., 2023).

Integrating AI into aviation safety practices aligns with the evolving paradigms of Safety I and Safety II. Safety I, which has traditionally focused on preventing failures and minimizing the likelihood of adverse outcomes, benefits from AI's ability to analyze historical data and identify risk factors associated with past incidents. AI systems can process vast amounts of flight data, maintenance records, and incident reports to detect patterns that may indicate underlying safety issues, thus supporting a reactive safety management approach (Demir et al., 2024).

Conversely, Safety II represents a shift toward a more proactive and resilient approach to safety management (Cooper, 2020). This paradigm emphasizes understanding how everyday operations succeed and how systems adapt to different conditions to maintain safety (Cutchen, 2020). AI plays a crucial role in this context by enabling real-time monitoring and predictive analytics. Through continuous data analysis, AI can identify what went wrong in previous events and what contributes to successful operations. This dual capability allows for a more comprehensive understanding of system performance and the factors that promote safety.

The current state of AI in aviation is characterized by its expanding role in supporting both traditional and modern safety management practices. As AI technologies evolve, their integration into aviation safety frameworks will likely become more sophisticated, enabling more effective risk assessment, decision-making, and continuous improvement in safety performance.

METHODOLOGY

The research methodology underpinning this study is guided by Saunders' Research Onion framework, which offers a comprehensive structure for research design (Saunders et al., 2019). This framework encompasses several layers, including research philosophy, approach, strategy, methodological choices, time horizon, and data collection techniques.

- Research Approach: This research used a deductive approach, with the testing of existing theories and models on AI and aviation safety against empirical data to ensure that the investigation into the effectiveness of AI in enhancing aviation accident investigations is structured.

- Research Strategy: The thematic analysis/case study strategy used in this research focuses on detailed analyses of specific aviation accidents in which AI could have influenced the investigation outcomes. This research identified patterns, challenges, and opportunities that come with implementing AI by looking at real incidents. This approach provides an opportunity for deep understanding of contextual factors that influence the integration of AI in aviation safety processes.
- Methodological Choices: A mixed-method approach is adopted, combining both quantitative and qualitative data to provide a comprehensive analysis. Quantitative data includes statistical information from aviation safety databases, such as incident frequencies, failure rates, and performance metrics of AI systems. Qualitative data is gathered through case studies, expert interviews, and content analysis of accident investigation reports. This dual approach ensures a holistic understanding of AI's impact on aviation safety (Aviation Human Factors Analyst Open AI application Case Study).
- Time Horizon: The study employs a cross-sectional time horizon, capturing data from a specific period to analyze current trends and practices in AI applications within aviation accident investigations. This time-bound approach allows for the assessment of contemporary AI technologies and their immediate effects on aviation safety.
- Data Collection Techniques: Data for this research is sourced from multiple channels, including aviation safety databases (e.g., ICAO, NTSB reports), peer-reviewed journals, industry white papers, and official accident investigation reports. Quantitative data is analyzed using statistical tools to identify correlations and trends, while qualitative data is examined through thematic analysis to extract meaningful insights.
- Data Analysis Techniques: Advanced statistical analyses, such as regression analysis and hypothesis testing, are employed to interpret quantitative data. AI modeling techniques use machine learning algorithms in data analytics to discover patterns and predict future trends. For qualitative data analysis, coding and thematic analysis were conducted, enabling the identification of recurring themes and insights about the role of AI in aviation accident investigations.
- Thematic analysis was conducted through a systematic review; the search of relevant material focused on peer-reviewed journals within the last five years. A total of 25 scholarly articles were identified and filtered down by relevance to AI in aviation accident investigation, regulatory frameworks such as FAA, EASA, ISASI, ICAO Annex 13, and safety management paradigms like Safety-I and Safety-II. (FAA, EASA, ISASI, ICAO Annex 13), and safety management paradigms (Safety-I and Safety-II).

The following filters were applied:

- Publication Date: 2019–2024;
- Source Type: Peer-reviewed journals and academic publications;

- Focus: Aviation safety, AI applications, accident investigations, human factors;
- Databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect.

The research implemented the following coding framework:
Code 1: Accident Analysis (identifying causal factors using AI);
Code 2: Investigation Processes (enhancement through AI tools);
Code 3: AI Applications (machine learning, NLP, predictive analytics);
Code 4: Safety-I (focus on failure prevention and risk mitigation);
Code 5: Safety-II (system resilience, proactive safety management).

This methodological framework aims to explore the multifaceted role of AI in aviation accident investigations, providing robust and reliable findings that contribute to the field of aviation safety.

RESEARCH

Identifying causal and contributing factors in aviation accident investigations offers an opportunity for improvement through AI applications. Harris and Li (2019) developed an AI model to assist in analyzing accident causes. The researchers trained a neural network using the accident reports of 523 military aviation incidents to identify the preconditions for human error (HFACS Level 2 to Level 1). Another exploratory study examined the use of large language models (LLMs) with HFACS as a framework (Saunders et al., 2024). The authors noted challenges faced by LLMs while analyzing pilots' cognitive processes, such as violations and decision-making (Saunders et al., 2024). Xu et al. (2024) utilized knowledge graphs to clarify patterns and relationships in accident causation. After analyzing 473 aviation accidents from 2018 to 2022, the authors discovered that graph analytics can help identify hidden risk patterns in aviation operations.

For process improvement during Aviation Accident investigations. AI's ability to process and analyze large volumes of data is particularly valuable in accident investigations. Traditional methods rely heavily on manual data review, which can be time-consuming and prone to human error. AI algorithms can quickly sift through flight data recorder (FDR) and cockpit voice recorder (CVR) information, identifying anomalies and patterns that may indicate causal factors (Strauch et al., 2017). Ray et al. (2023) studied the benefits of using AI to summarize and analyze aviation incident reports. The authors examined using Generative Pre-trained Transformer (GPT) model to generate incident synopsis from the incident's narratives from investigators. Kurian et al. (2020) developed an AI incident analysis model that classifies events by type and severity. The researchers combined machine learning with an incident database of 15,000, finding 75 to 90% accuracy to determine probable causes.

Predictive analytics is another critical area where AI has made significant contributions. AI can predict potential safety risks by analyzing past incidents and accident data while suggesting preventive measures. This proactive approach aligns with the Safety-II framework, which emphasizes understanding how systems succeed under varying conditions and focuses on enhancing resilience rather than solely preventing failures (Hollnagel, 2017). Zeng et al. (2022) applied the Least Absolute Shrinkage and Selection Operator (LASSO) and Long Short-Term Memory (LSTM) to analyze 138 aviation safety events. The authors found that predictive analytics models could be useful in identifying aviation safety predictors. Machine learning models can analyze historical accident data to uncover trends and correlations that might not be apparent through traditional analysis. These insights assist investigators in understanding the sequence of events leading to an accident and identifying contributing factors, such as mechanical failures, human errors, or environmental factors conditions.

Safety professionals use the concept of *Safety* as the lack of incidents and accidents (Aven, 2021). However, the absence of accidents or incidents does not describe a safety system. Therefore, a more appropriate definition incorporates the concept of freedom of unacceptable risks (Bieder, 2023). Consequently, safety can be regarded as the cumulative outcome of the choices and behaviors of all individuals capable of engaging with the operating system (Aven, 2021). In the literature, Safety-I is described as the traditional approach to safety that focuses on preventing negative outcomes (Hollnagel, 2018). In practice, this means organizations focus on reactive measures: investigating incidents for root causes, counting and reducing error rates, and ensuring compliance with procedures (Hollnagel, 2018). Safety-I aims to achieve a centralized approach to safety where the organization and people are aligned on the definitions of what is safe (Provan et al., 2019). The limitations of Safety-I in complex socio-technical systems were explored by Ham (2021). The author explained that the reactive nature of Safety-I and the assumption of bi-modal outcomes fail to recognize and prevent safety events in complex industries. Similarly, Safety-I does not understand success, focusing only on failures. By concentrating solely on failures, Safety-I may not fully explain why the same system that usually works occasionally breaks (Hollnagel, 2018).

Safety-II then emerges as a contemporary shift in paradigms that complements Safety-I. Going further from focusing on failures, Safety-II focuses on the ability of the system to overcome safety challenges under varying or complex conditions (Shimizu & Nishigori, 2020). Safety-II may be described as a resilient risk control model that diverges from reactive analytic procedures to proactive adaptive and co-adaptive models & measurements to predict and identify process disruptions and variability (Cooper, 2020). Safety-II enhances system resilience by emphasizing the *"presence of safety rather than the absence of safety"* (McCarthy et al., 2020, p. 369). The Safety-II approach to safety aims to provide guided flexibility, allowing the people and organization to overcome unexpected events (Provan et al., 2019). Safety-II complements Safety-I by learning from the conditions where the system is able to manage unexpected events and regain safety (Cutchen, 2020). Aviation safety has evolved from reactive to proactive and predictive to meet the requirement for intelligent and refined safety management (Zeng et al., 2022).

Artificial intelligence (AI) is revolutionizing the methodology of accident analysis investigations to continue advancing aviation safety. AI-driven risk assessment tools are capable of simulating different accident scenarios, enabling investigators to explore various hypotheses and identify the most likely causes. These simulations provide a deeper understanding of complex interactions between human, technical, and environmental factors. The case study presented in the Findings section of the Aviation Human Factors Analyst Open AI application (https://chatgpt.com/g/g-67681ccba4908191bd5e8f932258cf4c-aviation-safety-analyst) provides an overview of the implementation of the literature review findings of AI capabilities in-flight safety—incident/accident investigations.

FINDINGS

The "*Aviation Safety Analyst*" is an innovative experimental custom GPT designed to revolutionize aviation safety and accident investigation. This sophisticated AI-driven tool is tailored to support aviation professionals, researchers, and investigators by offering comprehensive analytical capabilities for various established accident analysis frameworks. Currently, it focuses on performing Human Factors Analysis and Classification System (HFACS), BowTie Analysis, AcciMap, Causal Analysis based on System Theory (CAST), Root Cause Analysis (RCA), and the Functional Resonance Analysis Method (FRAM).

The *Aviation Safety Analyst* exhibits high reliability in structuring and processing complex data inputs to generate detailed, evidence-based analyses. It is designed to minimize cognitive biases, provide consistent results, and adapt to diverse aviation scenarios. Its data-driven approach ensures objectivity, while its integration of multiple analytical frameworks enhances comprehensive safety evaluations.

The FAA, EASA, and ISASI play crucial roles in shaping the guidelines for AI's application in aviation safety. The FAA emphasizes rigorous safety assessments and validation procedures before AI technologies are integrated into operational environments. EASA's AI Roadmap 2.0 outlines a comprehensive approach to AI governance, advocating for explainable, transparent, and ethically sound AI systems in aviation (EASA, 2023). ISASI complements these regulatory frameworks by promoting investigative methodologies that leverage AI to enhance data accuracy and decision-making.

Annex 13 to the Convention on International Civil Aviation provides the international standards for aircraft accident and incident investigations. It underscores the importance of factual data collection, analysis, and unbiased reporting—principles that align seamlessly with AI's capabilities. AI can automate data extraction from flight recorders and operational logs, increasing the efficiency and precision of investigations. Its role in simulating accident scenarios and predicting causal factors aligns with Annex 13's objective to prevent future occurrences (ICAO, 2020).

- **The Shift from Safety-I to Safety-II in AI-Driven Investigations**

Safety-I focuses on understanding failures to prevent recurrence, while Safety-II emphasizes system resilience and the capacity to succeed under varying conditions. AI supports both paradigms: It enhances Safety I by identifying root causes of failures through data analytics and promotes Safety II by monitoring real-time data to foresee potential disruptions and adapt strategies proactively (Hollnagel, 2017). This dual capability fosters a comprehensive safety culture that reacts to incidents and anticipates and mitigates risks.

AI's strength lies in its data-driven approach. Machine learning algorithms analyze vast datasets to uncover patterns that might elude human investigators. These patterns help reconstruct accident sequences, understand human-machine interactions, and evaluate the effectiveness of safety interventions. AI-driven predictive models can simulate various accident scenarios, providing insights into how different factors could have influenced outcomes (EASA, 2023).

Human factors are critical in aviation accidents, and AI significantly enhances this analysis. Natural Language Processing (NLP) tools analyze cockpit voice recordings and communication logs to detect signs of stress, cognitive overload, or miscommunication among crew members. This capability provides investigators with a deeper understanding of the human elements involved in accidents, leading to more targeted safety recommendations (Kirwan, 1994).

Finally, the presented *Aviation Safety Analyst* application embodies a significant advancement in aviation safety analysis. Integrating diverse, robust analytical methods into a single AI-powered platform enhances the efficiency, depth, and accuracy of aviation accident and incident investigations. This tool not only aids in understanding past events but also contributes to proactive safety management and risk mitigation strategies.

CONCLUSION

AI represents a transformative force in aviation accident investigations, offering capabilities that enhance data analysis, predictive modeling, and decision support. By aligning with international regulatory frameworks and embracing Safety I and II principles, AI can significantly improve aviation safety outcomes. However, addressing ethical concerns, ensuring data integrity, and fostering a culture of innovation are critical to maximizing AI's impact in this field.

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