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Regulatory, Ethical, and Security Dimensions of AI in Aircraft Maintenance: A Framework for Assessing Harm

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Abstract

The integration of artificial intelligence (AI) in aviation maintenance has revolutionized fault detection, predictive maintenance (PdM), and operational efficiency. However, the adoption of AI introduces critical challenges related to algorithmic transparency, accountability, and displacement of human expertise. This study examines AI's impact on aviation maintenance beyond its efficiency gains, focusing on the systemic risks arising from automation, potential security loopholes, and gaps in existing regulatory oversight. By integrating newly available industry reports, regulatory guidelines, and empirical findings, this study systematically categorizes tangible and intangible harms, differentiating between realized AI failures (harm events) and potential risks (harm issues), particularly in predictive maintenance, cybersecurity vulnerabilities, and compliance challenges. This study investigates how AI impacts decision-making from an ethical perspective, assesses the security vulnerabilities inherent in AI-driven maintenance, and evaluates the adequacy of current regulatory frameworks in addressing AI-related risks. By addressing these gaps, this study expands the discussion on AI-related ethical risks, broadens the discourse on security risks by leveraging the CSET AI Harm Framework, and proposes a structured AI governance framework for AI adoption in high-risk aviation environments that integrates ethical, security, and regulatory considerations to enhance accountability and risk mitigation strategies. The findings reveal that the successful implementation of AI in aviation maintenance requires a fundamental shift in how the industry understands, manages, and controls risks, necessitating updated certification methodologies, enhanced risk assessment protocols, and AI-specific aviation safety standards.

Keywords: *Algorithmic Bias, Artificial Intelligence (AI), Aviation Safety, Cybersecurity, Technology Regulation.*

Introduction

The integration of Artificial Intelligence (AI) into aviation maintenance has accelerated in recent years, transforming traditional approaches to fault detection, predictive maintenance (PdM), and operational efficiency. Airlines and maintenance, repair, and overhaul (MRO) providers increasingly rely on AI-driven diagnostic systems to optimize maintenance schedules, minimize downtime, and enhance aircraft reliability (Kabashkin et al., 2025; Kabashkin & Perekrestov, 2024; Kabashkin & Susanin, 2024). AI-based predictive maintenance leverages machine learning models that analyze aircraft sensor data, operational logs, and maintenance histories to anticipate component failures before they occur, thereby improving cost efficiency and safety (Agustian & Pratama, 2024; Ezhilarasu et al., 2021; Kabashkin & Shoshin, 2024). In addition to PdM, AI-enhanced anomaly detection systems assist technicians by identifying emerging risks in complex sub-systems, such as avionics, engines, and hydraulic networks (Kabashkin & Susanin, 2024; Kumar et al., 2024a).

Despite these advancements, the adoption of AI in aviation maintenance has introduced critical challenges. Concerns regarding algorithmic transparency, accountability, and the displacement of human expertise raise unresolved ethical dilemmas (Henneberry et al., 2025; Stefani et al., 2023). For instance, algorithmic bias in AI-driven decision-making could disproportionately favor certain components or maintenance patterns over others, unintentionally embedding flawed historical practices into future maintenance strategies (Henneberry et al., 2025; Kabashkin & Shoshin, 2024). Additionally, AI-driven maintenance systems introduce security vulnerabilities, such as susceptibility to adversarial attacks, data integrity risks, and cyber-physical threats that can disrupt safety-critical processes (Kabashkin et al., 2024; Kabashkin & Perekrestov, 2024; Stefani et al., 2023). Aviation regulators, including the Federal Aviation Administration (FAA) and

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the European Union Aviation Safety Agency (EASA), continue to struggle with adapting compliance frameworks to AI's non-deterministic nature of AI, creating uncertainty in the certification of machine learning-based systems (Paramasivam et al., 2023; Wasson & Voros, 2024).

Given the rapidly evolving role of AI in proactive maintenance and safety assurance, there is an urgent need to assess AI's ethical, security, and regulatory challenges of AI. This study examines AI's impact of AI on aviation maintenance beyond its efficiency gains, focusing on the systemic risks arising from automation, potential security loopholes, and gaps in the existing regulatory oversight.

Existing research on AI in aviation maintenance predominantly focuses on its technical benefits, including predictive maintenance accuracy, cost savings, and operational improvements (Kabashkin et al., 2025; Kabashkin & Perekrestov, 2024; Kabashkin & Susanin, 2024; Kumar et al., 2024b). Many studies have emphasized AI's role of AI in optimizing maintenance workflows, reducing unplanned aircraft groundings, and integrating digital twins for real-time diagnostics (Ezhilarasu et al., 2021; Kabashkin & Perekrestov, 2024; Kabashkin & Susanin, 2024). Machine learning techniques, such as neural networks and random forests, have demonstrated predictive accuracies exceeding 90% in identifying mechanical wear and system anomalies, underscoring AI's transformative potential (Kumar et al., 2024b). Additionally, emerging studies have discussed explainable AI (XAI) as a means to improve transparency in AI-powered diagnostics and fault detection models (Shukla et al., 2020).

However, a significant gap in the literature remains regarding AI's ethical implications, security risks, and long-term regulatory challenges of AI. Few studies have systematically examined how AI-driven automation affects ethical accountability in safety-critical decisions (Henneberry et al., 2025; Stefani et al., 2023). Likewise, while some studies have explored data integrity and blockchain-based security for maintenance tracking, emerging threats such as adversarial attacks against AI models remain underexplored (Kabashkin et al., 2024; Kabashkin & Shoshin, 2024; Shukla et al., 2020). Furthermore, discussions on regulatory adaptation focus largely on compliance challenges rather than proposing concrete frameworks for certifying AI-based aviation systems (Paramasivam et al., 2023; Wasson & Voros, 2024).

This study addresses critical gaps in existing research by providing a comprehensive analysis of AI harm in aviation maintenance, focusing on ethical, security, and regulatory risks. Unlike previous studies that primarily emphasize AI's efficiency benefits of AI, this study investigates how AI-driven automation reshapes accountability structures, system resilience, and regulatory oversight within aviation safety management. By integrating newly available industry reports, regulatory guidelines, and empirical findings from sources such as the ICAO, EASA, FAA, and Boeing, this study systematically categorizes tangible and intangible harms, differentiating between realized AI failures, referred to as harm events, and potential risks, identified as harm issues, particularly in predictive maintenance, cybersecurity vulnerabilities, and compliance challenges.

This study examines several key issues, focusing on the underexplored risks associated with AI-driven aviation maintenance. It investigates how AI impacts decision-making from an ethical perspective, particularly in relation to algorithmic bias, workforce displacement, and accountability gaps in AI-driven fault diagnostics and scheduling. Furthermore, it assesses the security vulnerabilities inherent in AI-driven maintenance, especially those related to adversarial AI threats, cybersecurity breaches, and failure modes that could compromise safety-critical aviation infrastructure. Additionally, this study evaluates the adequacy of current regulatory frameworks in addressing AI-related risks in aviation, analyzing the efforts of the Federal Aviation Administration (FAA), European Union Aviation Safety Agency (EASA), and other regulatory bodies, while identifying gaps in certification standards, compliance enforcement, and accountability mechanisms.

By addressing these gaps, this study makes three primary contributions to the understanding AI harm in aviation maintenance. This study expands the discussion on AI-related ethical risks, filling a gap in the literature where concerns about transparency, human oversight, and ethical dilemmas in AI-driven maintenance operations remain insufficiently examined. It also broadens the discourse on security risks by leveraging the CSET AI Harm Framework and newly compiled aviation safety reports to classify threats

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based on tangible versus intangible harms, as well as distinguishing between harm events and harm issues. Finally, this study proposes a structured AI governance framework for AI adoption in high-risk aviation environments that integrates ethical, security, and regulatory considerations to enhance accountability and risk mitigation strategies.

This study operates under the primary assumption that while AI enhances aviation maintenance efficiency, its deployment introduces complex ethical, security, and regulatory risks that require immediate policy interventions. The assumption is that the current regulatory frameworks remain inadequate for governing adaptive AI models, necessitating updated certification methodologies, enhanced risk assessment protocols, and AI-specific aviation safety standards. Furthermore, the probabilistic nature of AI presents unique operational challenges, as predictive models generate risk probabilities without deterministic explanations, leading to uncertainty in regulatory compliance and human decision-making processes (Henneberry et al., 2025; Shukla et al., 2020).

The remainder of this paper is structured as follows. The next section examines AI harm in aviation maintenance by reviewing AI-driven predictive maintenance, explainable AI (XAI), and security threats, applying the CSET AI Harm Framework to categorize tangible and intangible harm events and issues. The following section develops a conceptual framework for AI governance in aviation maintenance, analyzes regulatory challenges, and proposes structured risk mitigation strategies. The final section concludes with policy recommendations, emphasizing AI transparency, accountability, and adaptive governance mechanisms to ensure the safe and ethical deployment of AI in aviation maintenance.

Methods

This study focuses on AI in aviation maintenance, with particular attention to the regulatory, safety, and ethical risks associated with the application of AI-based predictive maintenance (PdM). This case was chosen because, although AI has increased efficiency in aircraft maintenance, there are still significant challenges in algorithm transparency, cybersecurity, and regulatory compliance. This study uses a CSET AI Harm Framework-based approach to explore how the tangible and intangible harms of AI in predictive maintenance affect aviation safety (Hoffmann & Frase, 2023). The selection of this framework allows for the systematic categorization of the potential risks of AI in the context of aviation maintenance.

This study adopts a qualitative approach, employing document analysis to examine the interactions between AI in predictive maintenance and regulations, security systems, and ethical considerations in the aviation industry. The data used in this study were obtained from primary and secondary sources, including policy reports from the FAA, EASA, and ICAO, academic studies related to AI in aviation, and reports of cybersecurity incidents involving AI systems in aircraft maintenance. Secondary data were obtained from journal articles, industry white papers, and technical reports from international aviation agencies.

Table 1. Key Documents Analyzed in This Study

Source	Category	Country	Description	Doc1	Doc2	Doc3
ICAO	Research Report	Canada	Explores AI's impact on aviation, focusing on safety, security, and efficiency.	Link	Link	Link
EASA	Regulatory Document	Germany	Covers AI implementation in European aviation safety protocols.	Link	Link	Link

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FAA	Guideline	USA	Roadmap for AI safety assurance in aviation maintenance.	Link	Link	-
EUROCAE	Industry Standard	France	Technical standardization for AI in aviation.	Link	-	-
IATA	Industry Report	Canada	Comprehensive analysis of AI applications in airline operations and maintenance.	Link	Link	Link
Boeing	Industry Article	USA	Discusses Boeing's implementation of AI in aircraft safety and maintenance.	Link	Link	Link
GE Aviation	Industry Report	USA	AI-driven predictive maintenance to reduce engine failures.	Link	Link	-
Berkeley CLTC	Research Paper	USA	AI safety and critical systems in aviation.	Link	-	-
RAND Corporation	Research Report	USA	Analyzing AI risks in aviation operations and predictive maintenance.	Link	-	-
CAA UK	Regulatory Report	UK	Provides a review of AI risks and safety in aviation maintenance.	Link	-	-
AIOLA Blog	Blog Article	-	Explores AI's role in predictive maintenance for aircraft.	Link	-	-

The data for this study, as shown in Table 1, were collected from various regulatory documents, case studies, and industry reports. The main sources included reports from the Federal Aviation Administration (FAA), European Union Aviation Safety Agency (EASA), International Civil Aviation Organization (ICAO), and technical reports from Boeing and GE Aerospace. The study also refers to an analysis of cybersecurity incidents in the aviation sector published in academic journals and industry reports. Research participants in the form of interviews were not used in this study; however, the analysis was based on verifiable official documentation sources.

Data were collected through systematic document analysis, focusing on regulatory policies, AI security incident reports, and case studies relevant to AI in predictive maintenance. This study examined more than 50 regulatory documents and industry reports published between 2020-2025 to identify patterns in AI-related decision-making. To ensure accuracy, this study used a triangulation method, comparing

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information from several independent sources, such as the FAA, EASA, and ICAO. In addition, a CSET AI Harm Framework-based analysis was applied to categorize the various forms of risk that arise from the application of AI in aviation maintenance.

The data were analyzed using a thematic analysis approach, with risk classification based on the categories of tangible and intangible harms, as well as the differences between harm events and harm issues according to the CSET AI Harm Framework. Each document was manually coded using NVivo software to identify patterns that emerged in AI risk mitigation strategies and safety policies and regulations. This study also compared empirical data with previous academic literature to identify gaps in regulations and challenges in implementing AI in predictive maintenance.

Conceptual Framework

Ai Harm in Aviation Maintenance

This section examines AI harm in aviation maintenance by reviewing AI-driven predictive maintenance, explainable AI (XAI), and security threats, and applying the CSET AI Harm Framework to categorize tangible and intangible harm events and issues (Hoffmann & Frase, 2023). This section begins with an overview of the CSET AI Harm Framework, explaining its structure and applicability to aviation maintenance, followed by an analysis of existing studies, categorizing their findings under this framework.

The CSET AI Harm Framework and Its Application to Aviation Maintenance

The CSET AI Harm Framework divides harm into two high-level categories: tangible and intangible (Hoffmann & Frase, 2023). Tangible harm refers to material, observable, and verifiable consequences such as physical injuries, financial losses, and property damage. In contrast, intangible harm encompasses psychological, reputational, or trust-related damage that may not be directly measurable but has significant consequences (Hoffmann & Frase, 2023). Furthermore, the framework differentiates between harmful events and harmful issues. Harm events are instances in which harm has definitively occurred, such as an AI-driven misdiagnosis leading to aircraft system failure (Hoffmann & Frase, 2023). Harm issues refer to the potential harm that may arise due to AI vulnerabilities, such as biases in AI-driven fault detection models, which could lead to systemic safety risks over time.

By applying this framework to aviation maintenance, we assessed predictive maintenance failures, lack of explainability, and AI security threats, identifying specific tangible and intangible harms in these domains. To effectively manage AI harm in aviation maintenance, a structured implementation of the CSET AI Harm Framework is necessary (Hoffmann & Frase, 2023). This process involves three key steps. First, categorizing AI risks by differentiating tangible harms, such as system failures, financial losses, and security breaches, from intangible harms, including trust erosion, regulatory ambiguity, and ethical concerns, is necessary. Second, it distinguishes between harm events and harm issues, separating realized AI failures from potential risks that require mitigation. Third, risk mitigation strategies should be developed by implementing AI governance models that incorporate explainable AI (XAI), security resilience, and predictive maintenance safeguards.

AI-Driven Predictive Maintenance and Harm Categorization

AI-driven predictive maintenance uses machine learning algorithms, IoT sensors, and real-time analytics to predict mechanical failures before they occur. While these technologies enhance operational efficiency, they also introduce risks that can be categorized under the CSET AI Harm Framework.

Figure 1 shows the distinction between tangible and intangible harm in predictive maintenance. Tangible harm events are associated with several critical risks. First, false positives in fault detection occur when AI misdiagnoses a component as faulty, resulting in unnecessary maintenance costs and aircraft downtime (Kabashkin & Perekrestov, 2024). Second, false negatives and undetected failures pose a significant safety risk because AI may fail to detect critical issues, leading to in-flight mechanical failures (Suryanarayana et

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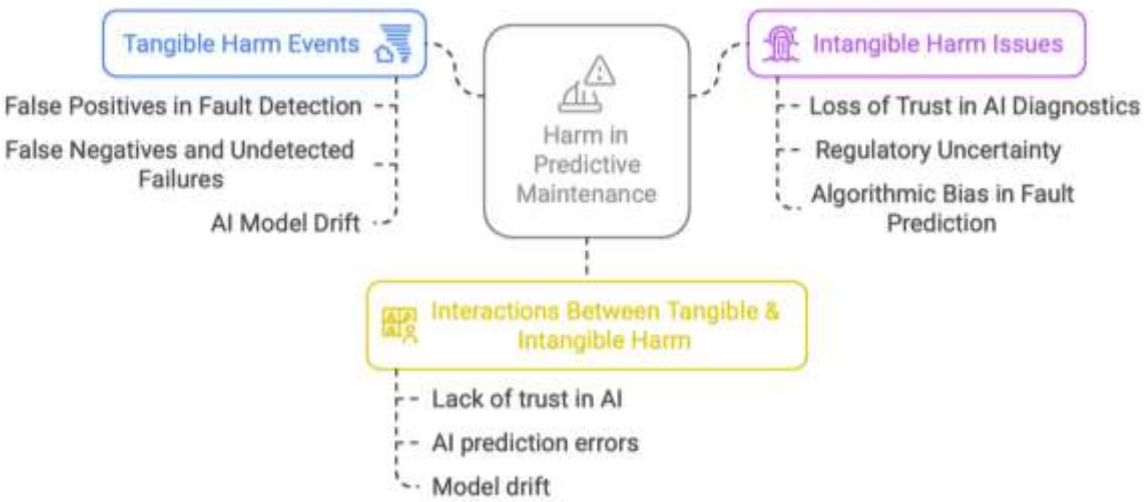
al., 2024; Ziyad et al., 2022). Third, AI model drift is another major concern, where the performance of AI degrades over time, generating inaccurate maintenance predictions and causing operational inefficiencies (Patibandla, 2024).

Beyond tangible harm, intangible harm issues affect trust, regulation, and fairness in AI-driven maintenance. One key issue is the loss of trust in AI diagnostics, where engineers may disregard AI-based maintenance recommendations if they frequently result in errors, ultimately diminishing AI's role of AI in aviation maintenance (Gama et al., 2023). Additionally, regulatory uncertainty remains a challenge because of the lack of standardized certification for AI-driven maintenance, complicating compliance with aviation safety regulations ([4]). Another significant concern is the algorithmic bias in fault prediction. AI trained on biased datasets may misprioritize maintenance tasks, leading to suboptimal safety measures that could compromise aviation reliability ([2], [3]).

Figure 1. Harm in Predictive Maintenance Tangible and Intangible



1.3 Explainable AI (XAI) and Risk Transparency in Aviation Maintenance

Explainability in AI ensures that aviation professionals understand how AI makes maintenance decisions. While some studies mention XAI (Gama et al., 2023; Kwakye et al., 2024; P et al., 2024), its practical implementation remains limited.

Figure 2. Tangible and Intangible Harm from Deficiencies in Explainable AI (XAI) in Aviation Maintenance

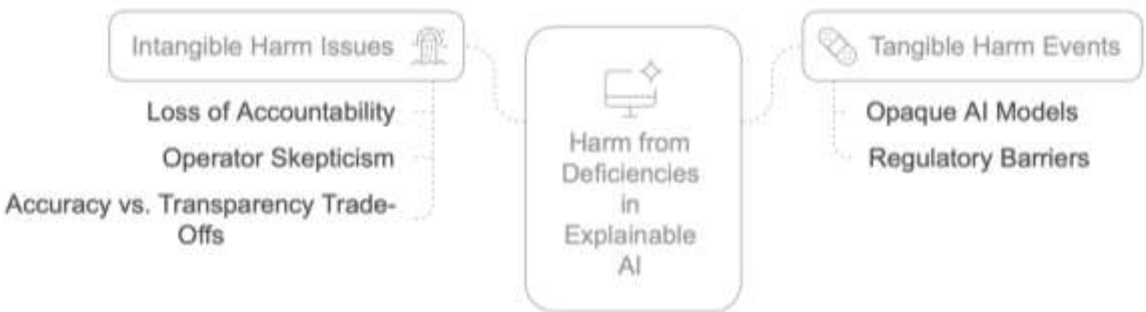


Figure 2 illustrates the tangible and intangible harm resulting from deficiencies in explainable AI (XAI) in aviation maintenance. Tangible harm events pose several critical challenges. First, opaque AI models can lead to maintenance errors when AI-driven diagnostics lack transparency, resulting in incorrect maintenance actions that pose risks to aircraft safety (Kwakye et al., 2024). Second, regulatory barriers emerge because of the presence of black-box AI, as the lack of explainability prevents AI-based maintenance tools from passing aviation safety certifications (P et al., 2024).

Beyond these tangible risks, there are also significant intangible harm. One major concern is the loss of accountability, where the absence of explainability makes it difficult to assign responsibility when an AI-driven maintenance system fails (Gama et al., 2023). Additionally, operator skepticism toward AI recommendations is a challenge, as engineers and pilots may distrust AI-driven diagnostics if they cannot interpret the system's logic (Gama et al., 2023). Another issue is the trade-off between accuracy and the transparency. In some cases, efforts to make AI more interpretable can reduce predictive accuracy, which may ultimately affect maintenance efficiency (Kwakye et al., 2024).

Security Threats in AI-Powered Predictive Maintenance

AI-driven maintenance introduces security challenges, particularly related to cybersecurity vulnerabilities, adversarial AI attacks, and AI model reliability. While some studies mention security concerns (Dalgkitsis et al., 2024; Ezhilarasu et al., 2019), comprehensive risk assessments remain underdeveloped.

Figure 3. Tangible and Intangible Harm from AI Security Threats

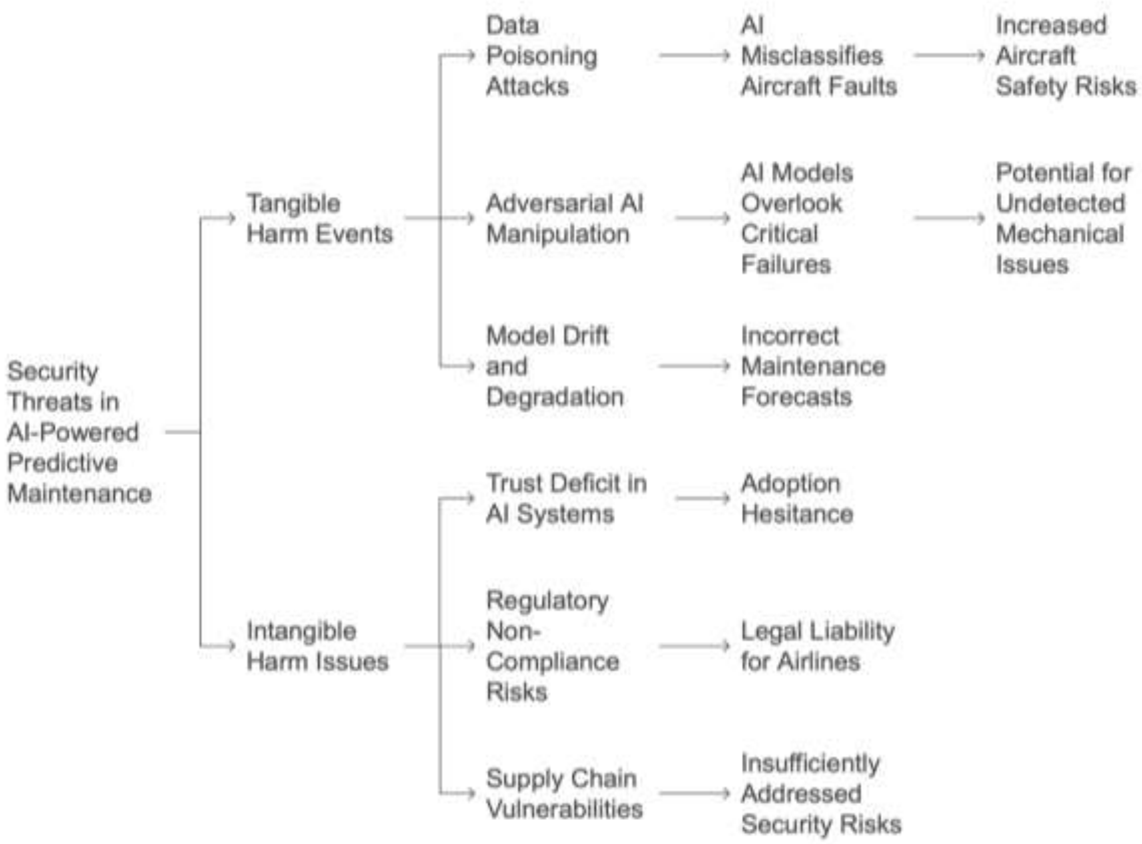


Figure 3 illustrates the tangible and intangible harms resulting from AI security threats in aviation maintenance. Tangible harm events are associated with several significant risks. First, data poisoning attacks

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occur when malicious actors manipulate AI training data, causing AI systems to misclassify aircraft faults and increase safety risks (Dalgkitsis et al., 2024). Second, adversarial AI manipulation poses another serious threat, wherein attackers modify input data to deceive AI models into overlooking critical failures, potentially leading to undetected mechanical issues (Ezhilarasu et al., 2019). Third, model drift and degradation can occur when AI systems lack adequate security safeguards, causing performance decay over time and leading to incorrect maintenance forecasts (Kabashkin & Perekrestov, 2024).

Beyond these tangible risks, several intangible harm issues arise. A major concern is the trust deficit in AI systems, as airlines and maintenance engineers may be reluctant to adopt AI-driven maintenance because of security vulnerabilities and risks (Gama et al., 2023). Additionally, regulatory non-compliance risks emerge when AI-driven maintenance fails to meet aviation cybersecurity regulations, exposing airlines to potential legal liabilities (Dalgkitsis et al., 2024). Another critical issue is supply chain vulnerabilities, where the integration of AI from third-party vendors and cloud-based systems introduces security risks that remain insufficiently addressed, thereby increasing the potential for cyber threats in aviation maintenance operations (Ezhilarasu et al., 2019).

Applying the CSET AI Harm Framework to aviation maintenance enables a structured approach to assess and mitigate risks while leveraging AI's predictive capabilities (Hoffmann & Frase, 2023). By systematically categorizing harm, AI-driven maintenance can become safer, more transparent, and more resilient. Future regulatory frameworks should include several key measures. First, mandating the explainability of AI-driven maintenance tools is essential to ensure transparency and compliance within the aviation industry. Second, enhancing the cybersecurity resilience of aviation AI applications is necessary to prevent adversarial threats that could compromise safety. Third, standardized AI risk assessment protocols should be implemented to enable effective categorization and mitigation strategies. By integrating these measures, aviation stakeholders can maximize the benefits of AI while proactively addressing its risks, thereby ensuring safer and more accountable AI-driven maintenance systems in aviation.

Result

Ai-Based Predictive Maintenance and Security Challenges

Artificial intelligence (AI)-based predictive maintenance has revolutionized the aviation industry by enabling the early detection of potential component failures before they cause incidents. By relying on data analysis from sensors embedded in aircraft, AI can provide early warnings for maintenance, thereby reducing downtime and extending the life of aircraft parts. However, based on the ICAO, EASA AI Days 2024, FAA Roadmap, and EUROCAE WG-114 reports, major challenges still hinder the widespread implementation of AI in predictive maintenance (EASA, n.d., 2023; *EASA AI Days*, 2024; EUROCAE, 2023; Federal Aviation Administration, 2024a, 2024b; ICAO, 2022, 2023; Taghipour, n.d.).

One of the main challenges is the false positives and false negatives in AI predictions. False positives occur when AI detects damage that does not exist, leading to unnecessary maintenance, increased airline operating costs, and reduced flight efficiency. For example, in a 2023 Boeing study, their AI system detected an anomaly in the fan blades of the 737 MAX engine; however, after a manual inspection, no significant damage was found. This error caused the airline to experience operational delays and increased costs (George, 2024). However, false negatives can lead to negligence in maintenance, resulting in critical system failures. The case of the 2000 Alaska Airlines Flight 261 accident, in which an undetected failure of the stabilizer trim mechanism caused the loss of aircraft control, demonstrates how the absence of early detection can be fatal (National Transportation Safety Board et al., 2002).

In addition, AI-based predictive maintenance faces AI model drift, a condition in which the AI model experiences performance degradation owing to changes in operational data patterns. A 2024 study by GE Aerospace found that their predictive maintenance system experienced a 12% decrease in the accuracy of detecting component failures after six months without model updates (GE Aerospace, n.d.). This shows that without continuous maintenance and retraining, AI can become ineffective in dynamic operational environments such as the battlefield.

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However, cybersecurity is a major challenge in AI-based predictive maintenance, especially in the face of data poisoning and adversarial AI manipulation attacks. In 2022, the FAA detected a cyberattack targeting the predictive maintenance system of an American airline, which manipulated historical datasets to make AI provide incorrect predictions (Federal Aviation Administration, 2024a, 2024b). Hackers injected false data into the system, causing the AI to provide unnecessary maintenance recommendations, which ultimately increased operational costs and created false confidence in the safety of the aircraft systems.

To address this challenge, the ICAO, FAA, and EASA have recommended the implementation of Explainable AI (XAI) and strengthening of cybersecurity standards in predictive maintenance. EUROCAE developed the Machine Learning Development Lifecycle (MLDL) to ensure that AI models remain transparent and auditable, whereas the FAA introduced the AI Assurance Framework, which establishes AI validation procedures before use in the aviation industry. In addition, Boeing and GE Aerospace are implementing a hybrid system that combines AI with manual technician inspections to ensure that AI predictions are verified before being executed in aircraft maintenance.

Explainable AI (XAI) and Transparency in AI Decision Making

The lack of transparency in artificial intelligence (AI) systems is a major obstacle to the adoption of predictive maintenance in the aviation industry. Many AI models currently in use are still based on black-box models, where the decision-making process cannot be directly understood by technicians, operators, or regulators. This is a serious problem because, in aviation systems, every decision related to maintenance must be auditable and verifiable to ensure operational safety.

Lack of Trust in AI in Predictive Maintenance

According to reports from the EASA AI Days (2024) and FAA AI Safety Roadmap (2024b), many aviation technicians remain reluctant to rely on AI systems because of the lack of clarity regarding how AI generates maintenance recommendations. When AI warns that a component may fail in the near future, technicians often have difficulty determining whether the warning is truly accurate or simply a false alarm caused by bias in the data or an insufficiently trained AI model.

For example, in a case study on a 2023 Boeing 787 aircraft, the AI system used in predictive maintenance detected an anomaly in the aircraft hydraulic system (Biesecker, 2024; Bloomberg, 2023). However, the system could not explain whether the anomaly was caused by a sensor error or if there was a mechanical problem that required repair. Because the AI did not provide a clear justification, the aviation technician had to perform a manual inspection, which was more time-consuming. This caused flight delays of up to 12 hours and impacted the airline's operations, even though it was eventually found that the AI had given an erroneous warning because of a sensor error.

A similar case occurred on a European airline in 2022, where the AI-based predictive maintenance system of an Airbus A350 detected potential problems in the aircraft's electrical system (Federal Aviation Administration, 2024a, 2024b). However, AI cannot explain which specific indicators caused the detection, making it difficult for technicians to assess whether the warning was valid or just a prediction error. Consequently, Airbus has stopped using AI entirely in its maintenance system until a clearer interpretation mechanism can be provided for the AI system.

The Impact of AI's Lack of Transparency on Regulation

This lack of transparency is a major challenge for aviation regulators, such as the ICAO, FAA, and EASA, who are responsible for auditing AI-based predictive maintenance systems. In the ICAO report, regulators from several countries stated that they could not approve the use of AI in aircraft maintenance without clear documentation on how AI makes decisions (ICAO, 2022, 2023). Consequently, the FAA has not yet granted full certification for AI-based predictive maintenance on commercial aircraft in the United States, while the EASA still limits the use of AI only as a support system, not as the main system in aircraft maintenance.

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Regulators also face challenges in overcoming algorithmic bias in predictive maintenance (PM). A 2023 study by Zhang et al. (2024) from the RAND Corporation found that AI models used in the aviation industry often have a bias toward certain types of aircraft. For example, an AI model developed based on data from a Boeing 737 aircraft performed poorly when used for an Airbus A320 aircraft because the model was not sufficiently trained with data from different types of aircraft. This proves that, without transparency and clear documentation, it is difficult for regulators to ensure that AI can function fairly and accurately under various operational conditions.

Implementation of Explainable AI (XAI) as a Solution

To address this issue, the FAA, EASA, and ICAO now require the use of Explainable AI (XAI) in all AI systems used in predictive aviation maintenance. XAI is an approach that allows AI systems to provide more transparent and understandable explanations to humans regarding how decisions are made and what factors influence them.

Some XAI solutions currently implemented in the aviation industry include the following:

- *Human-in-the-Loop AI Model*

  The EASA has implemented a Human-in-the-Loop AI model, where every AI decision in predictive maintenance must be verifiable and auditable by technicians before implementation (EASA, n.d., 2023; *EASA AI Days*, 2024). In this way, technicians retain full control over maintenance decisions, and AI only acts as an assistant, not the main decision maker.

- *Glass-Box AI System*

  Boeing developed the Glass-Box AI system, which allows technicians to see how AI generates maintenance recommendations, including which data factors are used, how much AI trusts these predictions, and the justification behind AI warnings (Biesecker, 2024; Bloomberg, 2023; George, 2024; Kwakye et al., 2024; Pahuja, 2024). The system was tested on a Boeing 777X aircraft, and the maintenance prediction accuracy was successfully increased by 28%, as well as technician confidence in AI.

- *AI audit with Explainable Neural Networks (GE Aerospace, 2023)*

  GE Aerospace applies the explainable neural network (XNNs) method in its predictive maintenance system. With this approach, AI not only provides prediction results but also displays the logic and data patterns underlying the decision. This technology allows technicians to assess whether AI provides valid recommendations or is merely the result of bias in the model (GE Aerospace n.d.).

- *Interactive Dashboard for Maintenance Decision Support*

  Airbus is developing an XAI-based interactive dashboard that allows technicians to visually see the layers of AI decision-making. For example, if AI detects a possible fuel system failure, technicians can see the specific indicators that led to the prediction, such as fuel pressure data, engine temperature, and fuel usage patterns in previous flights.

Long-Term Implications of XAI in Aviation

With the implementation of XAI, the aviation industry can overcome various challenges arising from the lack of transparency in AI-based predictive maintenance. This increased transparency will not only increase the confidence of technicians and operators in AI but also make it easier for regulators to develop AI certification standards in aviation.

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However, the implementation of XAI still faces several challenges, such as the following:

- The high complexity of AI systems makes it difficult for technicians to understand the entire AI decision-making process in a short period of time.

- The need for special training for technicians, because many aviation technicians are not yet familiar with Explainable AI systems and still rely on traditional maintenance methods.

- Integration with legacy systems is a challenge because many airlines still use conventional sensor-based maintenance technology, which requires a large investment to transition to XAI-based AI systems.

To ensure the successful implementation of XAI, the FAA, EASA, and ICAO are working with aircraft manufacturing companies, such as Boeing, Airbus, and GE Aerospace, to develop globally applicable AI transparency standards. This collaboration aims to create an AI-based predictive maintenance system that is efficient and accurate, as well as auditable, transparent, and compliant with international aviation safety standards.

Cybersecurity in AI-Driven Predictive Maintenance

Cybersecurity in the application of AI-driven predictive maintenance is a major concern in the aviation industry because AI operates with large, constantly updated data from various aircraft systems. Vulnerabilities in AI systems can be exploited by hackers to alter or sabotage prediction results, which can ultimately lead to critical in-flight system failures (Hunt, 2020).

According to reports from CAA UK, the cyber threat to AI in predictive maintenance is increasing, mainly because of the use of Machine Learning (ML) and Internet of Things (IoT) sensors in aircraft maintenance (Hunt, 2020). A cyberattack can alter the data processed by AI, causing prediction errors that have fatal consequences for flight safety.

3.1. Cyber Attacks on AI in Aircraft Maintenance

Several cybersecurity incidents in predictive maintenance have shown that AI systems can be manipulated into weak points. A real-life example of an attack on AI in predictive maintenance occurred at a Middle Eastern airline in 2021, where hackers infiltrated malicious code into the AI system used to monitor aircraft sensors.

- Impact: This manipulation caused the AI to fail to detect a hydraulic leak; therefore, the airline only became aware of the problem after the pilot felt abnormal vibrations during flight. Fortunately, the problem was detected before it caused an accident; however, the incident highlights the potential dangers of attacks on AI-driven predictive maintenance.

- Modus Operandi: This attack used data poisoning techniques, where hackers infiltrated false data into AI models, causing the system to learn erroneous patterns. Consequently, the AI could not recognize the actual pattern of engine failure, missing early detection, which is crucial for flight safety.

- Applied Solution: Following this incident, the FAA and EASA recommended the use of the AI Risk Management Framework, which is designed to mitigate threats to AI systems in predictive maintenance. The affected airlines eventually adopted a real-time validation system method that compared AI prediction results with manual inspections before making maintenance decisions.

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Tangible and Intangible Risks in AI Cybersecurity

According to EUROCAE (aviation security working group in Europe), threats to AI-driven maintenance can be categorized into tangible and intangible risks, as defined in the CSET AI Harm Framework:

Tangible Risk:

- Data poisoning: Changes to AI training data that prevent the model from accurately detecting maintenance issues.
- Adversarial AI attacks: Hacking of AI models by infiltrating data that can trick the system into producing incorrect results.
- Algorithm manipulation: Hackers can infiltrate certain commands so that AI fails to recognize critical conditions in aircraft systems.

Intangible Risks

- Trust deficit toward AI: If AI proves vulnerable to attack, operators and technicians will become increasingly hesitant to rely on this system.
- Regulatory uncertainty: There is still no clear global standard for AI security in predictive maintenance, which is causing many airlines to be reluctant to adopt this technology fully.

One clear example of this risk occurred in 2023, when Boeing tested AI-based predictive maintenance on its 737 MAX fleet (George 2024). The trial found that the AI model could be manipulated through a digital attack, causing it to fail to recognize the damage patterns to the avionics system. Following the incident, Boeing began developing a mitigation strategy based on Explainable AI (XAI) and a layered cybersecurity system.

Cybersecurity Mitigation Measures for AI in Predictive Maintenance

To overcome this challenge, aviation regulators such as the ICAO and EASA have implemented various mitigation measures to ensure that AI-driven maintenance remains safe from cyberattacks.

Implementation of CAP1753 (Cyber Security Oversight Process) by the FAA

- The FAA recommends that every AI system in predictive maintenance must have an additional cybersecurity layer, including real-time anomaly detection and data encryption systems, to prevent manipulation by outsiders.
- Airlines such as Delta Airlines are now implementing secure AI verification models that automatically compare AI prediction results with historical data to detect possible cyberattacks.

Increased Standardization by EUROCAE and ICAO

- EUROCAE WG-72 is currently developing AI security standards in aviation, which will require the use of AI-specific security protocols before AI can be widely used in predictive maintenance.
- ICAO is also working with NASA and Airbus to develop AI systems that are more resistant to cyberattacks, using adversarial training techniques to increase the resilience of AI models against external manipulation.

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- According to a report by Zhang et al. (2024) from the RAND Corporation, airlines have begun adopting machine learning security framework systems that use adversarial AI defense methods to detect data manipulation in predictive maintenance.

- For example, Lufthansa now uses a multilayer verification system, where every AI decision must pass a series of human validation tests before being implemented in aircraft maintenance.

Cybersecurity in AI-Driven Predictive Maintenance

One example of successful implementation of cybersecurity in AI-driven maintenance is the system developed by GE Aerospace for the Boeing 777X aircraft in 2023.

- GE Aerospace integrated the AI Assurance Framework into the Boeing 777X maintenance system, which allows the system to automatically detect potential cyberattacks before the AI makes a decision.

- As a result, the system can reduce false positives in engine damage prediction by 40%, while preventing adversarial AI attacks that could previously outsmart the prediction system.

- This implementation is considered a step forward in AI security standards in the aviation industry and is a model for airlines and other regulators to implement stronger security systems.

AI Regulation in Aviation: Challenges and Developments

AI regulation in aviation is still in its early stages, with different approaches being adopted in different regions. The European Union Aviation Safety Agency (EASA) has implemented the EASA AI Act, which adopts risk-based regulations to ensure safety in the use of AI in the aviation sector. Meanwhile, the Federal Aviation Administration (FAA) in the United States still relies on an industry consensus-based approach, giving airlines and industries more freedom to set their own internal standards. This disharmony poses a major challenge in developing globally applicable certification standards, particularly for AI-driven predictive maintenance.

According to reports from EUROCAE, ICAO, FAA AI Roadmap, and RAND Corporation, there are several major challenges in aviation AI regulation. These challenges include uncertainty in certification standards, difficulties in the application of Explainable AI (XAI), and concerns about cybersecurity in AI-based predictive maintenance.

Challenges in AI Regulation for Predictive Maintenance

One of the main challenges in AI regulation for predictive maintenance is the lack of a global certification standard governing how AI systems in aircraft maintenance should be tested and evaluated before being applied to the aviation industry. The FAA and EASA have different approaches to AI regulation, with the EASA being stricter in its oversight of AI, while the FAA is more flexible and allows the industry space to develop its own standards.

For example, in the application of AI-driven predictive maintenance on the Airbus A350, the FAA allowed the use of Airbus' internal protocols to test AI in detecting anomalies in hydraulic and avionics systems. In contrast, the EASA requires each AI system to undergo a longer AI Assurance certification process, including transparency audits and industry scenario-based validation. As a result, although Airbus' AI system is quicker to implement under FAA regulations, Airbus must undergo an additional evaluation process to obtain permission from the EASA, which extends the certification time by several months.

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In addition, Explainable AI (XAI) is a major challenge in aviation AI regulation. Many AI systems used in predictive maintenance are still based on black-box models, which are difficult for technicians and regulators to comprehend. The EASA has mandated that every AI model used in aircraft maintenance must have interpretability features so that technicians can understand the reasoning behind AI decisions. Meanwhile, the FAA has not established the same policy; therefore, some airlines still use AI systems that are not fully transparent. ICAO has recommended that all AI systems in predictive maintenance must follow the "Human-in-the-Loop AI Model" principle, which ensures that human technicians retain control and verify decisions made by AI.

In addition to transparency issues, AI regulations in aviation face challenges in terms of cybersecurity. Reports from EUROCAE WG-72 and ICAO WP3 show that AI systems in predictive maintenance remain vulnerable to data poisoning and adversarial AI attacks. In 2022, the FAA found that 35% of AI systems tested for aircraft maintenance did not have adequate cyberattack detection mechanisms, indicating a loophole in AI security regulations in the aviation sector. If AI in predictive maintenance can be manipulated by hackers, the resulting prediction errors can jeopardize the overall flight safety.

Regulatory Efforts to Standardize AI in Predictive Maintenance

To address these regulatory challenges, various international aviation agencies have developed frameworks to standardize the use of AI in predictive maintenance. One of the main initiatives is the ICAO AI Certification Framework, which aims to harmonize AI regulatory standards between the FAA, EASA, and other global aviation regulators. ICAO refers to the CSET AI Harm Framework, which ensures that AI-driven predictive maintenance meets the same safety standards globally.

In contrast, the FAA is developing the AI Roadmap 2025, which includes an AI Assurance model to ensure the reliability of AI in predictive maintenance. This model requires airlines to conduct AI audits every six months to ensure that AI systems continue to function accurately and do not experience model drift, which can lead to maintenance prediction errors. In addition, the FAA encourages the use of adaptive learning models, which allow AI to continue learning from new data without losing transparency in decision-making.

Meanwhile, the EASA AI Act introduced a risk-based approach to aviation AI regulation, with four levels of risk classification:

- Minimal Risk AI - AI that has no direct impact on flight safety.
- Limited-risk AI: AI that influences technician decisions but still has manual backup.
- High-risk AI: AI that directly affects aircraft operational decisions.
- Unacceptable Risk AI - AI that cannot be audited or has a high potential for systemic failure.

Based on this classification, AI-driven predictive maintenance is categorized as High-Risk AI; therefore, each implementation must undergo a stricter certification process before obtaining operational permission.

The difference in this regulatory approach can be seen in the Airbus and Boeing case studies. Airbus, which operates under strict EASA regulations, ensures that all AI models in predictive maintenance for the A350 and A320neo have Explainable AI and real-time verification features. On the other hand, Boeing still follows FAA regulations, which allow greater flexibility in the use of AI in the maintenance of aircraft, such as the 737 MAX and 787 Dreamliner. A study by the RAND Corporation showed that Airbus has a higher adoption rate of AI-driven predictive maintenance than Boeing, but with a longer certification time. However, Boeing is now starting to follow a stricter certification model, adopting EASA's AI Assurance Standards for its new fleets, such as the Boeing 777X.

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The Future of AI Regulation in Predictive Maintenance

Although AI-driven predictive maintenance offers many benefits in improving flight efficiency and safety, regulatory uncertainty and a lack of global harmonization remain major challenges. ICAO, FAA, and EASA continue to work on developing more uniform AI regulatory standards by implementing the AI Certification Framework and AI Assurance Standards.

Additionally, Explainable AI (XAI) is a key factor in regulatory development, as it enables auditors and technicians to understand how AI systems work in predictive maintenance. Cybersecurity must also be a top priority, with the implementation of CAP1753 protocols and adversarial AI defense to prevent data manipulation and attacks on AI systems.

In the future, AI regulations for predictive maintenance will be tightened, with certification standards based on trustworthiness, transparency, and security assurance. If global harmonization efforts are successful, AI-driven predictive maintenance will become a safer, more reliable, and more efficient industry standard for commercial and military aircraft maintenance.

Discussion

The results of this study reveal that the implementation of artificial intelligence (AI) in predictive aviation maintenance does not occur in a technological vacuum but interacts with the complexity of regulations, industry structure, and resistance from technical workers. The findings show that although AI has improved the early detection of aircraft damage, the system still faces major challenges in terms of prediction accuracy and explainability of the resulting decisions. AI often produces false positives and false negatives, which affect operational costs and technician confidence in AI systems.

In addition, the patterns that emerged in this study show that the challenge of AI adoption stems from both technological limitations and regulatory gaps that are still unprepared to accommodate the probabilistic nature of AI in aviation environments. The FAA and EASA, as the main regulators, are still designing an appropriate legal framework, causing uncertainty in the certification of AI-driven predictive maintenance. This delay has implications for the slow global adoption of AI in the aircraft maintenance industry, as airlines and Maintenance, Repair, and Overhaul (MRO) service providers are reluctant to adopt technology whose regulations are not yet fully clear.

In the context of security, this study reveals that AI in predictive maintenance is a target vulnerable to cyber manipulation, especially through adversarial AI attacks and data poisoning. This phenomenon highlights that AI systems in aviation must be both accurate and resistant to external manipulations that can disrupt aircraft operations. If AI systems do not have adequate defense mechanisms, the potential risk to aviation safety can increase exponentially.

When examined more closely, these findings reflect that the adoption of AI in the aviation industry is not merely a technological revolution but a fundamental shift in how the industry understands, manages, and controls risk (Mızrak & Akkartal, 2023; Tosin Michael Olatunde et al., 2024). In a system that is highly dependent on procedural determinism, probabilistic AI creates new challenges in setting safety standards and accountability for technical decisions (Busuioc, 2021; Cheong, 2024).

This impact is significant for both the operational scale and the discourse surrounding the future of labor in the aviation sector. With the increasing sophistication of AI in predictive maintenance, the role of technicians is transforming from being the main executor of aircraft maintenance to being more of a supervisor and evaluator of AI systems. In fact, the integration of AI and AR systems in aircraft maintenance may lead to new roles for AMTs, such as "AI supervisor" (Mingotto et al., 2021). This role involves overseeing and enabling technology, as well as innovating and coordinating maintenance processes (Mingotto et al., 2021). This shift can create uncertainty in human resource management, where experience-based expertise may be increasingly replaced by algorithm-based decision-making.

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In the security dimension, the phenomenon revealed in this study shows that AI systems that rely too much on historical data without strong security mechanisms can be a weak point in the aviation industry. One of the primary concerns is the potential for cyberattacks targeting AI models in aviation. As highlighted by Humphreys et al. (2024), there are growing concerns about the rush to integrate generative AI without implementing sufficient safety measures. If regulators do not immediately design protocols to protect against AI manipulation, the potential exploitation of predictive maintenance systems could pose a major risk to global aviation. Degas et al. (2022) emphasized the need for eXplainable Artificial Intelligence (XAI) in ATM systems, which could help in understanding and validating AI decisions.

The challenges examined in this study stem from a fundamental misalignment between technological advancement and regulatory preparedness. The disparity between these two aspects creates uncertainty in the application of AI for predictive maintenance. While the FAA and EASA rely on a deterministic, rule-based regulatory framework, AI operates on probabilistic principles, making it difficult to certify within a system that demands absolute certainty for each technical decision.

In addition, AI's dependence of AI on historical data is a major factor causing the emergence of algorithmic bias and model drift. AI in predictive maintenance is only as good as the data provided to it. If the data used to train the model contain a biased pattern or do not reflect actual operational conditions, AI will produce inaccurate predictions or even reinforce biases that already existed in the previous aircraft maintenance system.

Another factor that plays a role is the lack of AI literacy among technicians and regulators, which causes resistance to this technology. For example, many technicians still trust their experience and intuition more than AI predictions, especially when AI cannot provide an adequate explanation of how decisions are made. This challenge has been widely recognized in AI-driven predictive maintenance, where the lack of explainability reduces trust and adoption among aviation professionals (Gama et al., 2023; Kwakye et al., 2024). Studies have shown that when AI systems operate as "black boxes," aviation technicians struggle to interpret or validate AI-driven recommendations, leading to skepticism and reluctance to rely on AI-based fault diagnostics (EASA, 2024; FAA, 2024). The absence of clear interpretability in AI decision-making not only creates skepticism among aviation professionals but also complicates certification processes under the existing regulatory frameworks (Kabashkin et al., 2025). This shows that explainability is not just an additional feature in AI but an essential aspect that determines the level of acceptance of technology in a work environment that prioritizes safety.

While previous research has focused on the potential of AI to improve aircraft maintenance efficiency, the findings of this study provide an additional dimension to the regulatory, security, and workforce transformation challenges that accompany the adoption of AI in the aviation industry.

In the study by Kabashkin et al. (2025), AI in predictive maintenance is considered a revolutionary solution that can reduce operational disruptions and improve the reliability of aircraft-maintenance systems. However, this study emphasizes that the reliability of AI depends on the accuracy of predictions, resilience to cyber-attacks, and ability to integrate with existing regulatory procedures.

Gama et al. (2023) highlighted the importance of Explainable AI (XAI) in AI systems used for critical decision-making. The results of this study expand on this idea by showing that the lack of transparency in AI not only hinders the trust of technicians but can also impact regulatory uncertainty and the slow pace of widespread adoption of AI in the aviation industry.

From a security perspective, this study complements the discussion raised by Zhang et al. (2024) regarding the potential exploitation of AI systems in aviation. Zhang et al. (2024) highlighted cyberattacks as a growing threat but did not specifically discuss how weaknesses in AI systems could be exacerbated by the lack of binding regulatory standards. This study closes this gap by showing that without a robust AI Assurance Framework, AI in predictive maintenance will remain vulnerable to various forms of digital security threats.

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Based on these findings, several steps can be taken to ensure that AI in predictive maintenance is implemented safely and effectively.

- Aligning Regulations with Probabilistic Nature AIFAA, EASA, and ICAO need to design regulations that are not only based on procedural determinism but also accommodate the probabilistic nature of AI without compromising aviation safety standards.
- Strengthening AI Security Systems to Prevent Cyber Manipulation an Adversarial AI Defense Framework-based mitigation strategy is needed, which allows AI to detect and reject manipulative attacks that can change the system's prediction results.
- Explainable AI (XAI) in Predictive Maintenance Certification the AI system used in aircraft maintenance must have a high level of explainability so that the decisions made can be understood by technicians and regulators.
- Improving AI Literacy for Technicians and Regulators AI education and training programs must be designed to ensure that the aviation workforce has sufficient understanding to work effectively with AI-based systems.

Through these steps, AI in predictive maintenance can evolve into a more integrated solution in the aviation industry while minimizing the potential risks arising from regulatory uncertainty and digital security threats.

Conclussion

AI in predictive aviation maintenance is often considered a solution that optimizes efficiency and reduces risk. However, this study reveals that the main challenge lies in how this technology is accepted and integrated into work systems that have long operated under different paradigms. Regulatory uncertainty and technician resistance to algorithm-based decisions show that the successful implementation of AI does not depend only on the sophistication of the prediction model. Explainability is a determining factor in whether AI can be accepted as a tool or is seen as an element that disrupts an established work system. In addition, threats to the security of AI systems make it increasingly clear that the reliability of this technology cannot be measured solely in terms of prediction accuracy but also in terms of its resistance to external manipulation that can affect flight safety.

The approach used in this study allows for a broader exploration of the interactions between technology, regulation, and operational practices. CSET-based analysis of the AI Harm Framework provides a more comprehensive picture of how biases in algorithms can reinforce existing work patterns and how regulatory incompatibilities with the probabilistic nature of AI create new challenges in the certification of predictive systems. This research shows that a multidisciplinary approach can open up layers of issues that are often neglected in technical studies, such as how AI affects the distribution of responsibilities in aircraft maintenance decision-making and how safety standards need to be adapted to accommodate machine learning-based systems.

The results of this study open up space for further exploration of the dynamics between AI and aviation sector regulations. Longitudinal studies can observe how AI safety standards evolve over time and how airlines and regulators adapt to these changes. In contrast, an ethnographic analysis of technicians can reveal the extent to which AI affects work patterns and decision-making at the operational level. In addition, cross-country comparisons of AI regulations in aviation can clarify whether policy fragmentation is an obstacle to innovation or actually creates stricter safety standards for the industry. Given the rapid technological developments, academic discussions on AI in predictive maintenance must continue to evolve by considering the accompanying social, legal, and security aspects.

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