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REVIEW ARTICLE

Integration of AI and Aviation

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ABSTRACT:
Artificial Intelligence (AI) can be defined as the technology that gives power to computers and machines to simulate human learning, problem solving, analysing and making predictions based on a given set of data. Integration of AI technologies in the field of aviation is enhancing efficiency, safety, and automation across the various domains of aviation. Before the introduction of AI, the aviation industry faced many challenges such as the use of traditional systems which include manual processes and rule-based decision making, which led to inefficient and slower operations. The aviation sector generates large quantities of data which were very difficult to process and extract valuable insights from using traditional systems. The infusion of AI technologies in the various domains of aviation such as Air Traffic Management (ATM), safety, maintenance and unmanned autonomous aircraft has had a significant impact. AI technologies, such as Explainable AI (XAI), are being used in various contexts ranging from predictive maintenance and anomaly detection to air traffic management to make their processes transparent and understandable. Long Short-Term Memory (LSTM) networks are applied across multiple use cases in the industry, including forecasting the paths of aircraft, air traffic movements and forecasting Runway Visual Range (RVR). Despite all these technological advances, the industry continues to experience challenges such as data security, ethics, and explainability of AI models, which remain major areas of research. This paper presents the revolutionary capabilities of AI in aviation, focusing on emerging technologies, applications, and future research directions.

KEYWORDS: artificial intelligence; aviation; machine learning; LSTM;

1. 1. INTRODUCTION

Aviation is one of the most safety-critical, data-intensive, and tightly regulated industries in the world. Every stage of an aircraft's life cycle — from design and manufacture to air traffic control, in-flight operation, maintenance, and eventual retirement — generates massive volumes of structured and unstructured data. Sensors on modern aircraft engines alone can produce several gigabytes of telemetry per flight hour, while air navigation service providers manage continuous streams of radar, ADS-B (Automatic Dependent Surveillance–Broadcast), weather, and flight-plan data. For decades, this data was processed using deterministic, rule-based software and manual human judgement. Such traditional systems, while dependable within narrow operating envelopes, struggled to scale with the exponential growth in air traffic, the complexity of modern airspace, and the increasing frequency of extreme weather events.

Artificial Intelligence (AI) — encompassing Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), computer vision, and reinforcement learning — has emerged as a transformative force capable of learning complex, non-linear patterns directly from historical and real-time operational data. Unlike static rule-based systems, AI-based models can continuously adapt to new patterns, detect subtle anomalies invisible to human observers, and generate probabilistic forecasts that support proactive rather than reactive decision-making. This capability is particularly valuable in aviation, where even marginal improvements in safety margins, fuel efficiency, or on-time performance translate into substantial economic and societal benefits.

The integration of AI in aviation spans multiple interconnected domains, including Air Traffic Management (ATM), predictive maintenance of aircraft components, flight safety

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and risk assessment, autonomous and unmanned aerial systems, airport operations, and passenger experience management. Within these domains, specific algorithmic families have proven particularly effective. Recurrent architectures such as Long Short-Term Memory (LSTM) networks excel at modelling sequential, time-dependent aviation data such as flight trajectories, engine degradation curves, and meteorological visibility trends. At the same time, the opacity of many high-performing deep learning models has raised concerns among regulators, pilots, and maintenance engineers, giving rise to the field of Explainable AI (XAI), which seeks to make AI-driven decisions interpretable, auditable, and trustworthy — a prerequisite for certification in a safety-critical domain governed by bodies such as the Federal Aviation Administration (FAA) and the European Union Aviation Safety Agency (EASA).

This paper provides a structured overview of how AI technologies are reshaping aviation. Section 2 reviews the evolution of the field and related literature. Section 3 discusses the core AI and machine learning techniques underpinning modern aviation systems. Section 4 examines domain-specific applications, supported by comparative tables. Section 5 presents illustrative case-oriented examples. Section 6 discusses persistent challenges relating to data, ethics, and explainability. Section 7 outlines future research directions, and Section 8 concludes the paper.

2. 2. LITERATURE REVIEW AND REVIEW METHODOLOGY

2.1. *2.1 Review Methodology*

This paper adopts a narrative-review methodology, informed by the structuring principles of systematic reviews, to synthesise peer-reviewed and industry literature on AI integration in aviation published predominantly between 2018 and 2026. Sources were identified through targeted searches of scholarly databases and publisher platforms (including ScienceDirect, IEEE Xplore, Springer Nature, MDPI, and arXiv) using combinations of keywords such as 'artificial intelligence AND aviation', 'LSTM AND trajectory prediction', 'explainable AI AND aerospace', 'runway visual range AND deep learning', and 'UAV AND artificial intelligence'. Priority was given to review articles, systematic literature reviews, and empirical studies reporting concrete model architectures, datasets, or performance outcomes. The resulting body of literature was thematically organised into five recurring domains — Air Traffic Management, predictive maintenance, flight safety, autonomous/unmanned systems, and weather/visibility forecasting — which form the structural basis for Sections 3 through 6 of this paper.

2.2. *2.2 Related Work*

Research on AI applications in aviation has grown rapidly over the past decade, tracking the broader rise of deep learning and big-data analytics. Comprehensive reviews of AI in Air Traffic Management describe a clear transition from rule-based automation towards machine- and deep-learning-based prediction, optimisation, surveillance, and communication capabilities across the core components of ATM — namely air traffic control, air traffic flow management, and airspace management [1,2]. Systematic reviews of AI applications in broader air operations, following PRISMA-based methodologies, have synthesised findings from more than a hundred studies and consistently report that AI improves trajectory prediction, conflict resolution, and aircraft performance optimisation, while also acknowledging persistent limitations in data variability and the integration of heterogeneous information sources [3].

A parallel stream of research has examined the role of ML and DL in aviation safety and security, highlighting applications in anomaly detection, predictive maintenance, flight-path optimisation, cybersecurity, and passenger screening, while cautioning that data dependency, computational cost, and limited model transparency constrain widespread operational adoption [4]. Broader data-science reviews of air transportation systems trace the evolution of analytical methods in aviation from early rule-based automation and mechanism-based simulation, through operations-research optimisation, to contemporary data-driven and increasingly agentic AI approaches, reporting measurable gains such as reduced delays, improved aircraft utilisation, and lower maintenance costs [5].

Within this literature, two technical threads recur consistently: the use of LSTM-based recurrent architectures for temporal forecasting problems (aircraft trajectory prediction, visibility and Runway Visual Range forecasting), and the growing emphasis on Explainable AI to support certification, trust, and regulatory compliance in safety-critical predictive-maintenance and diagnostic applications. Studies on aircraft trajectory prediction have progressively moved from single LSTM networks toward hybrid architectures — combining LSTM with convolutional layers, attention mechanisms, and social or graph-based interaction modelling — to better capture the spatial and temporal interdependencies among multiple aircraft operating in shared airspace [6-11]. In parallel, the explainability literature has matured from conceptual discussions of the need for interpretability in aerospace predictive maintenance to concrete implementations using model-agnostic techniques such as SHAP (Shapley Additive exPlanations) and LIME (Local Interpretable Model-Agnostic Explanations) for fault diagnosis, incident prediction, and regulatory-liability analysis in both crewed and unmanned aircraft systems [12-17].

Despite this substantial body of work, most existing reviews focus narrowly on either a single AI technique or a single aviation sub-domain. There remains a need for an integrative perspective that connects the technical foundations of AI (particularly sequence models such as LSTM and interpretability frameworks such as XAI) with their cross-cutting applications across ATM, maintenance, safety, and autonomous systems, while also consolidating the associated ethical, security, and explainability challenges. This paper addresses that gap.

3. 3. CORE AI AND MACHINE LEARNING TECHNOLOGIES UNDERPINNING AVIATION SYSTEMS

3.1. *3.1 Machine Learning and Deep Learning Foundations*

Classical machine learning techniques such as decision trees, random forests, support vector machines (SVM), and gradient-boosted ensembles remain widely used in aviation for structured, tabular problems such as delay prediction, fuel-burn estimation, and rule-based fault classification, owing to their relative interpretability and lower data requirements. Deep learning architectures — including Convolutional Neural Networks (CNNs) for image and sensor-pattern analysis, and recurrent architectures for sequential data — have become dominant wherever raw, high-dimensional, or temporally structured data (radar tracks, vibration signals, camera feeds, weather rasters) must be processed with minimal manual feature engineering.

3.2. *3.2 Long Short-Term Memory (LSTM) Networks*

LSTM networks are a specialised form of Recurrent Neural Network (RNN) designed to retain information over long sequences through gated memory cells (input, forget, and output gates), which mitigate the vanishing-gradient problem that limits standard RNNs. Because aviation generates continuous streams of time-ordered data — aircraft position updates, engine sensor readings, and meteorological observations — LSTM networks are particularly well suited to forecasting problems in this domain. Reported applications include: (i) aircraft trajectory prediction from ADS-B surveillance data, where LSTM and hybrid CNN-LSTM or attention-LSTM models have been used to predict short- and medium-term 3-D/4-D flight paths with lower positional error than physics-based or classical statistical baselines [6-11]; (ii) forecasting of Runway Visual Range (RVR) and airport visibility, where hybrid CNN-LSTM architectures combine spatial feature extraction from meteorological imagery with temporal modelling of fog, haze, and precipitation dynamics to support Low Visibility Procedure (LVP) decisions [18-21]; and (iii) prognostics for engine health monitoring, where LSTM-based Remaining Useful Life (RUL) estimation models learn degradation trends from multivariate sensor time series.

3.3. *3.3 Explainable AI (XAI)*

Explainable AI refers to a family of methods designed to make the internal reasoning of complex, often 'black-box' AI models understandable to human stakeholders such as pilots, air traffic controllers, maintenance engineers, and regulators. Common techniques include SHAP and LIME (which attribute a prediction to individual input features), attention-weight visualisation (which highlights which time-steps or spatial regions most influenced a recurrent or transformer model's output), and surrogate 'white-box' models such as decision trees or Random Forests that approximate a more complex model's behaviour for auditability [12,13,17]. In aviation, XAI is not merely a convenience but an emerging regulatory expectation: certification frameworks such as the EASA Artificial Intelligence Roadmap explicitly call for human-centric, explainable AI to support trust-building between AI-based decision-support tools and the certified human operators who remain accountable for final decisions [15,33].

3.4. *3.4 Natural Language Processing and Computer Vision*

Beyond sequence-forecasting and explainability methods, Natural Language Processing (NLP) and computer-vision techniques underpin several aviation-specific applications that do not fit neatly into the trajectory- or maintenance-forecasting categories above. NLP models trained on aviation-specific vocabulary support automatic transcription and verification of pilot-controller communications, automated parsing of maintenance logs and incident reports, and voice-based cockpit assistants designed to reduce crew workload [2]. Computer-vision models, often built on convolutional backbones, are used for runway and foreign-object-debris detection, automated visual inspection of airframes and engines, and passenger/baggage screening, frequently working in tandem with LSTM or attention-based temporal models when the underlying task involves a sequence of frames or sensor images rather than a single static image [4,18,19].

3.5. *3.5 Reinforcement Learning and Autonomous Control*

Reinforcement Learning (RL), in which an agent learns an optimal policy through trial-and-error interaction with an environment, underpins many autonomous and semi-autonomous aviation applications, including UAV navigation and obstacle avoidance, dynamic air-traffic flow control, and swarm coordination for multi-drone operations [27,29]. RL-based approaches are especially valuable where explicit analytical models of the environment are unavailable or too complex to hand-craft, such as UAV navigation in cluttered or dynamic environments.

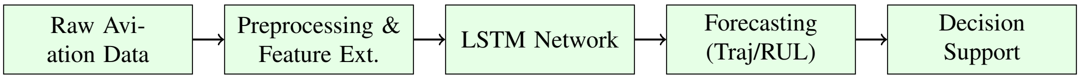

Figure 1: Generic LSTM-based sequence-prediction pipeline

Table 1. Summary of core AI/ML techniques and their representative roles in aviation.

Technique	Typical Aviation Task	Key Strength	Representative Reference(s)
Random Forest / SVM / Gradient Boosting	Delay prediction, fault classification, RVR ensemble forecasting	Interpretable, low data requirement	[3,22]
Convolutional Neural Network (CNN)	Weather-image feature extraction, defect detection in imagery	Strong spatial feature learning	[18,19]
LSTM / Recurrent Networks	Trajectory prediction, RVR/visibility forecasting, RUL estimation	Captures long-term temporal dependencies	[6-11,18-21]
Hybrid CNN-LSTM / Attention-LSTM	4-D trajectory prediction, multi-step visibility forecasting	Combines spatial and temporal learning	[10,11,18,19]
Explainable AI (SHAP, LIME)	Fault diagnosis explanation, safety-incident prediction	Model transparency, auditability	[12-17]
Reinforcement Learning	UAV navigation, swarm coordination, dynamic ATM flow control	Learns policies without explicit models	[27,29]

4. 4. DOMAIN-SPECIFIC APPLICATIONS OF AI IN AVIATION

4.1. *4.1 Air Traffic Management (ATM)*

Air Traffic Management is arguably the domain in which AI integration has advanced furthest. AI-enabled ATM systems support conflict detection and resolution, dynamic airspace sectorisation, and traffic-flow optimisation. Trajectory-clustering and functional-sectorisation techniques informed by AI now allow controllers to reconfigure terminal-area airspace according to observed traffic-flow functions rather than fixed geometric boundaries, helping reconcile growing traffic demand with limited airspace capacity [1,2]. Natural-language-processing-based systems trained on aviation-specific vocabulary are being explored to automatically verify pilot approach briefings for completeness, supporting future reduced-crew flight-deck operations [2]. Collectively, these tools shift ATM from a reactive, radar-and-radio paradigm toward a predictive, data-fused paradigm.

4.2. *4.2 Predictive Maintenance and Prognostics*

Predictive maintenance uses AI models trained on historical sensor data (vibration, temperature, oil debris, acoustic emissions) to forecast component degradation and estimate Remaining Useful Life, allowing maintenance to be scheduled just before failure rather than at fixed intervals or after breakdown. This shifts maintenance strategy from reactive/scheduled maintenance toward condition-based maintenance, reducing unscheduled groundings and lowering total maintenance cost [4,17,23]. Because maintenance decisions carry direct safety and cost implications, XAI methods such as Failure Diagnosis Explainability (FDE) frameworks and SHAP/LIME-based feature attribution are increasingly embedded directly into predictive-maintenance pipelines so that maintenance engineers can validate, rather than blindly trust, an AI-generated failure alert [17-19].

4.3. *4.3 Flight and Operational Safety*

AI supports safety through anomaly detection in flight-data-recorder streams, automated incident and accident-risk prediction, and cybersecurity monitoring of avionics and ADS-B communication links. Studies applying LIME and SHAP to incident/accident prediction models report that combining high predictive accuracy with post-hoc explainability improves both performance and the trustworthiness of the resulting risk assessments for safety analysts [14,16]. AI-based passenger and baggage screening systems similarly use computer vision and anomaly detection to improve threat-detection accuracy at airport security checkpoints [4].

4.4. *4.4 Autonomous and Unmanned Aircraft Systems*

Unmanned Aerial Vehicles (UAVs) represent a domain where AI is not merely an enhancement but a functional necessity, since UAV navigation, obstacle 'sense-and-avoid', and swarm coordination all depend on real-time perception and decision-making without a human pilot on board. AI-enabled UAVs are used for traffic monitoring, surveillance, precision agriculture, disaster response, and increasingly for cargo and urban-air-mobility applications; large-scale reviews report measurable operational gains such as improved traffic-flow estimation accuracy from UAV-based monitoring [26]. At the same time, because UAV fault-diagnosis models are frequently 'black-box' deep networks, researchers have highlighted specific legal-accountability and regulatory-compliance challenges that arise when opaque AI systems are used to certify UAV airworthiness or attribute liability after an incident, reinforcing the case for XAI integration in this sub-domain specifically [15].

4.5. *4.5 Weather and Visibility Forecasting*

Low visibility due to fog, haze, and precipitation is a leading cause of flight delay and diversion. Hybrid CNN-LSTM models have been developed to forecast Runway Visual Range using historical RVR observations together with exogenous meteorological variables, outperforming ensemble-learning and purely statistical baselines in short-term forecasting accuracy at operationally significant airports [18-21]. Such AI-based visibility-forecasting tools directly support Low Visibility Procedure decision-making, giving airports and pilots additional lead time to adjust operations before visibility deteriorates below regulatory minima.

4.6. *4.6 Airport Operations and Passenger Experience*

Beyond the flight deck and control tower, AI supports gate and stand allocation, baggage-handling optimisation, queue and crowd-flow prediction, and personalised passenger services through chatbots and recommendation systems. These applications, while less safety-critical, contribute significantly to overall operational efficiency and airline profitability, and often serve as lower-risk proving grounds for AI adoption before extension into safety-critical domains [3,5].

4.7. *4.7 Fuel Efficiency and Environmental Sustainability*

AI-driven flight-planning and optimisation tools are increasingly used to reduce fuel burn and associated carbon emissions by recommending optimal cruise altitudes, speeds, and routes based on real-time wind, temperature, and traffic data. Machine-learning-based continuous-descent and take-off-optimisation models can reduce unnecessary thrust and holding patterns, while AI-assisted maintenance reduces the incidence of underperforming, fuel-inefficient components remaining in service. Although sustainability applications are not always the primary focus of aviation-AI research, they represent a rapidly growing intersection between operational-efficiency gains and environmental-impact reduction, and are likely to attract increasing regulatory and commercial attention as airlines pursue net-zero emissions targets [3,5].

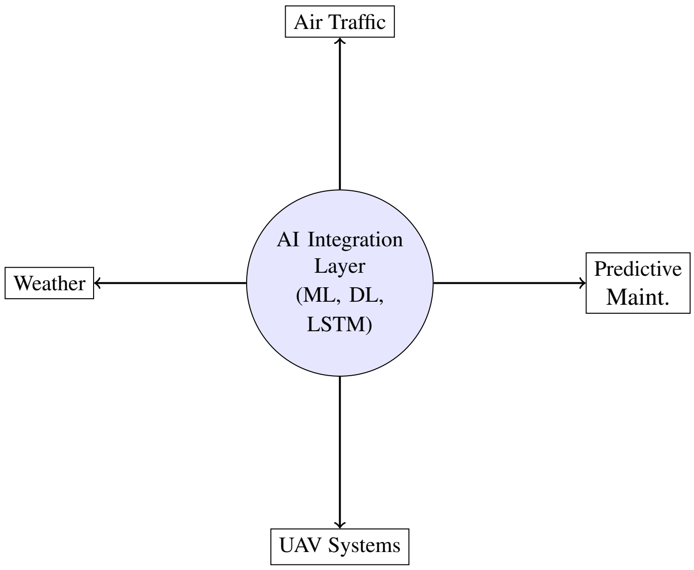

Figure 2: Conceptual framework showing how a shared AI integration layer supports multiple interconnected aviation domains

Table 2. Representative AI applications across aviation domains, associated data sources, and reported benefits.

Domain	Representative AI Application	Primary Data Source	Reported Benefit
Air Traffic Management	Trajectory clustering, functional sectorisation, conflict detection	Radar, ADS-B, flight plans	Improved capacity utilisation and predictability [1,2]
Predictive Maintenance	RUL estimation, failure diagnosis explanation (XAI)	Engine/airframe sensors	Reduced unscheduled downtime [4,17,23]
Flight Safety	Anomaly detection, incident/accident risk prediction	Flight data recorders, incident reports	Improved risk-model trust via XAI [14,16]
Autonomous/UAV Systems	Navigation, sense-and-avoid, swarm coordination	Onboard cameras, LiDAR, IMU	Enhanced autonomy and monitoring accuracy [26-29]
Visibility/RVR Forecasting	Hybrid CNN-LSTM short-term RVR forecasting	RVR sensors, METAR, satellite imagery	Improved Low Visibility Procedure decisions [18-21]
Airport/Passenger Ops	Gate allocation, chatbots, crowd-flow prediction	Airport operational and passenger data	Higher operational efficiency [3,5]

5. 5. ILLUSTRATIVE CASE PERSPECTIVES

To ground the preceding discussion, this section synthesises three illustrative, literature-derived perspectives rather than presenting new experimental results.

5.1. *5.1 Trajectory Prediction with LSTM-Family Models*

Across multiple independent studies, LSTM and hybrid LSTM-based architectures (Social-LSTM, CNN-LSTM, Attention-LSTM) have consistently outperformed classical statistical and physics-based baselines such as Hidden Markov Models, Support Vector Machines, and back-propagation neural networks on aircraft trajectory-prediction benchmarks using real ADS-B and historical flight-track datasets, with reported horizontal positional errors in the range of a few hundred metres and demonstrable improvements from adding attention or convolutional feature-extraction layers on top of the base LSTM [6-11].

5.2. *5.2 RVR Forecasting for Low-Visibility Operations*

Hybrid CNN-LSTM frameworks applied to real airport RVR datasets (e.g., studies conducted at Patna Airport, India) demonstrate that combining convolutional spatial-feature extraction with LSTM temporal modelling improves short-term RVR forecast accuracy relative to ensemble-learning and single-architecture deep-learning baselines, which directly supports safer and more efficient Low Visibility Procedure decision-making at fog-prone airports [18-21].

5.3. *5.3 Explainability in Predictive Maintenance and UAV Fault Diagnosis*

Case-level studies applying SHAP and LIME to aviation predictive-maintenance and UAV fault-diagnosis models show that post-hoc explainability techniques can maintain high predictive accuracy while giving maintenance engineers feature-level justifications for flagged failures, and that structured explainability frameworks (e.g., Failure Diagnosis Explainability) help establish the auditability required for regulatory and liability contexts, particularly for autonomous UAV systems where no human pilot is available to exercise final judgement [12-17,19].

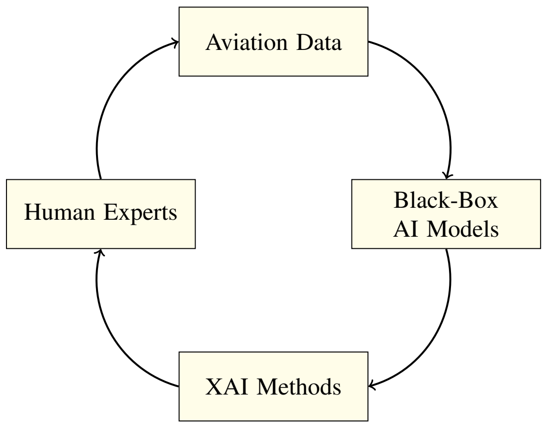

Figure 3: Closed-loop explainable-AI decision-support cycle

6. 6. CHALLENGES AND OPEN RESEARCH ISSUES

6.1. *6.1 Data Quality, Availability, and Security*

High-performing AI models require large volumes of high-quality, well-labelled data; however, aviation data is often fragmented across airlines, manufacturers, and air navigation service providers, subject to strict confidentiality and competitive-sensitivity constraints, and vulnerable to cybersecurity threats such as ADS-B spoofing or sensor tampering. Rare-event data — particularly for accidents and severe incidents — is inherently scarce, complicating the training of robust risk-prediction models [4,5].

6.2. *6.2 Explainability and Certification*

Deep learning models, especially large recurrent or hybrid architectures, remain difficult to interpret using classical model-inspection tools, which conflicts with the deterministic, verifiable assumptions embedded in existing aviation certification frameworks. Regulators such as the FAA and EASA must adapt legacy certification processes designed for deterministic software to accommodate probabilistic, self-learning AI systems, a transition that remains slow and resource-intensive [15,18].

6.3. *6.3 Ethical and Legal Accountability*

As AI systems take on greater decision-making responsibility — particularly in autonomous UAV fault diagnosis and safety-risk scoring — questions of legal liability, algorithmic bias, and appropriate human-AI role allocation become increasingly pressing. Current research highlights the fragmented nature of existing legal and regulatory frameworks for AI-based UAV fault diagnosis and calls for structured frameworks that integrate interpretability, regulatory compliance, and liability attribution [15].

6.4. *6.4 Human Trust and Operational Integration*

Even technically sound AI tools can fail to deliver operational benefit if pilots, controllers, and maintenance engineers do not trust or understand their outputs. Building calibrated trust — neither over-reliance nor rejection — requires not only accurate models but also carefully designed explanation interfaces, adequate training, and a clear specification of the boundary between AI-generated recommendations and human final authority [13,14].

6.5. *6.5 Computational Scalability and Real-Time Constraints*

Many of the highest-performing hybrid architectures described in Section 3 (e.g., attention-augmented LSTM networks, CNN-LSTM ensembles) carry substantial computational overhead, which can conflict with the low-latency, real-time requirements of onboard avionics or live air-traffic-control decision support. Research into model compression, quantisation, and edge-optimised inference is therefore an important complement to accuracy-focused model development, particularly for applications such as UAV onboard navigation where computational resources and power budgets are tightly constrained [27,29,38].

Table 3. Key challenges in AI-aviation integration and associated research directions.

Challenge Category	Core Issue	Associated Research Direction
Data	Fragmented, siloed, and security-sensitive aviation data; scarcity of rare-event (accident) data	Federated learning; secure multi-party data sharing; synthetic/rare-event data augmentation
Explainability	Black-box deep learning models conflict with deterministic certification norms	Standardised XAI evaluation frameworks; regulator-aligned explanation formats
Ethics & Liability	Unclear accountability when autonomous/AI-assisted systems err	Legal-technical frameworks combining XAI with liability attribution
Human Factors	Risk of miscalibrated trust (over-reliance or rejection) in AI recommendations	Human-centred explanation-interface design; operator training programmes
Scalability	High computational cost of large DL/hybrid models for real-time use	Model compression, edge deployment, energy-aware architectures

7. 7. FUTURE RESEARCH DIRECTIONS

Building on the challenges identified above, several research directions appear particularly promising for the next phase of AI-aviation integration. These directions cut across technical, regulatory, and human-factors dimensions, reflecting the reality that further gains in AI-aviation integration will depend as much on organisational and policy innovation as on algorithmic advances.

- Standardised, regulator-aligned XAI evaluation frameworks that allow certification bodies to consistently assess the interpretability and reliability of AI-based aviation systems across manufacturers and use cases.
- Hybrid physics-informed deep learning models that combine aerodynamic and meteorological domain knowledge with data-driven LSTM/attention architectures to improve trajectory- and visibility-forecasting robustness under rare or extreme conditions.
- Federated and privacy-preserving learning approaches that allow airlines, airports, and manufacturers to collaboratively train predictive-maintenance and safety models without directly sharing sensitive operational data.
- Integrated legal-technical accountability frameworks that combine explainability methods (SHAP, LIME, attention visualisation) with clear liability-attribution rules for autonomous and semi-autonomous aviation systems, including UAVs and future urban-air-mobility vehicles.
- Human-centred design research on explanation inter-

faces for pilots, controllers, and maintenance engineers, aimed at achieving calibrated trust rather than blind reliance on AI recommendations.

- Energy-aware and edge-deployable AI architectures that reduce the computational footprint of onboard and airport-based AI systems, supporting real-time inference under strict power and latency constraints.
- Extension of reinforcement-learning-based autonomy to multi-agent, swarm-level UAV and urban-air-mobility coordination, with embedded safety constraints and explainable policy representations.

7.1. *7.1 Limitations of this Review*

As a narrative synthesis rather than a quantitative meta-analysis, this review does not statistically aggregate performance metrics across the studies discussed, and the pace of publication in this field means that some very recent developments may not be captured. The domains and technologies discussed were selected for their prominence in the current literature and may not exhaustively represent all AI applications emerging in aviation, such as generative-AI-based documentation, agentic AI for maintenance-crew scheduling, and large-language-model-based pilot and controller assistants, which remain nascent but are likely to feature prominently in future reviews.

8. 8. CONCLUSION

The integration of Artificial Intelligence into aviation marks a fundamental shift from static, rule-based operational paradigms toward dynamic, data-driven, and increasingly predictive systems. Across Air Traffic Management, predictive maintenance, flight safety, autonomous and unmanned aircraft systems, weather forecasting, and airport operations, AI — and particularly sequence-modelling techniques such as LSTM networks — has demonstrably improved forecasting accuracy, operational efficiency, and early-warning capability. At the same time, the safety-critical and highly regulated nature of aviation means that technical performance alone is insufficient: explainability, data security, ethical accountability, and human trust must advance in parallel with predictive accuracy. Explainable AI has emerged as a central enabling technology in this respect, bridging the gap between high-performing but opaque deep learning models and the transparency, auditability, and certifiability that aviation stakeholders and regulators require. Future progress will depend on coordinated advances in standardised XAI evaluation, privacy-preserving data collaboration, legal-technical accountability frameworks, and human-centred system design, ensuring that AI integration in aviation continues to enhance — rather than compromise — the industry's foundational commitment to safety. As aviation moves toward higher levels of automation, from AI-assisted decision support to increasingly autonomous unmanned and urban-air-mobility platforms, the interplay between predictive performance, explainability, and accountable human oversight will remain the defining research and regulatory challenge of the field.

9. AUTHOR CONTRIBUTIONS

H.P. conceived the review scope, conducted the literature synthesis, and drafted the manuscript. S.I. contributed to structuring the technical sections, prepared tables and figures, and reviewed and edited the manuscript. Both authors read and approved the final manuscript.

10. CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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