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RESEARCH ARTICLE

Artificial intelligence for sustainable aviation: a review on operational implementations and future perspectives

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Abstract

This study presents a systematic review of peer-reviewed academic literature to explore the current landscape of artificial intelligence (AI) applications in sustainable aviation operations. Using a qualitative content analysis approach, four main thematic domains were identified, encompassing emission and fuel efficiency, maintenance reliability, infrastructure sustainability and education- or policy-related applications. In addition to thematic synthesis, the study mapped the annual publication frequency, the AI methods employed and the aviation domains targeted. The results reveal an increasing interest in hybrid and deep learning models, such as long short-term memory (LSTM), convolutional neural networks (CNN) and attention-based architectures, particularly in-flight optimisation and delay prediction tasks. AI-based flight optimisation techniques, such as trajectory prediction and adaptive fuel management, contribute to reducing CO_2 emissions through more efficient flight planning and operations. Moreover, predictive maintenance supported by AI-driven digital twin systems has gained prominence due to its potential to reduce downtime and increase safety. The discussion further addresses regulatory challenges, the importance of explainable AI and integration barriers within complex aviation ecosystems. Findings are derived from a focused corpus of 27 peer-reviewed studies, which, although limited in number, offer representative insights into current sectoral trends. This review makes a significant contribution to both academia and industry by offering a comprehensive framework that categorises AI applications and highlights future research directions. Key implications include the need for regulatory harmonisation, real-time decision-support tools, and interdisciplinary approaches that integrate AI with behavioural sciences and sustainability goals.

Nomenclature

AI	artificial intelligence
ADS-B	automatic dependent surveillance – broadcast
AEI	aggregated-embodied emissions intensity
CNN	convolutional neural networks
DL	deep learning
EASA	European Union Aviation Safety Agency
EGT	exhaust gas temperature
ELM	extreme learning machines
FAA	Federal Aviation Administration
GAM	generalised additive model
GAN	generative adversarial networks
GCN	graph convolutional network
GDPR	general data protection regulation

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IATA	international air transport association
ICAO	International Civil Aviation Organisation
IoT	Internet of Things
LLM	large language models
LOF	local outlier factor
LSTM	long short-term memory
MAE	mean absolute error
ML	machine learning
MPC	model predictive control
PCA	principal component analysis
PdM	predictive maintenance
PRISMA	preferred reporting items for systematic reviews and meta-analyses
P2MPC	power prediction-based model predictive control
RF	random forest
RUL	remaining useful life
SAF	sustainable aviation fuel
SOC	state of charge
TCN	temporal convolutional network
UAV	unmanned aerial vehicles
QAR	quick access recorder
VAE	variational autoencoder
WoS	web of science
XGB	XGBoost

1.0 Introduction

In 2025, the aviation sector stands at a critical crossroads in the global climate action agenda. At the Third ICAO Conference on Aviation and Alternative Fuels (CAAF/3), member states collectively adopted an aspirational global goal of a 5% reduction in CO_2 emissions from aviation fuel by 2030 through the expanded use of sustainable aviation fuels (SAFs), complementing the International Civil Aviation Organisation (ICAO) long-term aspirational goal (LTAG) objective of net-zero by 2050 [1, 2]. Despite the momentum, the sector continues to face major challenges, particularly concerning the availability and cost of SAF, which remains a top barrier to decarbonisation [1]. In this context, artificial intelligence (AI) is increasingly recognised for its transformative potential in achieving sustainability goals across multiple aviation domains.

The aviation sector accounts for approximately 2%–3% of global greenhouse gas emissions, positioning it as a critical domain in the fight against climate change [3]. Increasing air traffic demand, tightening environmental regulations and growing consumer awareness have necessitated a transformation of the industry in line with both operational efficiency and sustainability goals. In this transformation process, technologies such as AI, machine learning (ML) and deep learning (DL) have drawn attention for their multifaceted contributions. AI-powered systems not only support environmental objectives such as reducing emissions and optimising fuel consumption but also drive transformation across a wide range of functions from safety and flight planning to maintenance processes and strategic decision-making [4, 5].

AI-supported systems are technological constructs that perform functions such as data analysis, prediction, learning and automation through algorithms that approximate human reasoning and decision-making processes [6]. Powered by subfields such as ML, DL and natural language processing (NLP), these systems enable the transformation of large-scale and complex data into meaningful information. In the aviation industry specifically, the use of AI-supported systems initially emerged in the early 2000s in limited areas such as flight planning and fault prediction. However, in recent years, their application has expanded into multidimensional domains including air traffic management, maintenance, fuel optimisation, emissions monitoring and strategic decision support [7, 8]. According to

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the European Union Aviation Safety Agency (EASA) [9], AI applications not only enhance operational safety but also enable environmental improvements that directly contribute to sustainability goals.

Over the past decade, AI has gained increasing influence in the aviation sector, offering transformative contributions in key areas such as safety, operational efficiency and sustainability. In this context, empirical and theoretical studies on the use of AI in aviation have also diversified. For instance, in the systematic review study presented by Fang [8], while emphasising the potential of AI to optimise decision-making processes in the aviation sector, it is stated that the implementation of these technologies in line with sustainable development goals should be evaluated in ethical, legal and cybersecurity contexts. Demir et al. [4] examined 224 articles and highlight China's AI-based contributions and international collaborations in the field of aviation safety. The authors state that AI plays an important role in flight safety, accident prevention, pilot behaviour and the development of preventive strategies. In addition, the systematic review conducted by Tafur et al. [10] details the effects of AI on air operations, such as air traffic management, flight route prediction and performance improvement. Despite the difficulties encountered in data diversity and the integration of multiple information sources, the study highlights the potential of AI to increase operational safety and efficiency. Similarly, Calvet [11], in a review focused on the optimisation of ground and air operations, draws attention to the contributions of AI-supported solutions in terms of airport capacity, flight duration and environmental impact reduction. A literature review conducted by Pik [12] discusses the potential of AI in airport security, particularly in areas such as biometric verification and threat detection, emphasising its ability to balance speed, accuracy and passenger experience.

In this context, the contributions of AI to sustainability in aviation stand out through its more flexible, predictive and real-time solutions compared to traditional methods. However, the vast majority of the literature focuses on a specific technology or application area, and comprehensive reviews reflecting sectoral integrity and thematic diversity are rarely included [8, 9]. Unlike prior reviews that focus on isolated domains such as air traffic management or airport operations, this study provides an integrative thematic classification encompassing the environmental, operational and policy-related dimensions of sustainable aviation. Accordingly, this study aims to address this gap by systematically evaluating the role of AI in advancing sustainable aviation goals.

The review was conducted in line with the following research objectives:

RQ1. How has AI been addressed in academic publications on sustainable aviation between January 2008 and May 2025?

RQ2. What are the most frequently used AI methods and thematic patterns in the sustainable aviation literature?

RQ3. In what dimensions are the technical and strategic contributions of AI to sustainable aviation classified across the reviewed studies?

2.0 Materials and methods

This study adopts a mixed-methods approach, using a systematic literature review, bibliometric analysis and content analysis to examine the contributions of AI to sustainable aviation. The methodological structure is designed to provide a holistic view of the literature and objectively reveal its trends.

2.1 Data source and search strategy

The literature review was conducted using the Web of Science (WoS) database, which was selected due to its comprehensive indexing system, interdisciplinary coverage and advanced bibliometric analysis capabilities. WoS was selected due to its multidisciplinary coverage and inclusion of most journals simultaneously indexed in Scopus and IEEE Xplore. Comparative pilot searches confirmed that additional databases yielded predominantly duplicate or non-aviation-specific results.

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The review process was structured based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 guidelines [13], which are widely recommended for systematic reviews and meta-analyses. Accordingly, the search was conducted in May 2025, and keyword combinations were designed to encompass the core concepts of sustainability, aviation and AI. The search string employed was as follows:

('artificial intelligence' OR 'AI') AND (aviation OR 'air transport') AND (sustainability OR 'sustainable aviation' OR 'green aviation')

This string made it possible to evaluate both the technical applications and the impact of AI on sustainable aviation in policy, management and strategic contexts.

2.2 Selection criteria

The studies included in this review cover literature published between January 2008 and May 31, 2025. The main reason for choosing 2008 as the starting year is that studies intersecting AI applications and sustainable aviation themes have started to increase significantly in the academic literature since this date. The findings obtained during the literature review show that academic interest in the applications of AI in the field of environmental sustainability has gained momentum, especially after 2008. This date also indicates a period when the concept of 'Green AI' began to take shape, and studies on the development of environmentally focused algorithms intensified [14]. Sustainability-focused AI interventions, especially emission modeling, fuel optimisation and predictive maintenance, began to appear more frequently in the literature after 2008. Therefore, the year 2008 was considered a significant threshold in terms of both the increase in the number of qualified publications and the conceptual development of the field and was included in the review in this context. Although the literature search covered the 2008–2025 period, only studies published from 2020 onward were included in Table 1 due to the emergence of applied AI methods in sustainable aviation during this period.

To ensure relevance and quality, publications were included in the review if they satisfied all of the following criteria:

- Published between 2008 and May 31, 2025.
- Addressed the application of AI or ML.
- Focused on the aviation sector (civil or commercial aviation).
- Contained sustainability-related goals, results or implications.
- Peer-reviewed full-text journal articles.
- Written in English.

The following studies were excluded from the review:

- Publications not directly related to aviation.
- Studies that were not associated with AI or aviation.
- Articles that excluded sustainability-related objectives or outcomes.
- Publications for which full-text access was unavailable.
- Articles published in languages other than English.

The PRISMA flow diagram illustrates the screening process in Fig. 1. The screening process was conducted in three main stages: identification, screening and inclusion. Initially, 337 records were identified through the WoS database. After applying the predefined inclusion and exclusion criteria, 310 records were excluded. Consequently, 27 peer-reviewed articles that met all eligibility requirements were included in the final analysis.

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Table 1. *Overview of included studies on AI applications in sustainable aviation*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2020	Kosir, S.; Heyne, J.; Graham, J.	A machine learning framework for drop-in volume swell characteristics of SAF	To develop a neural network model to predict volume swell of aircraft fuel system materials exposed to SAF compounds and optimise blends that meet performance and safety requirements for high-performance jet fuels	230 observations across 10 materials; neural network with PCA-based input reduction; ant colony optimisation for SAF blend formulation based on swell limits and energy values	The ML framework accurately predicts swell values within jet fuel tolerances. Cycloalkane-based SAF blends optimise energy and environmental performance while maintaining material compatibility.	SAF Compatibility, Neural Networks, Swell Prediction, Fuel Optimisation	AI-based prediction and optimisation of SAF blends for aircraft fuel system compatibility and emissions reduction	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2021	Wei, Z.; Ma, Y.; Xiang, C.; Liu, D.	Power prediction-based model predictive control for energy management in land and air vehicle with turboshaft engine	To propose a power prediction-based model predictive control (P2MPC) strategy for hybrid land-air vehicles using turboshaft engines, aiming at battery SOC regulation and exhaust gas temperature (EGT) reduction for enhanced energy efficiency and sustainability.	Simulation-based study using a hybrid vehicle model with turboshaft engine; experimental data used to build a data-driven dynamic engine model; deep learning-based power predictor trained on multiple driving cycles; implemented in MATLAB/Simulink for comparative analysis with conventional MPC methods	P2MPC strategy with deep learning-based power prediction significantly improved SOC control and reduced EGT. Demonstrated better real-time performance and lower emissions compared to conventional rule-based or static MPC approaches.	Hybrid Propulsion, DL, Model Predictive Control, Turboshaft Engine, Emission Reduction	AI-based power prediction and optimisation in hybrid aerial vehicles for fuel efficiency and sustainability enhancement.	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2022	Apostolidis, A.; Bouriquet, N.; Stamoulis, K.P.	AI-Based Exhaust Gas Temperature Prediction for Trustworthy Safety-Critical Applications	To predict EGT using a ML method to enhance trustworthiness in data-driven, safety-critical aviation maintenance	Simulation data (N-CMAPSS) from NASA; method: generalised additive model (GAM); training and testing of predictive EGT models.	GAM effectively predicts EGT, demonstrating high accuracy and interpretability. The model supports predictive maintenance and can be a foundation for certifiable AI in aviation.	Predictive Maintenance, ML (GAM), Safety-Critical AI, Engine Health Monitoring	Engine maintenance in commercial aircraft	Aircraft Maintenance and Reliability with AI Support

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2022	Sun, Y.-F.; Zhang, Y.-J.; Su, B.	How does global transport sector improve the emissions reduction performance? A demand-side analysis	To explore the demand-side aggregated embodied emissions intensity (AEI) of the global transport sector using EE-MRIO and structural path analysis models across four dimensions: global, regional, transmission layer, and final demand	EXIOBASE input–output data for 49 regions and 163 sectors; EE-MRIO and structural path analysis; decomposition by transport mode and demand structure; analysis by layers of emissions transmission.	Transport contributes 4.2% to global AEI. Land transport dominates AEI, while air and water transport dominate direct emissions. AEI structure varies by region, with demand-side reduction focused on land transport and final demands such as household and investment.	Demand-Side Emissions, EE-MRIO, Transport Sector, AEI vs. AI, Structural Path Analysis	Air transport emissions significantly impact AEI in developed countries; AEI highlights indirect climate responsibilities beyond direct aviation fuel consumption	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2022	Demir, A.S.	Modeling and forecasting of CO_2 emissions resulting from air transport with genetic algorithms: the United Kingdom case	To model and forecast CO_2 emissions from domestic and international air transport in the UK using genetic algorithms, and provide insights for sustainable aviation strategies	Flight and passenger data from 32 European countries (2001–2015); GA-based modeling using 928 two-variable and 3764 single-variable functions for forecasting until 2029.	High correlation models show GA can effectively forecast aviation-related CO_2 emissions. Results inform emission mitigation strategies such as fuel-efficient aircraft and route planning.	Emission Forecasting, Genetic Algorithms, Sustainable Aviation Policy, Time Series Modeling	Air transport CO_2 modeling for UK domestic and international flights	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2022	Gao, Z.; Mavris, D.N.	Statistics and ML in Aviation Environmental Impact Analysis: A Survey of Recent Progress	To survey and classify recent research that applies statistics and ML methods to aviation environmental impact analysis (fuel burn, emissions, noise) and to identify prevailing research trends and future opportunities	Review article; literature-based classification into 7 themes: data reduction, efficient computation, predictive modeling, uncertainty quantification, pattern discovery, verification and validation, infrastructure/tools.	AI and statistical methods are increasingly critical in modeling aviation's environmental impact. The study highlights the importance of data-driven simulation, uncertainty-aware decision-making, and scalable predictive systems.	Environmental Impact Modeling, ML, Emissions & Noise, Research Trends	System-level AI integration for modeling fuel burn, emissions, and noise in sustainable aviation	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2022	He, Y.; Hu, C.; Jiang, B.; Sun, Z.; Ma, J.; Li, H.; Tang, D.	Data-driven approach to predict the flow boiling heat transfer coefficient of liquid hydrogen aviation fuel	To develop ML models for accurately predicting the heat transfer coefficient in flow boiling of liquid hydrogen aviation fuel, addressing challenges related to fuel transport and heat leakage	864 experimental data points from three sources; comparison of 8 ML algorithms (extra tree, random forest (RF), XGBoost, etc.); focus on regression accuracy using dimensionless parameters.	The Extra Tree model outperformed other models and traditional empirical correlations, offering highly accurate and physically validated predictions. The Ja number was identified as a key feature.	Hydrogen Aviation Fuel, ML, Heat Transfer Prediction, Cryogenic Fuel Safety	AI-based modeling for cryogenic hydrogen fuel systems in next-generation sustainable aircraft	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2022	Jun, L.Z.; Alam, S.; Dhief, I.; Schultz, M.	Towards a greener Extended-Arrival Manager in air traffic control: A heuristic approach for dynamic speed control using machine-learned delay prediction model	To enhance extended arrival manager systems by integrating ML-based delay prediction with heuristic speed optimisation for dynamic speed control in en-route airspace	Case study in Singapore Flight Information Center; ADS-B and weather data; ML (CatBoost) for control area delay prediction; dynamic speed control modeled with heuristic optimisation.	Dynamic speed control can absorb 65% of control area delay into the en-route phase, leading to 1524 kg fuel savings and 48,000 kg CO_2 reduction. ML-based prediction enhances extended arrival manager efficiency and environmental impact.	Air Traffic Management, Delay Prediction, Fuel Efficiency, ML Optimisation	AI-supported extended arrival manager to optimise flight arrival manage-ment and reduce congestion, fuel use, and emissions	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2023	Chen, J.; Qi, G.; Wang, K.	Synergizing ML and the Aviation Sector in Lithium-Ion Battery Applications: A Review	To review ML applications in lithium-ion battery technologies and assess their integration with green aviation advance-ments, focusing on battery materials, health estimation, and fault diagnosis	Review article based on existing literature; qualitative synthesis of ML use in battery research and aviation applications.	ML enhances performance prediction, battery health monitoring, and fault diagnosis. In aviation, it optimises battery safety, energy management and operational efficiency for sustainable aviation systems.	Battery Technology in Aviation, ML Applications, Health Monitoring, Green Aviation Integration	Battery systems for electric aircraft and aviation energy man-agement	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2023	Ramakrishnan, J.; Seshadri, K.; Liu, T.; Zhang, F.; Yu, R.; Gou, Z.	Explainable semi-supervised AI for green performance evaluation of airport buildings	To develop an explainable semi-supervised learning model for assessing the green performance of airport buildings with minimal human input, generating transparent green performance rules	312 global airport sustainability reports; PCA for dimensionality reduction; Agglomerative and Divisive Hierarchical Clustering; model validation via silhouette coefficient, accuracy, mean absolute error (MAE), and green rule extraction.	Semi-supervised learning models can reliably evaluate environmental sustainability of airport buildings with reduced expert bias. Green rules derived from clusters support operators in targeting specific environmental improvements (e.g. S1/S3 emissions, energy use).	Green Airport Buildings, Semi-Supervised Learning, Explainable AI, Environmental Assessment	AI-driven framework for evaluating and improving environ-mental sustainabil-ity of existing airport infrastruc-tures	Airport and Infrastructure Sustainability

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2023	Wandelt et al.	AI-driven assistants for education and research? A case study on ChatGPT for air transport management	To investigate the potential impact of ChatGPT on aviation education and research through empirical analysis with graduate students	Survey of 102 graduate students at Beihang University; assessment of ChatGPT performance in programming, terminology explanation, and identifying state-of-the-art methods.	AI-driven assistants like ChatGPT enhance learning efficiency and research accessibility but require critical evaluation due to potential limitations in reliability, data quality, and problem specificity.	Infrastructure, Operations & Strategic AI – Aviation Education & Research Tools	The study is situated within air transport management education and research. It examines the role of ChatGPT in supporting graduate-level learning tasks such as programming, terminology explanation, and identifying state-of-the-art methods in aviation. The context emphasises integrating AI tools like LLMs into aviation-specific educational and research workflows.	AI Applications in Aviation Education, Decision Support and Policy Making

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Shojaei, S.M.; Aghamolaei, R.; Ghaani, M.R.	Recent Advancements in Applying ML in Power-to-X Processes: A Literature Review	To provide a comprehensive review of recent advancements in applying ML techniques to Power-to-X (PtX) processes, including Power-to-Gas, Power-to-Liquid, and Power-to-Heat, highlighting aviation applications and sustainability implications	Systematic review of 507 papers (2008–2024) via Scopus; 53 selected for detailed review; categorised by ML task (prediction, optimisation, diagnostics, etc.); domains include hydrogen, green ammonia, PtL, PtH, SAFs, etc.	ML techniques (e.g. deep RL, diagnostics, process control) significantly enhance the efficiency, reliability, and sustainability of PtX systems. Applications in aviation include green fuel synthesis (PtL), SAF optimisation, and real-time decision support.	PtX Systems, ML Review, Green Hydrogen, SAF, Optimisation	PtX-derived e-fuels and ML-driven SAF synthesis are directly relevant to sustainable aviation transition and carbon-neutral fuel adoption	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Sapra, H.; Hessel, R.; Miganakallu, N.; Stafford, J.; Amezcua, E.; Rothamer, D.; Kim, K.; Kweon, C.M.; Kokjohn, S.	Computational fluid dynamics and ML-based Piston-Bowl optimization for Energy-Assisted compression ignition of low cetane number SAF blends	To optimise the Energy-Assisted Compression Ignition (EACI) strategy for low-cetane SAF blends in UAV applications using CFD simulations and Gaussian Process Regression (GPR)-based ML for piston-bowl design	Optical and metal single-cylinder engine experiments with CN 30–48 SAFs; CFD simulations using CONVERGE; DoE with 12 parameters; GPR ML model trained on 780 samples; optimisation across 20 million piston designs.	Optimised pistons improved ignition delay and CA50 by 17–22% for CN 30 SAF, reducing ignition-assist power requirements by 21–28%. ML-guided design enhances EACI reliability and fuel flexibility under aerial conditions.	CFD-ML Optimisation, EACI Strategy, Piston Design, UAV Propulsion, SAF Combustion	AI-driven piston optimisation for UAV propulsion systems using low cetane SAFs under high-altitude conditions	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Pushparaj, N.; Cormier, L.; Cappelletti, C.; Portapas, V.	Real-Time Contrail Monitoring and Mitigation Using CubeSat Constellations	To design and simulate a 3×3 CubeSat constellation capable of real-time contrail monitoring and mitigation over high-traffic flight corridors like the North Atlantic, integrating atmospheric data and ML for flight path optimisation	System-level simulation of CubeSat constellation; use of KalmanNet AI framework with temperature, humidity, and aircraft emissions data; orbit design optimised for 100% regional visibility and minimal blackout durations.	A 9-satellite, highly eccentric orbit constellation enables near-continuous monitoring with real-time contrail risk prediction. Integrating CubeSat data with flight management systems allows dynamic route adjustments to mitigate contrail-related warming.	Contrail Mitigation, CubeSat Constellation, KalmanNet, Climate Impact, AI-Driven Routing	AI-powered CubeSat system for minimising non-CO_2 climate impacts of aviation through real-time atmospheric monitoring and flight path adjustments	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Plastropoulos, A.; Fan, I.-S.; Avdelidis, N.P.; Angus, J.P.; Maggiore, J.; Atkinson, H.	The 'hangar of the future' for sustainable aviation	To explore the integration of AI, robotics, and smart digital technologies in maintenance hangars, aiming to develop a sustainable, efficient, and human-centric aircraft maintenance ecosystem	Conceptual and applied framework based on the DARTeC smart hangar; use cases include UAV-based thermography, robotic visual inspections, wearable devices, and digital twin infrastructure.	Smart hangars reduce downtime, support predictive maintenance, enhance safety, and promote sustainability. Key technologies include AI, IoT, AR/VR, UWB localisation, and robotic platforms, enabling MRO 4.0 and aligning with Industry 5.0 principles.	Smart Hangars, Predictive Maintenance, Industry 5.0, Digital Twins, Robotics, AI	AI-enhanced hangar operations integrating predictive MRO and sustainability principles for next-generation aircraft maintenance	Aircraft Maintenance and Reliability with AI Support

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Oh, J.H.; Oldani, A.; Solecki, A.; Lee, T.	Learning to predict SAF properties: A deep uncertainty quantification viewpoint	To develop a trustworthy ML framework using Bayesian neural network ensembles (BNNE) for predicting SAF flash points while quantifying epistemic and heteroscedastic uncertainty	Training and testing on SAF property data (esp. flash point) using GC × GC features; Bayesian neural network ensembles (BNNE); uncertainty decomposition; three datasets (D1–D3) and two feature sets (F68, F8) tested for coverage and resolution impacts.	Overparameterised networks are more robust to out-of-distribution data and can maintain accuracy despite low training similarity. Heteroscedastic uncertainty from limited feature resolution is a major bottleneck. The study proposes big data integration and finer chemical features as solutions.	Uncertainty Quantification, Deep Learning, SAF Property Modeling, Bayesian Neural Networks	Deep learning for reliable flash point prediction in SAFs with limited data to accelerate sustainable fuel certification	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Wu, C.; Wang, Y.; Tao, L.	Machine learning-enabled techno-economic uncertainty analysis of SAF production pathways	To develop a ML-based framework for efficient uncertainty analysis in techno-economic assessments of three SAF production pathways (ATJ, HEFA, FT), focusing on MFSP prediction under various input scenarios	SAF pathways analysed: ATJ, HEFA, FT; stochastic TEA using Monte Carlo simulations; input variable randomisation; ML methods include ridge regression, linear SVM, RF, and gradient boosting; MFSP predicted using trained ML models.	ML models reduce the time and computational burden of traditional simulation-based TEA while providing accurate MFSP estimations. Sensitivity analyses show feedstock cost, enzyme loading, and CAPEX as major uncertainty drivers.	Techno-Economic Assessment, SAF Pathways, ML Regression, MFSP Uncertainty, Monte Carlo	Accelerates SAF commercialisation by providing rapid, accurate cost predictions for SAF production routes (ATJ, HEFA, FT), aiding investment and policy decisions under uncertainty	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Wiersema, P.; Oh, J.-H.; Kim, K.; Godsell, A.; Lee, T.	Analysis of constraining a chemical kinetic mechanism using hybrid response surface networks	To develop and apply a ML-based hybrid response surface network (HRSN) method for optimising and constraining chemical kinetic mechanisms for jet fuel combustion under uncertainty	Jet-A ignition delay data; HRSN combined with stochastic gradient descent ensemble (SGDE); one million samples and 1000 optimisation runs; constrained by experimental ignition and species data; applied to low- and high-temp chemistry via HyChem model.	HRSN-SGDE enables rapid mechanism development with uncertainty quantification. Constraining even one species (e.g. C2H4, CH4) dramatically reduces uncertainty space. Framework is adaptable to SAFs and guides efficient experimental validation.	Chemical Kinetics, Jet Fuel Combustion, HRSN-SGDE, Uncertainty Quantification, SAF Mechanism Development	AI-accelerated development and validation of combustion models for SAFs to enable fast, accurate simulation and certification of SAF	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Kilic, U.; Villareal-Valderrama, F.; Ayar, M.; Ekici, S.; Amezquita-Brooks, L.; Karakoc, T.H.	Deep learning-based forecasting modeling of micro gas turbine performance projection: An experimental approach	To develop and test deep learning models, specifically LSTM networks, for forecasting key performance indicators (thrust, shaft speed, EGT) of a micro turbojet engine under varying flight conditions	Experimental data from SR-30 turbojet engine; 321 flight condition data points; LSTM deep learning models trained and tested with different hyperparameters for prediction accuracy.	LSTM networks demonstrated high prediction accuracy ($R^2 > 0.98$ for all outputs). Models captured performance behaviour of turbojet engines under environmental changes, aiding efficiency and sustainability.	Aeroengine Performance Forecasting, Deep Learning (LSTM), Experimental Modeling, Emissions Awareness	Experimental LSTM-based modeling for turbojet engine efficiency and environmental performance optimisation	Aircraft Maintenance and Reliability with AI Support

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Kabashkin, I.; Perekrestov, V.; Tyncherov, T.; Shoshin, L.; Susanin, V.	Framework for Integration of Health Monitoring Systems in Life Cycle Management for Aviation Sustainability and Cost Efficiency	To develop a comprehensive framework integrating Advanced Health Monitoring Systems (AHMSs), modular design, and Life Cycle Management (LCM) to enhance sustainability and cost efficiency in aviation operations	Mixed-methods study; literature review, framework modeling, and validation through case studies using quantitative cost models.	Integrated LCM-AHMSs-modular architecture can reduce maintenance costs by up to 30% and extend component life by 20%. Provides real-time monitoring, predictive maintenance, and operational adaptability.	Life Cycle Management, Predictive Maintenance, Health Monitoring, Modular Aircraft Design	AI-driven integration of modular aircraft components with LCM and predictive AHMSs for sustainable operations	Aircraft Maintenance and Reliability with AI Support

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	He, X.; Wang, N.; Zhou, Q.; Huang, J.; Ramakrishna, S.; Li, F.	Smart aviation biofuel energy system coupling with machine learning technol-ogy	To review recent advances in ML-enabled smart biofuel systems, focusing on the integration of ML with SAF production from biomass	Review article; thematic categorisation of SAF technologies (1st to 3rd generation), catalysts, and ML-supported optimisation in SAF production and evaluation.	ML technologies can reduce cost, improve catalyst design, and optimise production in SAF systems. The review synthesises three SAF generations and highlights ML's role in intelligent, low-emission aviation fuel systems.	SAF, ML, Biomass Conversion, Catalyst Optimisation	AI-supported SAF production and evaluation systems for sustainable commercial aviation fuel supply	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Filelis-Papadopoulos, C.K.; Kirshner, S.N.; O'Reilly, P.	Sustainability with Limited Data: A Novel Predictive Analytics Approach for Forecasting CO_2 Emissions	To develop a predictive analytics approach for forecasting aircraft-specific CO_2 emissions using a sparse, high-volume aviation dataset impacted by shocks such as COVID-19 and geopolitical crises	29,707 aircraft; CO_2 emissions time series (32 months); Adaptive Auto-Regression with Thresholding (NNAART); comparison with ML methods (LSTM, SVR, GRNN, etc.)	The NNAART method outperforms other ML approaches in both accuracy and computational efficiency for large-scale, sparse aviation emissions data. It enables scenario-based fleet emissions forecasting for financial and environmental decision-making.	CO_2 Emissions Forecasting, Aviation Analytics, ML, Predictive Modeling	Aircraft-level emissions forecasting for ESG compliance and sustainable fleet management	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2024	Chen, Y.; Huang, Z.; Ma, C.; Wang, Y.; Chen, W.; Zhang, Z.; Tan, T.; Chen, Y.	China's bioenergy potential will be stable and decoupling from economy and population at national level: A study based on machine regression prediction model	To develop a ML model using economic and population data to predict China's national and provincial-level bioenergy potential, with implications for SAF planning	Provincial data from 1978–2021 (GDP, population); BP neural network model optimised with marine predators algorithm (MPA) and snake optimiser (SO); prediction of bioenergy potential through 2050.	Bioenergy potential in China will remain stable and decoupled from economic/population growth. ML models offer reliable forecasts. Promoting SAF and high-value fuels from biomass is critical for sustainable aviation.	Bioenergy Forecasting, ML, SAF, Economic Modeling	Forecasting SAF availability and bioenergy planning for aviation sector	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2025	Wang, Z.; Xue, D.; Wu, L.; Yan, R.	A reliable predict-then-optimize approach for minimizing aircraft fuel consumption	To develop a predict-then-optimise model using quick access recorder (QAR) data and ML to minimise aircraft fuel consumption for sustainable aviation operations	QAR data from 4,597 flights (A320, A321, B737, B738); RF regression for fuel rate prediction across nine flight phases; optimisation framework for minimum fuel load using real-time inputs and confidence intervals.	The model reduced loaded fuel and fuel consumption by 3.67% on average across all aircraft; ensures flight safety by integrating ICAO buffer/reserve fuel guidelines; suitable for dispatch optimisation and sustainability.	Predict-Then-Optimise, Fuel Load Optimisation, RF, QAR Data, Sustainable Aviation	AI-enhanced fuel planning model for minimising emissions and costs while maintaining operational reliability in commercial aircraft operations	AI-Driven Emission Reduction and Fuel Efficiency

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2025	Mohammadi, S.; Rahmanian, V.; Karganroudi, S.S.; Adda, M.	Smart Defect Detection in Aero-Engines: Evaluating Transfer Learning with VGG19 and Data-Efficient Image Transformer Models	To evaluate and compare the performance of CNN-based (VGG19) and transformer-based (DeiT) models in detecting aero-engine defects, with a focus on efficiency, accuracy, and generalisability under limited data conditions	Aero-engine blade defect dataset from Kaggle; applied transfer learning and RandomizedSearchCV for hyperparameter tuning; evaluated with precision, recall, and ROC-AUC metrics using cross-validation.	The DeiT model outperformed VGG19 in accuracy, recall, and generalisation. Results show that transformer-based models are highly effective for early defect detection in aero-engines, supporting predictive maintenance and sustainable aviation.	Defect Detection, Deep Learning, Transformers vs. CNN, Predictive Maintenance	AI-powered inspection of aero-engine blades using deep learning for predictive maintenance and sustainability	Aircraft Maintenance and Reliability with AI Support

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2025	Selvam & Al-Humairi	Environmental impact evaluation using smart real-time weather monitoring systems: a systematic review	To explore how IoT, ML, and deep learning contribute to smart real-time weather monitoring systems and how these systems align with sustainability goals (e.g. SDGs)	Systematic literature review (SLR) of 130 studies using the PRISMA framework, focusing on IoT-based weather monitoring integrated with mobile/web apps and AI techniques.	Smart real-time weather systems enhanced by AI enable improved forecasting, support SDGs 7, 9, 11 and 13, and offer actionable insights for environmental sustainability and resilience.	Environmental Performance and Efficiency – AI-based Weather Prediction	The study is indirectly connected to aviation through its systematic analysis of smart weather monitoring systems that incorporate IoT, ML and deep learning. While not limited to aviation, the technologies and systems reviewed in the paper have critical relevance for aviation operations, especially in enhancing weather forecasting accuracy, real-time atmospheric data collection, and climate impact assessment. These tools support sustainable practices in air traffic management, airport operations, and flight safety under changing environmental conditions.	Airport and Infrastructure Sustainability

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Table 1. *Continued*

Year	Author(s)	Title	Objective	Participants & method	Conclusions	Classification	Aviation context	Thematic category
2025	Klophaus, R.	AI-generated SWOT analysis of emerging technologies in air transportation: Potential and limitations	To conduct an AI-generated comparative SWOT analysis of five emerging aviation technologies (UAM, UAVs, electric aircraft, supersonic aircraft, SAFs) and evaluate the feasibility and limitations of using AI for strategic decision-making	AI-generated SWOT analyses using ChatGPT for five technologies; qualitative evaluation of outputs; comparison with human expert-based SWOT examples.	AI-generated SWOTs offer meaningful, structured content, reduce subjectivity, and support strategic planning. Limitations include lack of factor prioritisation and possible superficiality. AI serves as a useful initial input for expert-driven analysis.	SWOT Analysis, Strategic Planning, Emerging Aviation Technologies, AI-Assisted Decision Making	Cross-technology AI analysis of UAM, UAVs, electric aircraft, supersonic aircraft, and SAFs for future sustainable aviation strategy	AI Applications in Aviation Education, Decision Support, and Policy Making

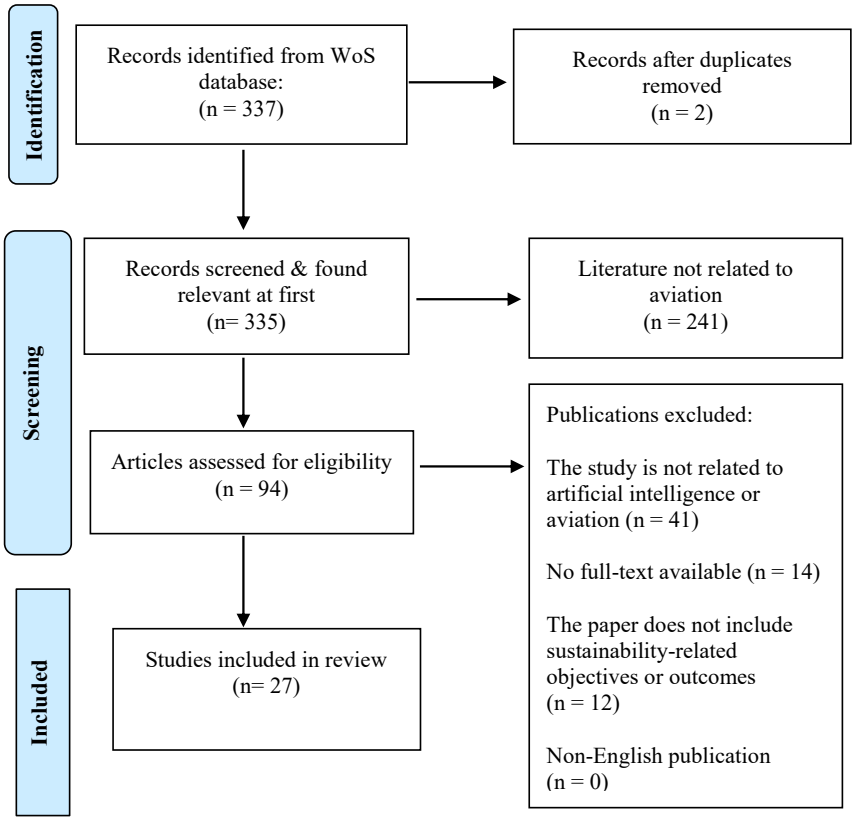


Figure 1. *PRISMA 2020 flow diagram for article selection.*

2.3 Conducting phase

Prior to analysis, a total of 337 articles initially identified through the WoS database were systematically imported into the EndNote20 reference management software. This step ensures accurate tracking of the bibliographic information and facilitates the export of the data required for the analysis process. The screening process was conducted within EndNote to facilitate systematic filtering and categorisation. As a result of this process, 27 articles that met all the eligibility criteria were retained for in-depth analysis. To increase the validity and reliability of the analysis process, EndNote20 reference management software, which is preferred in systematic reviews, was used. User guides and literature indicate that EndNote accelerates the work process and provides a systematic structure by supporting operations such as adding, removing, tagging and full-text association centrally and consistently [15]. EndNote 20 was used to manage and de-duplicate references and to facilitate systematic screening [16]. In addition, the features of this software, such as multi-user support, version tracking and annotation, have strengthened the traceability and reportability of the study.

Following this, a comprehensive review of the full texts was conducted. The articles were then subjected to a combination of qualitative content analysis and descriptive mapping, following established methodological recommendations [17, 18]. Manual coding was performed based on a structured coding scheme developed in line with the research objectives. The coding focused on key dimensions such as:

- AI technique used (e.g. ML, DL, hybrid models)
- Aviation domain (e.g. aircraft maintenance, flight operations, airport systems)
- Sustainability focus (e.g. emissions reduction, resource efficiency, noise mitigation)
- Data type and source (e.g. ADS-B data, simulation outputs, maintenance logs)

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To ensure the validity and reliability of the analysis, several strategies were implemented. Initially, the coding scheme was pilot-tested on a sample of articles to refine the category definitions and ensure alignment with the research objectives. To assess the inter-coder reliability, an independent aviation researcher was invited to code a subset of the data. Any discrepancies were discussed collaboratively until a full consensus was reached, thereby minimising subjective bias and enhancing consistency. Additionally, expert opinion was sought regarding the relevance and clarity of the coding framework and analytical procedures. Feedback from the domain experts contributed to the refinement of both the coding categories and the overall research design. Methodological triangulation was also applied by combining qualitative content analysis with descriptive mapping, supporting the credibility and depth of the interpretation.

MAXQDA 2024 software was used for the management and analysis of the coded data, thus ensuring systematic categorisation and traceability. Biblioshiny (an R-based interface) and VOSviewer 1.6.20 were employed to create visual representations such as the frequency distributions of the AI methods.

3.0 Results

3.1 Systematic review

Based on the findings of this systematic review, it has been identified that AI applications in the sustainable aviation sector assume multidimensional roles in the context of sustainability. The 27 analysed studies stand out with solutions developed especially in line with the sustainability goals. The findings obtained from the studies were classified thematically and gathered under four main themes in Table 1. This thematic framework was structured to more clearly reveal the application areas where AI contributes to sustainable aviation.

The findings of the 27 studies analysed were gathered under four main themes. The main themes in question are: AI-driven emission reduction and fuel efficiency; aircraft maintenance and reliability with AI support; airport and infrastructure sustainability; and AI applications in aviation education, decision support and policy making.

3.1.1 AI-driven emission reduction and fuel efficiency

This theme covers studies where AI and ML methods are used to reduce carbon emissions, optimise fuel consumption and improve environmental performance in aviation. A total of 18 studies were included in the review under this theme. These studies cover various applications such as the optimisation of SAF, hybrid engine modeling, fuel load planning, engine emission prediction and preventing unnecessary fuel consumption caused by air traffic operations. AI applications have demonstrated a significant effect on enhancing sustainability by improving operational efficiency and supporting the ICAO's long-term CO_2 reduction goals. ML-supported predictive analytics play a critical role in reducing carbon emissions in production processes and offer decision-support systems that enhance energy efficiency through real-time monitoring and anomaly detection [19]. This approach sheds light on similar processes used in aviation and highlights the general potential of AI-based sustainability strategies. The artificial neural network-based model developed by Kosir et al. [20] predicts the material compatibility of SAF blends within aircraft fuel systems and enables the development of fuel types optimised for both safety and environmental performance. Similarly, Oh et al. [21] developed deep learning models that included uncertainty calculations to predict flash points of sustainable fuels. These studies suggest that AI can be used as a reliable tool, especially in SAF certification processes. Additionally, Wang et al. [22] demonstrated that fuel consumption predictions and optimisation based on the QARQAR data provided an average fuel saving of 3.67%. These models consider ICAO-recommended reserve fuel policies and contribute to strategies that reduce the environmental impact while maintaining operational safety. The power prediction-based model predictive control (P2MPC) system developed by Wei et al. [23] provided fuel efficiency and emission reduction by controlling the battery status and EGT in hybrid land-air vehicles. This represents a critical AI application in the context of the anticipated proliferation of electric

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and hybrid aircraft. Sun et al. [24] analysed the final demand-based emission intensity of the transportation sector on a more macroscale and showed that air transportation increases the indirect climate burden in developed countries. AI-supported data analysis techniques provide significant advantages in such analyses. Similarly, Miller et al. [25] emphasised the transformative potential of AI technologies in increasing energy efficiency and reducing greenhouse gas emissions in the transportation sector. The study states that AI-supported solutions in flight route optimisation, management of alternative fuel systems and fleet planning contribute to reducing the carbon footprint in aviation. AI facilitates production, distribution and performance optimisation in hydrogen and biofuel-based systems by enabling process modeling, yield prediction and energy-flow optimisation functions that accelerate SAF integration into existing aviation fuel infrastructures [25]. In the literature, it is emphasised in many sources that such AI applications play a critical role in achieving sustainability goals. Likewise, the ICAO's Environmental Report [2] emphasised AI as a technology that should be integrated into carbon reduction strategies. In this context, it is seen that AI technologies in the aviation sector offer multidimensional contributions to achieving sustainability goals not only at the operational level but also at the strategic, environmental and infrastructural levels. The studies examined reveal the potential of AI to increase environmental performance, especially fuel efficiency and emission reduction, with concrete applications.

3.1.2 Aircraft maintenance and reliability with AI support

In the aviation industry, maintenance operations play a critical role in ensuring flight safety and operational continuity. Particularly for airline operators functioning under high safety requirements and cost pressures, optimising aircraft maintenance processes is important [26]. While traditional maintenance approaches are mostly based on time-based or reactive strategies, in recent years, AI-based solutions have transformed the sector by making these processes data-driven, predictive and predictive [27]. AI technologies such as ML, robotics, Internet of Things (IoT), computer vision and natural language processing have been integrated into maintenance processes, enhancing both operational efficiency and technical reliability [28]. For instance, Rolls Royce's Intelligent Borescope system reduces engine inspection time by 75%, while Lufthansa Technik's Condition Analytics solution analyses sensor data to predict maintenance needs in advance [29]. These systems not only detect current faults but also contribute to the optimisation of maintenance planning by making future-oriented predictions based on historical usage data and failure trends. These thematic findings are consistent with the studies analysed in this review. For instance, Kabashkin et al. [30] demonstrated that AI-supported maintenance optimisation in unmanned aerial vehicles (UAVs) led to a 20% cost reduction. In addition, other studies on this theme emphasise various technical dimensions regarding the applications of AI in maintenance processes. For example, Apostolidis et al. [31] developed a solution for the damage detection of engine components using neural network-assisted image processing algorithms. Plastropoulos et al. [32] emphasised the role of AI-driven data collection and predictive analytics within the context of 'smart hangars', highlighting how technologies such as digital twins, robotics and IoT can optimise aircraft maintenance processes, enhance safety and contribute to sustainability in line with Industry 5.0 principles. In studies conducted within the Turkish context, Kilic et al. [33] demonstrated the applicability of deep learning-based models, particularly LSTM networks, for forecasting micro turbojet engine performance, highlighting their potential to improve maintenance efficiency and support environmental sustainability in local aviation practices. Furthermore, Mohammadi et al. [34] highlighted the effectiveness of transformer-based deep learning models, particularly DeiT, for early aero-engine defect detection under limited data conditions, demonstrating their potential to enhance predictive maintenance strategies and support sustainability in aircraft operations. By reducing unscheduled maintenance events, extending component lifespans and minimising resource waste, AI-driven predictive maintenance contributes directly to the environmental and economic dimensions of sustainability in aviation.

3.1.3 Airport and infrastructure sustainability

Consistent with the UN's 2030 Sustainable Development Goals, AI-supported airport operations have increasingly focused on optimising energy consumption, waste management and traffic flow efficiency

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to reduce environmental impact [35]. Integrating AI into airport operations enables the optimisation of numerous processes, ranging from apron management and passenger flow to baggage logistics and terminal energy management. In the literature, the gains obtained through the integration of AI into airport infrastructure are gathered under the following headings: operational efficiency, environmental sustainability, energy savings, improvement of passenger experience and strengthening of cybersecurity [36, 37]. For example, passenger flows within the terminal are analysed with camera and sensor data, reducing congestion at security, passport control and boarding gates, thus increasing passenger satisfaction. AI-based biometric systems and facial recognition technologies accelerate identity verification processes and increase the accuracy of security protocols. Moreover, AI-supported systems in terminal energy management optimise lighting, HVAC (heating, ventilation, and air conditioning) and overall energy consumption; AI algorithms predict peak usage hours and dynamically adjust operations accordingly [37]. These applications contribute to environmentally friendly air transportation by reducing airports' carbon emissions. The studies analysed within this theme also confirm the developments observed in the literature. For instance, Ramakrishnan et al. [38] evaluated the green performance of airports worldwide using explainable semi-supervised learning models. Their model offers sustainability-enhancing strategies to airport operators based on environmental parameters such as S1/S3-type greenhouse gas emissions and energy usage. Similarly, a systematic review by Selvam and Al-Humairi [39] emphasised the contribution of IoT- and AI-based weather monitoring systems to sustainable airport operations. The use of these systems as decision-support tools in air traffic management helps reduce weather-related operational risks and enhances energy efficiency. The integration of AI into airport and infrastructure sustainability is driving a multi-dimensional transformation that not only increases operational efficiency but also increases environmental awareness. In light of the increasing air traffic, energy costs and environmental regulations, the comprehensive adoption of these technologies has become a critical strategic priority to both meet climate goals and improve passenger satisfaction.

3.1.4 AI applications in aviation education, decision support and policy making

As part of the digital transformation process, the aviation sector has begun to effectively use AI technologies not only in operational processes but also in education, decision support and policy making. In the context of education, large language models (LLM) and AI-supported assistants facilitate students' access to information, improve programming skills and personalise learning processes [40]. The study by Wandelt and colleagues [40] empirically demonstrated the potential of ChatGPT to enhance student performance in aviation management education, while also highlighting the need for critical evaluation in terms of accuracy, reliability and contextual alignment. Within the scope of decision support systems, Klophaus [41] conducted a study utilising AI to perform SWOT analyses on five emerging aviation technologies (Urban Air Mobility, UAVs, electric aircraft, supersonic flights and SAFs). The study emphasises that AI's capacity to produce analytical outputs can provide meaningful contributions to decision-making processes when complemented by expert opinions. This indicates that AI systems can play a supporting role in aviation strategies. AI-supported education and decision-making tools also foster sustainability by promoting safety culture, energy awareness and data-driven policy-making aligned with sustainable operational standards. When evaluated in this context, it is seen that AI-supported systems have significant potential in aviation education, decision support mechanisms and policy production. Nevertheless, the reliability, ethical implementation and human-centred design of such technologies must be carefully addressed. The principles of human oversight, transparency, and accountability should be upheld [35]. Thus, AI will continue to contribute to the digitalisation and sustainability goals of the aviation sector not only at the operational level but also in the areas of governance and education.

Collectively, these four themes demonstrate that AI technologies are being increasingly integrated into aviation operations to enhance sustainability, safety, and efficiency. While the corpus of 27 studies provides a structured overview of emerging trends, its limited size constrains the generalisation of sector-wide conclusions and should be interpreted as exploratory rather than exhaustive.

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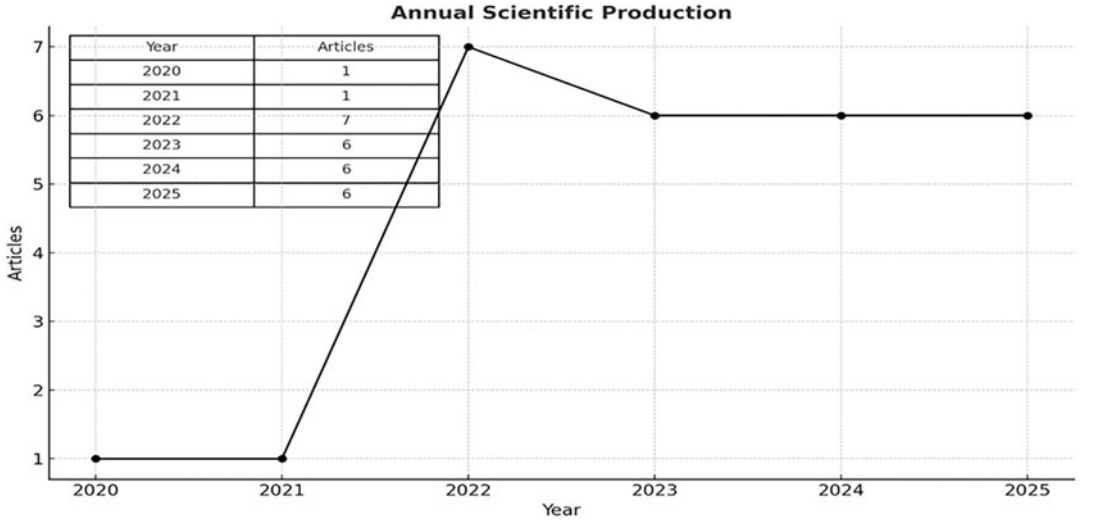


Figure 2. *Distribution of the studies used in the research according to years.*

3.2 Search results

The distribution of the 27 academic publications analysed in years is shown in Fig. 2. This figure is a descriptive bibliometric visualisation illustrating publication trends, not a statistical analysis. It reflects the development trends of AI applications in the aviation field. According to the data, there was only one publication in 2020, and it is seen that the subject was represented by a limited number of studies in this period. Similarly, there was only one publication in 2021. However, there was a remarkable increase in the number of publications in 2022, and a total of seven publications were identified. This increase shows that academic interest in the relevant field has started to increase significantly.

In the years 2023, 2024 and 2025, six studies were encountered in each year, suggesting a steady continuation of research production in the field. This distribution shows that AI technologies have increasingly become a focal point in the aviation sector, especially over the last five years, and are being academically discussed in multidimensional application areas such as sustainability, maintenance processes, educational systems and decision support mechanisms.

The annual distribution data obtained show that AI is gaining more and more importance in aviation, both theoretically and practically, and inter-disciplinary research is intensifying. In particular, the peak in 2022 can be associated with the acceleration of digitalisation and automation trends following the pandemic. It is anticipated that this trend will deepen further in the coming years.

3.3 Findings of AI in sustainable aviation operations

The infographic in Fig. 3 summarises the aviation operations in which AI methods were applied in 27 studies analysed within the scope of the systematic review. The most frequently used AI algorithms under each operational domain are indicated in the visual.

Figure 3 presents the key dimensions of AI applications in sustainable aviation operations, each of which is briefly explained to illustrate their specific contributions to environmental, operational and strategic goals.

3.3.1 AI-based safety prediction: random forest (RF)

AI offers significant contributions to enhancing operational safety in aviation. In particular, RF, a supervised learning algorithm, is widely used to predict safety-critical events by analysing flight data. This method enables the identification of patterns that are difficult to detect using traditional inspection techniques, thus allowing risky situations to be anticipated in advance [42, 43]. In this context, AI-powered

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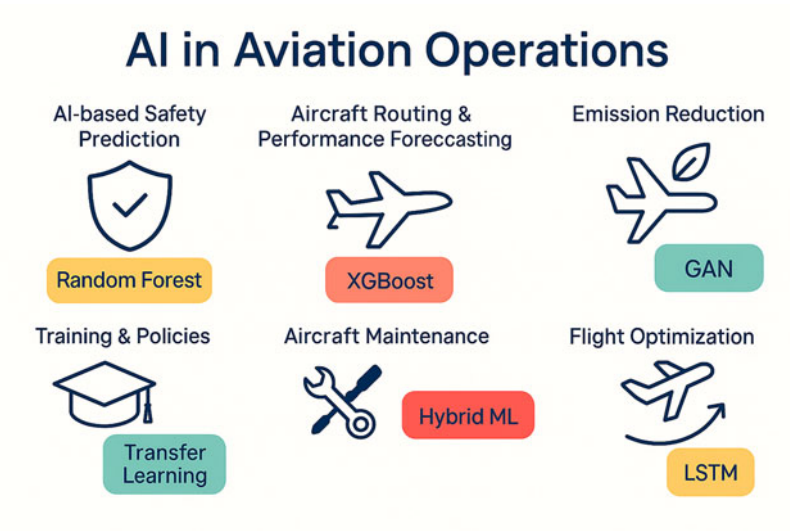


Figure 3. *AI in sustainable aviation operations.*

predictive maintenance (PdM) applications are rapidly gaining importance in the aviation industry. With systems based on historical maintenance records, IoT-based sensor data and visual inspections, it is possible to predict mechanical failures with high accuracy before they occur. This not only reduces maintenance costs but also increases system reliability [44]. An example of this innovative approach is the camera-based PdM system developed by the Israel-based company OdysightAI. This system was developed following the 2017 crash of an Apache helicopter caused by a failure in a flight control rod that was not monitored by existing maintenance systems. Using micro-cameras and specialised AI models, the system continuously monitors critical components and provides early warnings. This development adds a visual layer to traditional prognostics and health monitoring (PHM) systems for components that are otherwise not covered [44]. The system is currently deployed in IDF Apache helicopters and is being tested for broader integration in other rotorcraft platforms and under extreme environmental conditions in collaboration with NASA. Analyses show that such systems provide a 40% cost saving compared to reactive maintenance methods and 8%–12% compared to preventive maintenance systems. AI's contribution to aviation safety is not limited to individual aircraft systems. Ricci [45] states that commercial aviation is still the safest form of transportation and that according to International Air Transport Association (IATA) data, only 0.16 accidents occur per million flight segments. However, increasing air traffic density and inadequacies in critical workforce areas such as pilots, air traffic controllers and maintenance technicians constitute the main safety challenges facing the aviation sector. At this point, ML techniques such as RF play an important role in operational decision support systems by increasing situational awareness and reducing the cognitive load of maintenance or flight crews. Moreover, in systems developed by Airbus, such as Wayfinder and Optimate, RF-based models are actively employed in advanced functions, including autonomous flight control and 4D trajectory management. These systems aim to conduct operations both safely and efficiently by analysing multivariate inputs such as weather, traffic density, fuel consumption and even pilot attention distributions in real-time [45]. In this context, it can be said that AI-based modeling and prediction tools offer a safety architecture that covers not only maintenance processes but also holistic flight systems.

3.3.2 Aircraft routing and performance forecasting: XGBoost

Flight routing and performance prediction hold strategic importance for airline operations in terms of both operational efficiency and energy management. Traditional route planning approaches typically rely on fixed rules and historical data, failing to adequately account for dynamic variables such as weather conditions, traffic density and real-time system behaviours. In this regard, powerful ML algorithms like

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extreme gradient boosting (XGBoost) offer significant advantages in predicting flight performance and routing decisions with high accuracy [46, 47]. XGBoost is particularly prominent in predicting micro-turbine engine performance and modeling parameters such as fuel consumption and aerodynamic drag during flight [48]. This algorithm predicts the behaviour of aircraft systems under certain operational conditions by learning from historical flight data. It enables the development of more efficient, environmentally sustainable and time-optimised flight plans in line with these predictions [43]. Moreover, XGBoost has demonstrated strong predictive capabilities in airport ground operations. In a study by Wang [22], the taxi-in time of arriving aircraft was predicted at an airport located in central-southern China. In the study, 15 affecting factors were determined, the importance of these factors was ranked by the RF method, and then the XGBoost-based prediction model was applied. The model, which was evaluated with criteria such as mean absolute error (MAE), mean square error (MSE) and root mean square error (RMSE), showed 92.78% accurate prediction success within ±5 minutes when compared to linear regression, support vector machines, and artificial neural networks. Paraschos [48] supported the success of XGBoost in flight time estimation with visual analysis. In the study, the relationship between the actual flight times and the times estimated by the XGBoost model was examined with a scatter plot, and the model's predictive ability was revealed with high accuracy. Each data point corresponds to a specific flight, with the actual values on the horizontal axis and the predicted values on the vertical axis. This graphical approach provides important clues in terms of the model's stability and predictive success. In addition, another study by Shengyuan et al. [49] showed that XGBoost is also used innovatively in the context of air-rail integrated transportation networks. In this study, a heuristic path planning algorithm (XGB-HPPA) based on XGBoost is proposed for the prediction of transfer stations in time-expanded graphs (TEG) with high data density. The model first reduces the complexity of the network by eliminating inefficient transfer nodes and greatly speeds up the processing time of path-planning algorithms. Comparative analyses show that XGB-HPPA both increase the number of valid solutions and obtains results that converge to the optimal solution. Such applications reveal that XGBoost can be effectively used not only in in-flight system predictions but also in macro-level multimodal transportation planning.

3.3.3 Emission reduction: generative adversarial networks (GAN)

Given that aviation accounts for approximately 2.5% of global greenhouse gas emissions [50], accurate emission modeling has become a priority area for sustainability-focused innovation. In this context, AI algorithms have become a critical tool, especially in scenario simulations aimed at modeling, estimating and reducing carbon emissions [51]. In particular, GAN algorithms provide significant benefits in synthesising low-quality or incomplete environmental data, determining emission sources and testing operational scenarios. Zhang et al. [52] stated that these algorithms can be used to estimate carbon emissions, especially at seaports and airports; GAN-based data enhancement methods provide more effective results than traditional sensor data in accurately modeling port-based emissions. The same study emphasises that software development processes should be systematically structured from the conceptual design to the final prototype to increase the accuracy of emission analyses. Similarly, a study developed by Zhou [53] demonstrated significant improvements in accuracy, F1-score and strategy adaptation capabilities in carbon emission prediction through optimisations made on the convolutional neural networks (CNN) architecture. This model was equipped with multi-scale feature extraction, attention mechanisms and advanced optimisation algorithms and was tested on datasets related to fuel use and the carbon footprint of airline companies. The findings showed that the proposed model has much higher accuracy and response time than other traditional AI architectures, and its performance is further improved, especially in environments with large data volumes [53]. On the other hand, a study conducted by Kosir et al. [20] revealed that GAN algorithms successfully predicted the volumetric swelling effects on aircraft fuel systems in contact with SAF. In this way, the environmental performance was increased by preserving material compatibility and optimum fuel mixtures could be created in terms of energy efficiency. The ability of GANs to model such physical interactions enables a much more comprehensive and dynamic structure compared to traditional statistical modeling. All these examples demonstrate the multifaceted contributions of AI in emission reduction. The use of models such as GAN,

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CNN, temporal convolutional network (TCN) and graph convolutional network (GCN) in both direct carbon estimations and operational improvement processes enables the design of environmental sustainability strategies based on scientific foundations. Thus, airlines are empowered to make more proactive and data-driven decisions, not only to comply with regulations but also to reduce operational costs and fulfill their environmental responsibilities.

3.3.4 Training and policies: transfer learning

The integration of AI technologies into aviation training processes and policy development increases the quality of learning in the sector and strengthens strategic decision-making processes. In particular, transfer learning allows models developed for use in different training scenarios to be adapted to other training environments, shortening learning times and increasing performance. For instance, transfer learning models developed for simulator environments in aviation training accelerate pilots' adaptation to emergency scenarios and significantly improve the effectiveness of such training processes [54, 55]. Transfer learning enables the adaptation of pre-trained models to specific aviation datasets, reducing the computational demand and training costs, which enhances energy efficiency and resource sustainability in AI model development. In addition, the integration of large language models (LLMs) such as ChatGPT into educational processes supports the faster acquisition of theoretical knowledge and facilitates the comprehension of complex aviation terminology for students [56]. These systems promote interactive and dynamic learning in training environments, thereby enhancing the retention and effectiveness of conceptual understanding. In terms of policy development processes, AI-supported decision-making mechanisms are of critical importance. In particular, AI-based data analytics methods help to better plan and manage operational and strategic decisions in aviation management. The detailed data analysis and predictive capabilities provided by the AI models make it possible to comprehensively evaluate the basic dimensions of air transportation policies, such as sustainability, economic efficiency and safety [30, 57]. For example, ML algorithms used in decision support systems play an active role in the planning of airspace management and air traffic policies, reducing the cognitive load of air traffic controllers and increasing the level of safety [58]. As a result, the integration of AI methods into education and policy development processes accelerates the future transformation of the aviation sector and contributes to the creation of a more efficient, safe and sustainable aviation ecosystem.

3.3.5 Aircraft maintenance: hybrid ML

Aircraft maintenance processes are one of the key components of ensuring safety and continuity in aviation operations. Hybrid ML approaches have recently come to the forefront to increase the effectiveness of maintenance activities and prevent operational disruptions. Hybrid models combine different types of algorithms to increase accuracy, early fault detection and predictability compared to the models used alone. Kaynak and Ervural [59] emphasised that the hybrid ARIMA-ANN model outperformed the classical linear and nonlinear methods in predicting machinery failures. These hybrid models can effectively identify both linear and nonlinear patterns in real-world data, significantly reducing unplanned downtimes. This approach is noted to improve operational efficiency and lower maintenance costs, thereby supporting the competitive advantage of airlines. Jasra et al. [60] recommended the use of the local outlier factor (LOF) algorithm together with hybrid statistical methods for anomaly detection in-flight data. This method not only detects anomalies occurring during the flight process but also increases flight safety by quantifying the degree of anomalies. Thus, detailed analysis is provided even during short periods when the flight exhibits abnormal behaviour. This method significantly supports maintenance and safety management processes by reducing human intervention in flight data analysis. Paredes et al. [61] developed a hybrid approach combining supervised learning (MLP) and reinforcement learning (Q-learning) algorithms to estimate the remaining useful life (RUL) of aircraft engines. The method was found to offer 15% higher accuracy compared to approaches using only supervised learning algorithms and 4% more accuracy than other hybrid methods. It provided an early warning approximately 17 cycles before failure, effectively preventing unexpected machinery downtimes and reducing

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maintenance costs. In addition to these studies, hybrid models effectively integrate data from different sources such as sensor data, historical maintenance records, and real-time aircraft component status data to predict potential failures more accurately [30–32, 34]. Furthermore, the integration of computer vision, transfer learning and digital twin technologies into hybrid methods significantly enhances both operational and financial outcomes in maintenance processes [30, 44]. As a result, hybrid ML approaches increase the accuracy of failure predictions in aircraft maintenance processes and provide significant advantages in terms of operational continuity and safety by reducing maintenance costs.

3.3.6 Flight optimisation: long short-term memory (LTSM)

Optimisation of flight operations is a critical goal in the aviation industry in terms of both reducing operational costs and increasing sustainability. In this context, long short-term memory (LSTM) models, which can capture long-term dependencies in time series data, are frequently preferred in-flight optimisation processes. The effectiveness of LSTM models has been confirmed by academic studies conducted at various stages of flight operations. For instance, Qu et al. [62] developed an Att-Conv-LSTM model that integrates temporal and spatial data to predict flight delays and found that it reduced prediction errors by 11.41% compared to conventional LSTM models. Similarly, Yousefzadeh Aghdam et al. [63] stated that bidirectional LSTM models (Bi-LSTM) in air traffic management optimisation, when used together with extreme learning machines (ELM), allow the development of more accurate and faster decision support systems. Xiong et al. [64] emphasised the importance of the DMPSO-LSTM model, which they developed based on QAR data, for the accurate prediction of fuel consumption at different stages of flight (climb, cruise and descent). This study increased the quality of data preprocessing by using the adaptive noise ensemble empirical mode decomposition (CEEMDAN) method, and then significantly improved the prediction performance of the LSTM model by using dynamic multi-dimensional particle swarm optimisation (DMPSO). The model results showed a decrease of more than 40% in the MAE value, more than 38% in the RMSE value, and more than 6% in R^2 value in the climb segment. Similar performance increases were obtained in the cruise and descent segments. The integration of such advanced models into flight operations offers three main advantages to airlines: (1) it provides the most appropriate balance between payload and fuel costs by quantitatively determining the load-fuel relationship; (2) it helps determine the most suitable flight profiles with more accurate predictions at different phases of flight (climb, cruise and descent); and (3) high-accuracy fuel consumption estimates support optimal fuel loading decisions by minimising safety margins [64].

4.0 Discussion

In this study, a systematic review of AI applications in the aviation sector from a sustainability perspective was conducted and analysed through 27 studies in the literature. The analyses undertaken in this scope focused on four main themes: AI-driven emission reduction and fuel efficiency; aircraft maintenance and reliability with AI support; airport and infrastructure sustainability; and AI applications in aviation education, decision support and policy making. Within the education-related studies, large-language-model tools were identified as emerging instruments to support simulation-based and personalised training processes. Despite their pedagogical value, these tools are constrained by issues of factual accuracy, bias and compliance with aviation-training regulations, necessitating human oversight.

A year-by-year analysis of publication frequencies reveals a notable increase in studies starting from 2020, with a consistent growth trend, especially after 2022. This situation can be explained by the increasing interest in sustainability applications in the sector and the acceptance of AI as an effective tool in this context [8, 65]. These findings align with and contribute to ongoing global sustainability initiatives in aviation. In particular, the emerging AI-driven approaches correspond with the objectives of the ICAO long-term global aspirational goal (LTAG) toward achieving net-zero carbon emissions by 2050, as well as IATA's Net Zero 2050 Roadmap. Moreover, the European Union's *Fit for 55* package highlights the importance of digitalisation and operational optimisation both of which are areas where

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AI technologies demonstrate tangible impact. By linking the identified AI applications to these international frameworks, this review underscores their strategic relevance for policy alignment and sustainable transformation in the sector.

While AI applications demonstrate growing potential in enhancing operational sustainability, the methodological robustness of the reviewed studies varies considerably. Most research relied on simulated data and relatively small sample sizes, which may limit the generalisability and reproducibility of the reported outcomes. Future investigations should therefore prioritise larger empirical datasets and standardised evaluation protocols to strengthen the evidence base.

When the distribution of AI applications in the aviation field was analysed, it was found that aircraft maintenance processes were the most frequently addressed area, followed by emission reduction and flight optimisation. This distribution is due to the direct association of maintenance activities with operational safety and economic sustainability. It was identified that methods such as hybrid ML and RF stand out in predictive maintenance and safety management applications [59–61].

Assessment of specific AI algorithms used in different aviation operations highlights the effectiveness of the RF algorithm in early risk prediction and enhancing operational safety [45]. Similarly, the XGBoost algorithm has shown superior success in aircraft route optimisation and performance predictions [22, 48, 62]. GAN algorithms are an effective tool in synthetic data production and emission predictions in aviation in terms of sustainability and emission management [52, 53].

It has been revealed that the transfer learning method provides significant advantages in education policies and training processes, especially in cases where there is a lack of data. This method offers efficiency and productivity by optimising resource usage in aviation training [40].

Under the theme of Aircraft Maintenance, hybrid ML models have shown superior performance in error prediction and predictive maintenance applications in maintenance operations. These models increase the operational reliability of aircraft and reduce costs by providing higher accuracy results than traditional methods [59–61].

In terms of flight optimisation, it has been observed that LSTM algorithms provide high accuracy, especially in time series predictions, and are successful in predicting critical performance indicators such as flight delays and fuel consumption [62–64]. It has been determined that flight processes can be planned more effectively, and operational efficiency is increased with the integration of LSTM.

The analysis of the frequency of AI methods revealed that while general ML methods are widely used, deep learning, neural networks (Artificial Neural Network – ANN, Bayesian Neural Network – BNN), LSTM, and RF algorithms are also frequently preferred. This indicates that data analytics-based approaches are increasingly embraced in the aviation sector and have a broad potential for application in this field [46].

The integration of AI into aviation systems requires not only technical advancement but also regulatory adaptation. Compliance with ethical and legal frameworks, such as the European Union's General Data Protection Regulation (GDPR) and the European Union Aviation Safety Agency's (EASA) AI Roadmap, is essential for the certification of AI applications in safety-critical domains. These frameworks emphasise explainability, data governance, accountability and human oversight as prerequisites for trustworthy and certifiable AI in aviation. Addressing these regulatory and certification challenges is therefore vital to ensure that AI deployment aligns with safety, transparency and ethical standards within the aviation ecosystem.

5.0 Conclusion

This systematic review comprehensively analysed the recent developments in the use of AI technologies in sustainable aviation operations. Four main thematic categories were identified by examining 27 academic studies published between 2020 and May 2025. The prominent AI methods in the studies include RF, LSTM, hybrid ML, GAN, and transfer learning; these methods are applied in various operational areas such as safety prediction, aircraft maintenance, emission management and flight optimisation. The findings clearly demonstrate the increasing importance of AI in the aviation sector and

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its critical role in achieving sustainability goals. Rather than proposing a definitive framework, this review provides an integrative thematic mapping that organises AI applications in sustainable aviation and outlines emerging research priorities.

5.1 Future research directions

In today's rapidly advancing technological landscape, the following areas are expected to guide future studies aimed at ensuring that AI applications in aviation become sustainable, reliable, and compliant with regulatory requirements.

5.1.1 Explainable and certifiable AI models

Explainability and certification are of critical importance for AI applications used in safety-critical systems. While models such as the generalised additive model (GAM) developed by Apostolidis et al. [31] are preferred in maintenance and safety applications due to their transparent structures, the dissemination of such explanatory approaches will increase the industry's trust and facilitate regulatory processes. In addition, studies showing that there are deficiencies in the literature on the certification of ML-based safety-critical systems emphasise the importance of considering elements such as verification, uncertainty and robustness together with explainability.

5.1.2 Expansion of hybrid and ensemble AI methods

As emphasised by Kaynak and Ervural [59], ARIMA–ANN combined conventional hybrid models have the potential to provide better accuracy in applied maintenance predictions than single methods. The hybrid SI-LOF model developed by Jasra et al. [60] demonstrates that hybrid methods can open new doors in aviation by offering a unique score-based approach to identify extreme anomalies in flight data. These studies show that the integration of different algorithms can be advanced both conceptually and practically, as demonstrated by Konar et al. [65], who combined artificial neural networks and the backtracking search optimisation (BSO) algorithm to reduce gas turbine engine emissions through a fast and effective modeling approach.

5.1.3 Real-time decision support systems:

The DMPSO–LSTM model proposed by Xiong et al. [64] has provided usability for decision support systems in both heavy traffic management and fuel optimisation by providing real-time fuel estimation over QAR. Increasing the accuracy and speed of such models can create significant performance gains in operational decision processes.

5.1.4 Generative AI in data-scarce environments

Generative AI-supported predictive maintenance models (e.g. GANs, VAEs) examined by Khan et al. [66] enhance model accuracy through synthetic data generation, particularly in contexts lacking 'run-to-failure' data. When used alongside digital twins, these methods are expected to further improve the quality of maintenance forecasting.

5.1.5 Integration of AI and behavioural sciences

Studies by Es-haghi et al. [67] and Mello and Macario [68] emphasise the potential of AI-supported personalised services in shaping passenger behaviour, enabling sustainability strategies and supporting circular economy approaches. This integration facilitates environmental management and systems optimisation in aviation through AI-based resource management, waste reduction and behavioural interventions.

5.1.6 Digital twin-based AI models

AI applications supported by digital twins have the potential to eliminate critical error sources in real-time monitoring and autonomous system management. Digital twin technology stands out as one of

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the building blocks of digital transformation in the aviation sector and plays an active role in real-time monitoring, decision support systems and predictive maintenance processes. Unlike traditional digital models, digital twins do not only provide static representations; they also function as dynamic, data-fed virtual copies that are constantly synchronised with physical systems. In this way, they can simultaneously reflect both system behaviours and environmental interactions [69]. Applications such as Airbus's [70] Skywise platform enable digital twins to be continuously updated with data from sensors integrated into aircraft, allowing more than 50,000 users worldwide to benefit from this infrastructure for maintenance planning, failure prediction and operational optimisation. This approach is not only applicable in aircraft design and production stages; it also increases efficiency in operational processes, reduces environmental impact and makes maintenance processes more proactive. For example, Airbus uses digital twins in industrial facilities such as the A321 production line to simulate production flows before the assembly process and thus reduce error rates [70]. One of the greatest contributions of digital twins in terms of engineering is the realisation of multi-disciplinary simulations of complex systems and the updating of these simulations with real-time data. This makes it possible to predict how systems will behave in 'off-design' situations and supports early-stage intervention [69]. Especially in high-risk areas such as the defense industry, this technology offers strategic advantages in areas such as mission planning, asset management and operational readiness. The integration of AI and digital twins further increases these benefits. AI algorithms perform predictive analyses on large data sets from digital twins, optimising system performance and enabling scenario modeling. Thanks to this integration, flexibility increases in many processes from production lines to fleet management, error sources decrease and operational decisions become data-based. In addition, AI-supported digital twins have begun to be used in sustainable cabin services, smart resource management and carbon emission reduction by analysing user behaviour [3]. However, structural challenges such as data security, platform compatibility and qualified human resources also come to the fore in the implementation of these technologies. Especially when systems are shared between different suppliers, issues such as data integrity and ownership stand out as important areas of research [69].

5.1.7 Data security and regulatory compliance

The rapid adoption of AI systems in the aviation sector brings with it multifaceted responsibilities, including data security, ethical compliance and adherence to regulations. AI solutions integrated into critical areas such as autonomous flight systems, predictive maintenance and air traffic control enable digital systems to guide operational decisions. However, this also raises concerns about the transparency, reliability and suitability of such systems [71]. While examining the adoption of AI in predictive maintenance systems, Azyus et al. [72] found that algorithmic accuracy alone is insufficient. Explainability and user comprehensibility of the systems are critical for building trust in the technology. A lack of transparency in how decisions are made may lead to resistance among technicians and maintenance teams, potentially threatening the sustainability of established operational routines. Furthermore, certification processes for predictive systems may face inconsistencies between the probabilistic nature of algorithms and traditional deterministic safety standards [72]. The development of regulatory frameworks plays a key role in integrating AI-based applications into operational systems. International organisations such as the International Civil Aviation Organisation (ICAO), the European Union Aviation Safety Agency (EASA) and the Federal Aviation Administration (FAA) have been developing regulations for AI and autonomous systems based on core principles such as transparency, traceability, human oversight and ethical decision-making [71]. However, regulatory differences between countries can lead to both technical incompatibilities and policy fragmentation, thus becoming an obstacle to innovation. Data security and resilience to cyber-attacks are critical for the sustainable use of these technologies. Considering that AI systems are fed with large data sets, affect operational decisions and are constantly updated over inter-system network connections, it is essential to protect these systems against malicious access. While legal frameworks such as the European Union's General Data Protection Regulation (GDPR) have introduced strong provisions for the protection of passenger data, a more holistic approach is required to

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reduce cyber risks that may threaten flight safety [71]. Ethical considerations, including privacy and the militarisation of low-altitude AI-powered flight technologies, also present emerging challenges for regulatory bodies, as highlighted by Li et al. [73]. In this context, holistic approaches that take into account both technical and socio-legal components will support the safe, ethical and sustainable integration of AI applications in aviation. Future research should focus not only on algorithmic efficiency but also on user behaviour, decision-making dynamics and interactions with legal frameworks. In doing so, AI's transformative role in aviation will be grounded in trust and regulatory alignment, not just technological advancement.

5.2 Limitations

This study has several methodological limitations that should be acknowledged. First, the analysis relied on a single bibliographic database (WoS), which, despite its multidisciplinary coverage, may not include all relevant publications available in other databases such as Scopus or IEEE Xplore. Second, the number of included studies (n = 27) is relatively limited, which constrains the generalisability of the findings to the entire aviation sector. Third, as with most systematic reviews, a potential publication bias favouring studies with positive outcomes of AI applications cannot be completely ruled out. Nevertheless, the use of a transparent PRISMA-based selection process and a clearly defined inclusion–exclusion protocol contributes to the reliability and replicability of the result in these.

References

[1] WEF. Global aviation sustainability outlook, 2025, https://reports.weforum.org/docs/WEF_Global_Aviation_Sustainability_Outlook_2025.pdf (accessed on 17 May 2025).

[2] ICAO. Environmental report, 2025, https://www.icao.int/environmental-protection/Documents/EnvironmentalReports/2025/ICAO%20EnvReport%202025.pdf (accessed on 10 June 2025).

[3] IATA. Air travel and sustainability, https://www.iata.org/en/youandiata/travelers/environment/#:~:text=The%20aviation%20industry%20is%20working,cut%20emissions%20by%20around%2080%25 (accessed on 17 May 2025).

[4] Demir, G., Moslem, S. and Duleba, S. Artificial intelligence in aviation safety: systematic review and biometric analysis, *Int. J. Comput. Intel. Syst.*, 2024, **17**, (279), pp 1–30. doi: 10.1007/s44196-024-00671-w

[5] Manchanda, D. Sustainable aviation, https://www.linkedin.com/posts/divya-manchanda-a233aaa3_a-global-call-to-action-for-the-accelerated-activity-7239799894096388097-WgDK (accessed on 17 June 2025).

[6] Russell, S.J. and Norvig, P. *Artificial Intelligence: A Modern Approach*, Pearson, UK, 2021.

[7] Alreshidi, I., Moulitsas, I. and Jenkins, K.W. Advancing aviation safety through machine learning and psychophysiological data: a systematic review, *IEEE Access*, 2024, **12**, pp 5132–5150. doi: 10.1109/ACCESS.2024.3349495

[8] Fang, Z. The impact of AI on the aviation industry: an industry view of opportunities and challenges for a sustainable future, *Eng. Proc.*, 2024, **80**, (1), pp 1–4. doi: 10.3390/engproc2024080002

[9] EASA. Artificial intelligence and aviation, https://www.easa.europa.eu/en/light/topics/artificial-intelligence-and-aviation-0#:~:text=The%20latest%20edition%2C%20the%20EASA,requirements%20and%20means%20of%20compliance (accessed on 16 June 2025).

[10] Tafur, C.L., Camero, R.G., Rodríguez, D.A., Rincón, J.C.D. and Saenz, E.R. Applications of artificial intelligence in air operations: a systematic review. *Results Eng.*, 2025, **25**, pp 1–21. doi: 10.1016/j.rineng.2024.103742

[11] Calvet, L. Towards environmentally sustainable aviation: a review on operational optimization, *Future Transp*, 2024, **4**, (2), pp 518–547. doi: 10.3390/futuretransp4020025

[12] Pik, E. Airport security: the impact of AI on safety, efficiency, and the passenger experience. *J. Transp. Secur.*, 2024, **17**, (9), pp 1–13. doi: 10.1007/s12198-024-00276-6

[13] Page, M.J., McKenzie, J.E., Bossuyt, P.M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., . . ., and Moher, D. The PRISMA 2020 statement: an updated guideline for reporting systematic reviews. *BMJ*, 2021, (372), pp 1–9. doi: 10.1136/bmj.n71

[14] Pachot, A. and Patissier, C. (Cornell University, New York, USA). Towards sustainable artificial intelligence: an overview of environmental protection uses and issues. *arXiv preprint arXiv,* 2022, pp 1–8, https://arxiv.org/abs/2212.11738

[15] EndNote. How to choose the best citation manager for your systematic review, https://endnote.com/blog/tag/systematic-review/?srsltid=AfmBOoqP6NyQBb3czoOBmDHx5IxKzv2IDi1-satUBT5MOuOkx7_-JeKE&utm (accessed on 21 June 2025).

[16] Bramer, WM. Reference checking for systematic reviews using Endnote, *J. Med. Libr. Assoc.*, 2018, **106**, (4), pp 542–546. doi: 10.5195/jmla.2018.489

[17] Elo, S. and Kyngäs, H. The qualitative content analysis process, *J. Adv. Nurs.*, 2008, **62**, (1), pp 107–115. doi: 10.1111/j.1365-2648.2007.04569.x

[18] Tranfield, D., Denyer, D. and Smart, P. Towards a methodology for developing evidence-informed management knowledge by means of systematic review, *Br. J. Manag.*, 2003, **14**, pp 207–222. doi: 10.1111/1467-8551.00375

https://doi.org/10.1017/aer.2026.10138 Published online by Cambridge University Press

[19] Ojadi, J.O., Onukwulu, E., Odionu, C. and Owulade, O. AI-driven predictive analytics for carbon emission reduction in industrial manufacturing: a machine learning approach to sustainable production, *Int. J. Multidiscipl. Res. Growth Eval.*, 2023, **4**, (1), pp 948–960. doi: 10.54660/.IJMRGE.2023.4.1.948-960

[20] Kosir, S., Heyne, J. and Graham, J. A machine learning framework for drop-in volume swell characteristics of sustainable aviation fuel, *Fuel*, 2020, **274**, pp 1–7. doi: 10.1016/j.fuel.2020.117832

[21] Oh, J.H., Oldani, A., Solecki, A. and Lee, T. Learning to predict sustainable aviation fuel properties: A deep uncertainty quantification viewpoint, *Fuel*, 2024, **356**, pp 1–9. doi: 10.1016/j.fuel.2023.129508

[22] Wang, Z., Xue, D., Wu, L. and Yan, R. A reliable predict-then-optimize approach for minimizing aircraft fuel consumption, *Transp. Res. Part D: Trans. Environ.*, 2025, **142**, pp 1–29. doi: 10.1016/j.trd.2025.104693

[23] Wei, Z., Ma, Y., Xiang, C. and Liu, D. Power prediction-based model predictive control for energy management in land and air vehicle with turboshaft engine, *Complexity*, 2021, **1**, pp 1–24. doi: 10.1155/2021/2953241

[24] Sun, Y.F., Zhang, Y.J. and Su, B. How does global transport sector improve the emissions reduction performance? A demand-side analysis, *Appl. Energy*, 2022, **311**, pp 1–14. doi: 10.1016/j.apenergy.2022.118648

[25] Miller, T., Durlik, I., Kostecka, E., Łobodzińska, A. and Matuszak, M. The emerging role of artificial intelligence in enhancing energy efficiency and reducing GHG emissions in transport systems, *Energies*, 2024, **17**, pp 1–31. doi: 10.3390/en17246271

[26] Ahmadi, A., Söderholm, P. and Kumar, U. On aircraft scheduled maintenance program development, *J. Qual. Maint. Eng.*, 2010, **16**, (3), pp 229–255. doi: 10.1108/13552511011072899

[27] Pınar, A. Artificial Intelligence supported aircraft maintenance strategy selection with q-rung Orthopair fuzzy TOPSIS method, *J. Aviat.*, 2022, **6**, (3), pp 260–265. doi: 10.30518/jav.1150219

[28] Amit, J. The future takes flight: AI in aircraft maintenance, https://aiola.ai/blog/ai-in-aircraft-maintenance/ (accessed on 12 June 2025).

[29] Lu, J. How is AI in aviation maintenance changing the industry? https://www.qoco.aero/blog/ai-in-aviation-maintenance-how-its-changing-the-industry (accessed on 12 June 2025).

[30] Kabashkin, I., Perekrestov, V., Tyncherov, T., Shoshin, L. and Susanin, V. Framework for integration of health monitoring systems in life cycle management for aviation sustainability and cost efficiency, *Sustainability*, 2024, **16**, (14), pp 1–40. doi: 10.3390/su16146154

[31] Apostolidis, A., Bouriquet, N. and Stamoulis, K.P. AI-based exhaust gas temperature prediction for trustworthy safety-critical applications, *Aerosp*, 2022, **9**, pp 1–16. doi: 10.3390/aerospace9110722

[32] Plastropoulos, A., Bardis, K., Yazigi, G., Avdelidis, N.P. and Droznika, M. Aircraft skin machine learning-based defect detection and size estimation in visual inspections, *Technol*, 2024, **12**, (9), pp 1–25. doi: 10.3390/technologies12090158

[33] Kilic, U., Villareal-Valderrama, F., Ayar, M., Ekici, S., Amezquita-Brooks, L. and Karakoc, T.H. Deep learning-based forecasting modeling of micro gas turbine performance projection: an experimental approach, *Eng. Appl. Artif. Intell.*, 2024, **130**, p 107769. doi: 10.1016/j.engappai.2023.107769

[34] Mohammadi, S., Rahmanian, V., Sattarpanah Karganroudi, S. and Adda, M. Smart defect detection in aero-engines: evaluating transfer learning with VGG19 and data-efficient image transformer models. *Mach*, 2025, **13**, (1), pp 1–21. doi: 10.3390/machines13010049

[35] Schulte-Sasse, U. The "AI" in sustainable initiatives: profitable, efficient, and sustainable aviation, https://www.aviationpros.com/airport-business/airport-infrastructure-operations/article/55039676/the-ai-in-sustainable-initiatives-profitable-efficient-and-sustainable-aviation (accessed on 10 June 2025).

[36] Cepsa. Planet energy, https://www.moeveglobal.com/en/planet-energy/sustainable-innovation/sustainable-smart-airports-digitalization (accessed on 10 June 2025).

[37] Markets & Markets. Sustainability certification industry worth $4.25 billion by 2030. https://www.marketsandmarkets.com/PressReleases/sustainability-certification.asp (accessed on 10 June 2025).

[38] Ramakrishnan, J., Seshadri, K., Liu, T., Zhang, F., Yu, R. and Gou, Z. Explainable semi-supervised AI for green performance evaluation of airport buildings, *J. Build. Eng.*, 2023, **79**, p 107788. doi: 10.1016/j.jobe.2023.107788

[39] Selvam, A.P. and Al-Humairi, S.N.S. Environmental impact evaluation using smart real-time weather monitoring systems: a systematic review, *Innov. Infrastruct.*, 2025, **10**, pp 1–24. doi: 10.1007/s41062-024-01817-7

[40] Wandelt, S., Sun, X. and Zhang, A. AI-driven assistants for education and research? A case study on ChatGPT for air transport management, *J. Air Transp. Manag.*, 2023, **113**, p 102483. doi: 10.1016/j.jairtraman.2023.102483

[41] Klophaus, R. AI-generated SWOT analysis of emerging technologies in air transportation: potential and limitations, *Res. Transp. Bus. Manag.*, 2025, **59**, p 101316. doi: 10.1016/j.rtbm.2025.101316

[42] Breiman, L. Random forests, *Mach. Learn.*, 2001, **45**, pp 5–32.

[43] Li, X., Wen, Z. and Su, H. An approach using random forest intelligent algorithm to construct a monitoring model for dam safety, *Eng. Comput.*, 2021, **37**, pp 39–56. doi: 10.1007/s00366-019-00806-0

[44] Rubinstein, C. Predicting the unpredictable: AI's new role in aviation safety, https://www.forbes.com/sites/carrierubinstein/2025/04/08/predicting-the-unpredictable-ais-new-role-in-aviation-safety/ (accessed on 13 June 2025).

[45] Ricci, D. Airline safety: 3 ways AI can help make flying even safer, https://www.the-future-of-commerce.com/2025/02/24/airline-safety-ai/ (accessed on 12 June 2025).

[46] Chen, T. and Guestrin, C. XGBoost: A Scalable Tree Boosting System. *Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, San Francisco, USA, 13-17, August, 2016.

[47] Rajendran, S. and Sundararajan, P. Predicting criminal recidivism using specialized feature engineering and XGBoost, *CrimRxiv*, 2021, pp 1–8, doi: 10.21428/cb6ab371.d95f8c48

https://doi.org/10.1017/aer.2026.10138 Published online by Cambridge University Press

[48] Paraschos, I., Trimble, T.E., Bhargava, E., Klingler, J. and Nicolai, B.R. A comparative study of neural networks and XGBoost models for flight time prediction, *Beyond: Undergrad. Res. J.,* 2025, **8**, pp 1–15, https://commons.erau.edu/beyond/vol8/iss1/3
[49] Shengyuan, W., Xinghua, S., Guangdong, B., Wu, J. and Zhao, N. XGBoost-based heuristic path planning algorithm for large scale air–rail intermodal networks, *Inventions*, 2025, **10**, pp 1–22. doi: 10.3390/inventions10020027
[50] ICAO. Enviromental Report 2022, https://www.icao.int/environmental-protection/Documents/EnvironmentalReports/2022/ICAO%20ENV%20Report%202022%20F4.pdf (accessed on 12 June 2025).
[51] Adewale, B.A., Ene, V.O., Ogunbayo, B.F. and Aigbavboa, C.O. Application of artificial intelligence (AI) in sustainable building lifecycle; a systematic literature review, *Build*, 2024, **14**, pp 1–25. doi: 10.20944/preprints202405.2113.v1
[52] Zhang, Z., Rong, W., Liu, Y. and Yang, Y. Port carbon emission estimation: Principles, practices, and machine learning applications, *Transp. Res. Part E: Logist. Transp. Rev.*, 2025, **199**, pp 1–26. doi: 10.1016/j.tre.2025.104159
[53] Zhou, H. Air passenger carbon offset and carbon neutrality strategies: implementation mechanism by convolutional neural network, *Heliyon*, 2024, **10**, pp 1–9. doi: 10.1016/j.heliyon.2024.e37495
[54] Savaş, T., Özdemir, U. and Esen, Y.E. The role of flight simulators in pilot training, *J. Aviat.*, 2025, **9**, (1), pp 137–145. doi: 10.30518/jav.1588557
[55] Cao, K., Zhang, Y. and Feng, J. Prediction of training cost and difficulty for aircraft-type transition based on similarity assessment, *Aerosp*, 2024, **11**, (2), pp 1–19. doi: 10.3390/aerospace11020166
[56] Liu, Y. Large language models for air transportation: a critical review, *J. Air Transp. Res. Soc.*, 2024, **2**, pp 1–15. doi: 10.1016/j.jatrs.2024.100024
[57] Yıldız, B. and Çulha, Ç. The use of artificial intelligence in air traffic control: a theoretical review, *Anadolu Strateji Derg.*, 2024, **6**, pp 175–193.
[58] Milićević, M. AI in air traffic control: pioneering the future of aviation safety and efficiency, https://avioportal.me/wp-content/uploads/2024/06/milica-micunovic-1.pdf (accessed on 13 June 2025).
[59] Kaynak, G. and Ervural, B. Predictive maintenance planning using a hybrid ARIMA-ANN model, *Bitlis Eren Üniversitesi Fen Bilimleri Derg.*, 2024, **13**, (3), pp 618–632. doi: 10.17798/bitlisfen.1466339
[60] Jasra, S.K., Valentino, G., Muscat, A. and Camilleri, R. Hybrid machine learning–statistical method for anomaly detection in flight data, *Appl. Sci.*, 2022, **12**, pp 1–18. doi: 10.3390/app122010261
[61] Paredes, J., Chávez, D., Isa-Jara, R. and Vargas, D. A hybrid machine learning algorithm approach to predictive maintenance tasks: a comparison with machine learning algorithms, *Results Eng*, 2025, **26**, pp 1–12. doi: 10.1016/j.rineng.2025.105137
[62] Qu, J., Xiao, M., Yang, L. and Xie, W. Flight delay regression prediction model based on Att-Conv-LSTM, *Entropy (Basel)*, 2023, **25**, (5), pp 1–16. doi: 10.3390/e25050770
[63] Yousefzadeh Aghdam, M., Kamel Tabbakh, S.R., Mahdavi Chabok, S.J. and Kheyrabadi, M. Optimization of air traffic management efficiency based on deep learning enriched by the long short-term memory (LSTM) and extreme learning machine (ELM), *J. Big Data*, 2021, **8**, pp 1–26. doi: 10.1186/s40537-021-00438-6
[64] Xiong, J., Zou, C., Wan, Y., Sun, Y. and Yu, G. Fuel consumption prediction for full flight phases toward sustainable aviation: a DMPSO-LSTM model using quick access recorder (QAR) data, *Sustainability*, 2025, **17**, (8), pp 1–26. doi: 10.3390/su17083358
[65] Konar M., Cam O. and Aktaş MO. BSO algorithm and artificial neural network aided emission optimisation for gas turbine engine, *Aeronaut. J.*, 2025, **129**, (1331), pp 107–122. doi: 10.1017/aer.2024.96.
[66] Khan, Z.U., Nasim, B. and Rasheed, Z. Generative AI-based predictive maintenance in aviation: a systematic literature review, *CEAS Aeronaut. J.*, 2025, **16**, pp 1–19. doi: 10.1007/s13272-025-00818-1
[67] Es-haghi, M.S., Anitescu, C. and Rabczuk, T. Methods for enabling real-time analysis in digital twins: a literature review, *Comput. Struct.*, 2024, **297**, p 107342. doi: 10.1016/j.compstruc.2024.107342
[68] Mello, F.P. and Macario, R. Tourist behavior and awareness in airline voluntary carbon offset programs: a Portuguese perspective, *J. Air Transp. Res. Soc.*, 2024, **3**, p 100042. doi: 10.1016/j.jatrs.2024.100042
[69] Charles, N. Using digital twins and AI for smarter engineering, https://aviationweek.com/aerospace/using-digital-twins-ai-smarter-engineering (accessed on 13 June 2025).
[70] Airbus. Digital Twins: Accelerating aerospace innovation from design to operations, 2025, https://www.airbus.com/en/newsroom/stories/2025-04-digital-twins-accelerating-aerospace-innovation-from-design-to-operations (accessed on 13 June 2025).
[71] Kaplan, L.S. The role and regulation of AI in aviation: current trends and key considerations, 2024, https://www.aviationturkey.com/en/content/the-role-and-regulation-of-ai-in-aviation-current-trends-and-key-considerations-1061
[72] Azyus, A.F., Wijaya, S.K. and Kurniawan, B. Regulatory, ethical, and security dimensions of AI in aircraft maintenance: a framework for assessing harm, *J. Ecohum.*, 2025, **4**, (1), pp 5534–5552. doi: 10.62754/joe.v4i1.6666
[73] Li J, Liu S, Huang W. and Yan B. Artificial intelligence in low-altitude flight: developmental opportunity or ethical challenge?, *Aeronaut. J.*, 2025, **129**, (1336), pp 1683–1701. doi: 10.1017/aer.2025.2

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