



VILNIUS GEDIMINAS TECHNICAL UNIVERSITY
FACULTY OF BUSINESS MANAGEMENT
DEPARTMENT OF MANAGEMENT

Giedrius Paulauskas

**EVALUATION OF THE BENEFITS OF USING ARTIFICIAL
INTELLIGENCE IN AVIATION**

**DIRBTINIO INTELEKTO PANAUDOJIMO AVIACIJOJE NAUDOS
VERTINIMAS**

Master's degree Thesis

Engineering Economics and Management study programme, state code 6211LX086

Aviation Management specialisation

Management study field

Vilnius, 2026

VILNIUS GEDIMINAS TECHNICAL UNIVERSITY
FACULTY OF BUSINESS MANAGEMENT
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Management Studies study field
Engineering Economics and Management study programme, state code 6211LX086
Aviation Management specialisation

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2025-12-17

OBJECTIVES FOR MASTER THESIS

No. AVfm-24-12091

Vilnius

For student Giedrius Paulauskas

Master Thesis title: Evaluation of the Benefits of Using Artificial Intelligence in Aviation

Deadline for completion of the final work according to the planned study schedule.

THE OBJECTIVES:

Tasks for the Master's Final Thesis:

The aim of the master's thesis is to evaluate the benefits and challenges of implementing artificial intelligence in aviation and develop a framework for systematically assessing and prioritising AI applications in aviation. In this regard, the following objectives are to be reached, namely:

Conduct a comprehensive literature review to examine the theoretical foundations of artificial intelligence, its key technologies, and its current and potential applications in aviation. The review must identify trends, benefits, challenges, and research gaps to inform the subsequent analysis and recommendations.

Develop a framework to reliably evaluate the benefits of implementing artificial intelligence in aviation.

Develop and justify an empirical methodology for validating the framework.

Apply the developed methodology to validate the framework and determine the prioritisation of AI benefit dimensions.

Academic Supervisor Associated Professor Andrius Tamošiūnas

<table border="1"> <tr><td>Vilnius Gediminas Technical University</td></tr> <tr><td>Faculty of Business Management</td></tr> <tr><td>Department of Management</td></tr> </table>		Vilnius Gediminas Technical University	Faculty of Business Management	Department of Management	<table border="1"> <tr> <td>ISBN</td> <td>ISSN</td> </tr> <tr> <td colspan="2">Copies No.</td> </tr> <tr> <td colspan="2">Date-.....-.....</td> </tr> </table>		ISBN	ISSN	Copies No.		Date-.....-.....	
Vilnius Gediminas Technical University												
Faculty of Business Management												
Department of Management												
ISBN	ISSN											
Copies No.												
Date-.....-.....												
Master Degree Studies Engineering Economics and Management study programme Master Final Thesis												
Title		Evaluation of the Benefits of Using Artificial Intelligence in Aviation										
Author		Giedrius Paulauskas										
Academic supervisor		Andrius Tamošiūnas										
		Thesis language: English										
Annotation The thesis examines the benefits of artificial intelligence applications in the aviation sector and proposes a systematic framework for evaluating their organisational value. The relevance of the research arises from the rapid expansion of AI-based solutions and the absence of structured assessment methods tailored to safety-critical aviation domains. Based on an extensive literature review, a multi-stage evaluation framework was developed, incorporating five benefit dimensions as well as risk assessment, feasibility analysis, make-or-buy decisions and regulatory compliance evaluation. The empirical part applies mathematical- statistical information processing methods, including expert survey data analysis and the Analytic Hierarchy Process used to determine the relative importance of benefit dimensions. The results show that the proposed model is logically structured, clear and suitable for practical use in aviation organisations. The thesis also outlines practical application directions illustrating how the model may support organisational decision-making processes when evaluating potential artificial intelligence initiatives. Structure: introduction, literature review, methodology, empirical analysis, conclusions and suggestions, references. Thesis consist of: 64 p. text without appendixes, 8 figures, 13 tables, 65 bibliographical entries. Appendixes included.												
Keywords: artificial intelligence, aviation, benefit evaluation, risk assessment, feasibility, decision-making.												

Vilniaus Gedimino technikos universitetas	ISBN	ISSN
Verslo vadybos fakultetas	Egz. sk.	
Vadybos katedra	Data-.....-.....	

Antrosios pakopos studijų Inžinerinės ekonomikos ir vadybos programos magistro baigiamasis darbas	
Pavadinimas	Dirbtinio intelekto panaudojimo aviacijoje naudos vertinimas
Autorius	Giedrius Paulauskas
Vadovas	Andrius Tamošiūnas

	Kalba: anglų
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Anotacija
Magistro baigiamajame darbe nagrinėjama dirbtinio intelekto taikymų nauda aviacijos sektoriuje ir siekiama sukurti sisteminių jų vertinimo modelių. Darbo aktualumą lemia spartus dirbtinio intelekto sprendimų diegimas bei objektyvių ir aviacijos specifikai pritaikytų vertinimo metodų trūkumas saugos požiūriu svarbiose srityse. Remiantis literatūros analize suformuotas daugiapakopis vertinimo modelis, apimantis penkias naudos dimensijas ir papildomus rizikos, įgyvendinamumo, sprendimo pirkti ar kurti bei reguliacinės atitikties vertinimo etapus. Empirinėje dalyje taikyti matematiniai statistiniai informacijos apdorojimo metodai: ekspertinės apklausos duomenų analizė ir analitinės hierarchijos procesas, skirtas naudos dimensijų reikšmingumui nustatyti. Tyrimo rezultatai parodė, kad sukurtas modelis yra logiškas, aiškus ir tinkamas praktiniam taikymui aviacijos organizacijose. Baigiamasis darbas taip pat pateikia praktinio taikymo kryptis, parodančias, kaip sukurtas modelis gali būti naudojamas organizacijų sprendimų priėmimo procesuose vertinant dirbtinio intelekto iniciatyvas. Darbo struktūra: įvadas, teorinė, metodologinė ir empirinė dalys, išvados ir literatūros sąrašas. Darbo apimtis – 64 puslapiai be priedų, 8 paveikslai, 13 lentelių, 65 bibliografiniai šaltiniai. Pridedami darbo priedai.

Prasminiai žodžiai: dirbtinis intelektas, aviacija, naudos vertinimas, rizikos analizė, įgyvendinamumas, sprendimų priėmimas.
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VILNIUS GEDIMINAS TECHNICAL UNIVERSITY

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Antanas Gustaitis' Aviation Institute

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(Study programme, academic group no.)

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The academic supervisor of my Final Degree Paper is Assoc Prof Doctor Andrius Tamošiūnas.

No contribution of any other person was obtained, nor did I buy my Final Degree Paper.



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ABBREVIATIONS

ACAS X — Airborne Collision Avoidance System X
AAM — Advanced Air Mobility
ADS-B — Automatic Dependent Surveillance–Broadcast
AHP — Analytic Hierarchy Process
AI — Artificial Intelligence
ANP — Analytic Network Process
ATO — Approved Training Organisation
CAMO — Continuing Airworthiness Management Organisation
CI — Consistency Index
CNN — Convolutional Neural Network
CR — Consistency Ratio
DEMATEL — Decision-Making Trial and Evaluation Laboratory
DL — Deep Learning
EASA — European Union Aviation Safety Agency
EU — European Union
EU AI Act — European Union Artificial Intelligence Act
eVTOL — Electric Vertical Take-Off and Landing
FAA — Federal Aviation Administration
FOD — Foreign Object Debris
FTO — Flight Training Organisation
GRA — Grey Relational Analysis
GDP — Gross Domestic Product
ICAO — International Civil Aviation Organization
IoT — Internet of Things
KPI — Key Performance Indicator
LLM — Large Language Model
LSTM — Long Short-Term Memory
MBSE — Model-Based Systems Engineering
ML — Machine Learning
MRO — Maintenance, Repair, and Overhaul
NLP — Natural Language Processing
NOTAM — Notice to Airmen
ODD — Operational Design Domain

PROMETHEE — Preference Ranking Organization Method for Enrichment Evaluations
R&D — Research and Development
ROI — Return on Investment
RL — Reinforcement Learning
RI — Random Index
SD — Standard Deviation
SMS — Safety Management System
TODIM — Interactive and Multicriteria Decision-Making method
TOPSIS — Technique for Order Preference by Similarity to Ideal Solution
UAV — Unmanned Aerial Vehicle
VIKOR — VlseKriterijumska Optimizacija I Kompromisno Resenje
XAI — Explainable Artificial Intelligence

INTRODUCTION

Relevance of the topic. Artificial intelligence (AI) is one of the most influential technologies of the 21st century. Its rapid progress shows strong potential to reshape industries, change business models, and open new ways to improve efficiency and innovation. In today's competitive environment, adopting AI is no longer only a strategic advantage—it is becoming a necessity for organizations that want to stay relevant and forward-looking.

The aviation industry, with its complex operations, strict safety requirements, and global reach, is no exception. AI is already being applied in many areas of aviation, including predictive maintenance, air traffic management, passenger services, and operational efficiency. Yet, because there are many different AI methods and tools, organizations face a major challenge: deciding which applications are most useful and realistic for their own context. The wide variety of options makes it difficult for decision-makers to allocate resources effectively and choose where to invest.

To overcome this challenge, a structured evaluation framework is needed. Such a framework can help aviation companies organize AI applications across different domains, assess their potential benefits, and highlight the most promising areas for use. By providing a systematic approach, it supports organizations in making informed decisions, balancing innovation with operational needs, and ensuring that AI adoption creates measurable value.

Problem – Lack of comprehensive evaluation frameworks to assess the value and feasibility of various artificial intelligence use cases in aviation

Research object – Artificial intelligence systems specifically designed for application within aviation.

Aim – To evaluate the benefits and challenges of implementing artificial intelligence in aviation and develop a framework for systematically evaluating and prioritizing AI applications in aviation.

Tasks:

1. Conduct a comprehensive literature review to examine the theoretical foundations of artificial intelligence, its key technologies, and its current and potential applications in aviation. The review must identify trends, benefits, challenges, and research gaps to inform the subsequent analysis and recommendations.
2. Develop a framework to reliably evaluate the benefits of implementing artificial intelligence in aviation.
3. Develop and justify an empirical methodology for validating the framework.
4. Apply the developed methodology to validate the framework and determine the prioritisation of AI benefit dimensions based on expert input.

Research Methods - literature review, expert survey, analytic hierarchy process.

1. LITERATURE REVIEW

The literature review forms the foundation of this thesis by situating the study within the broader body of knowledge on artificial intelligence in aviation. It will examine how AI is conceptualized, regulated, and applied across different domains, while also identifying its benefits, challenges, and unresolved questions. By reviewing and connecting insights from academic research, industry reports, and regulatory roadmaps, the review will highlight the current state of AI adoption in aviation and reveal areas where further investigation is needed. This provides the necessary background for developing an evaluation framework and ensures that the subsequent analysis is grounded in both theoretical understanding and practical realities.

1.1. Importance of AI implementation

Artificial intelligence has become a transformative technology, reshaping industries and changing how organizations create value. Companies that adopt AI most successfully often become “AI-fueled,” meaning they integrate AI into core strategy, operations, and innovation rather than using it only as separate tools. This integration helps firms improve efficiency, optimize decision-making, and create new products and services that were previously out of reach. Research by Deloitte and Harvard Business Review shows that enterprises going “all-in” on AI gain a competitive advantage by applying it across business processes, customer interactions, and data-driven systems, effectively turning themselves into learning organizations (Davenport & Mittal, 2023).

At a global level, the economic potential of AI is very significant. The McKinsey Global Institute estimates that widespread AI adoption could add about \$13 trillion to global output by 2030, raising annual GDP growth by 1.2 percent. This impact is comparable to earlier general-purpose technologies such as steam engines or information technology. However, benefits are not expected to be equal. Early and bold adopters will gain more, while latecomers may fall behind. AI adoption will also reshape labor markets, increasing demand for digital and cognitive skills while reducing reliance on repetitive tasks (Bughin et al., 2018).

In Europe, adoption is already visible in enterprise trends. Eurostat data shows that in 2024, 13.5% of EU enterprises were using at least one AI technology, with adoption rising above 41% among large firms. Common applications include text analysis, natural language generation, and machine learning for data analysis. Adoption rates differ widely—from 27.6%

in Denmark to 3.1% in Romania—but the overall upward trend shows AI’s growing role in competitiveness and innovation in the European economy (Eurostat, 2024).

Returns on investment also demonstrate AI’s value. A Deloitte survey from 2024 reported that 41% of organizations worldwide achieved ROI of 11–30% from generative AI initiatives, while 14% reached 31–50% ROI. Another 6% achieved over 50% ROI. Although some companies saw smaller gains or had not yet measured returns, the findings show that AI is moving beyond small pilots and generating measurable economic impact (Deloitte, 2025).

The distribution of ROI outcomes for generative AI initiatives is shown in Figure 1, illustrating how organisations report varied levels of financial return.

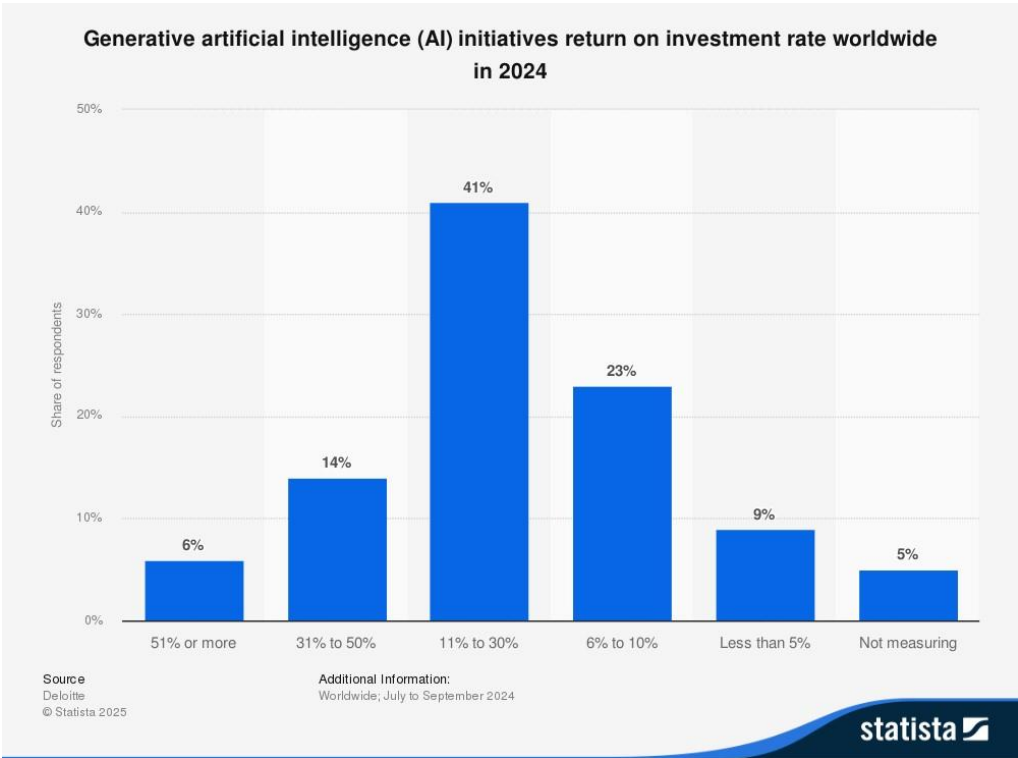


Fig. 1. Generative AI initiatives ROI worldwide

Source: Deloitte (2025)

Together, these findings confirm that AI is no longer optional. It is a foundation for competitiveness across all industries, including manufacturing, healthcare, finance, transport, and aviation.

1.1.1. The Importance of Implementing AI in Aviation

In aviation, AI is increasingly seen as a strategic enabler of efficiency, customer service, and competitiveness. As global passenger numbers rise and the industry returns to record revenues, airlines and airports face pressure to manage complexity while improving

sustainability and resilience. AI offers strong solutions in predictive analysis, optimization, and automation across the aviation value chain (SITA, 2024).

Industry data confirms this trend. According to SITA's 2024 Air Transport IT Insights, airline IT spending reached \$37 billion, much of it directed toward AI, data platforms, and cloud migration. Nearly 90% of airlines now use data platforms, and more than half are investing in generative AI and machine learning to improve operations, customer service, and flight efficiency (SITA, 2024). These are not short-term projects but long-term investments in digital infrastructure, showing that airlines see AI as essential for the future.

The International Air Transport Association (IATA) also emphasizes AI's transformative role. Its 2025 report highlights AI and digital identity solutions as key to improving operational excellence and regulatory compliance, particularly in safety-critical processes like cargo handling and passenger management (IATA, 2025). In addition, IATA's 2023 study on generative AI identifies new applications such as disruption management, route optimization, dynamic pricing, and personalized travel planning (IATA, 2023). These examples show that AI has become central to aviation's digital transformation.

Aircraft manufacturers share this perspective. Airbus, in its 2024 Annual Report, identifies AI as a driver of efficiency in aircraft design, production, and maintenance. The company invests heavily in predictive maintenance and digital twins to reduce downtime, optimize resources, and improve sustainability. These efforts support the industry's goal of achieving net-zero emissions by 2050, where AI is expected to play a critical role in fuel efficiency and sustainable aviation fuel use (Airbus, 2025).

Finally, regulators also recognize AI's importance. Both the European Union Aviation Safety Agency (EASA) and the U.S. Federal Aviation Administration (FAA) have published AI roadmaps. These stress AI's potential for improving safety and efficiency but also call for careful, step-by-step, and trustworthy adoption. The detailed challenges and regulatory frameworks will be discussed later in this thesis.

In summary, the importance of AI in aviation goes beyond improving efficiency. It positions airlines, airports, and manufacturers to remain competitive in a digital transport sector while upholding the industry's highest safety standards. AI's dual role—as a driver of efficiency and as an added layer of safety—makes it essential for meeting future passenger expectations, sustainability targets, and long-term industry growth.

1.2. Regulatory and ethical considerations for AI in aviation

The use of artificial intelligence in aviation is developing within one of the most highly regulated industries in the world. This means that AI adoption cannot be separated from certification, oversight, accountability, and ethical concerns. Regulatory agencies such as the European Union Aviation Safety Agency and the Federal Aviation Administration have begun adapting their frameworks to address the challenges posed by machine learning and generative AI, while industry actors and associations are also developing ethical guidelines to ensure responsible use (SITA, 2024).

EASA's AI Roadmap 2.0 places trustworthiness at the center of AI integration in aviation. It proposes a hybrid approach, combining a cross-domain "Part-AI" framework with specific rules for flight operations, maintenance, and air traffic management. Key requirements include human oversight, transparency in decision-making, and certification levels that match the degree of system autonomy. EASA also highlights the importance of lifecycle monitoring, recognizing that adaptive or continuously learning AI systems create challenges for certification models originally designed for static, deterministic technologies. This approach reflects the broader European regulatory orientation under the EU AI Act, but is tailored to aviation's safety-critical context and the need to maintain public trust in air transport (EASA, 2023).

The regulatory evolution described by EASA is summarised visually in Figure 2.

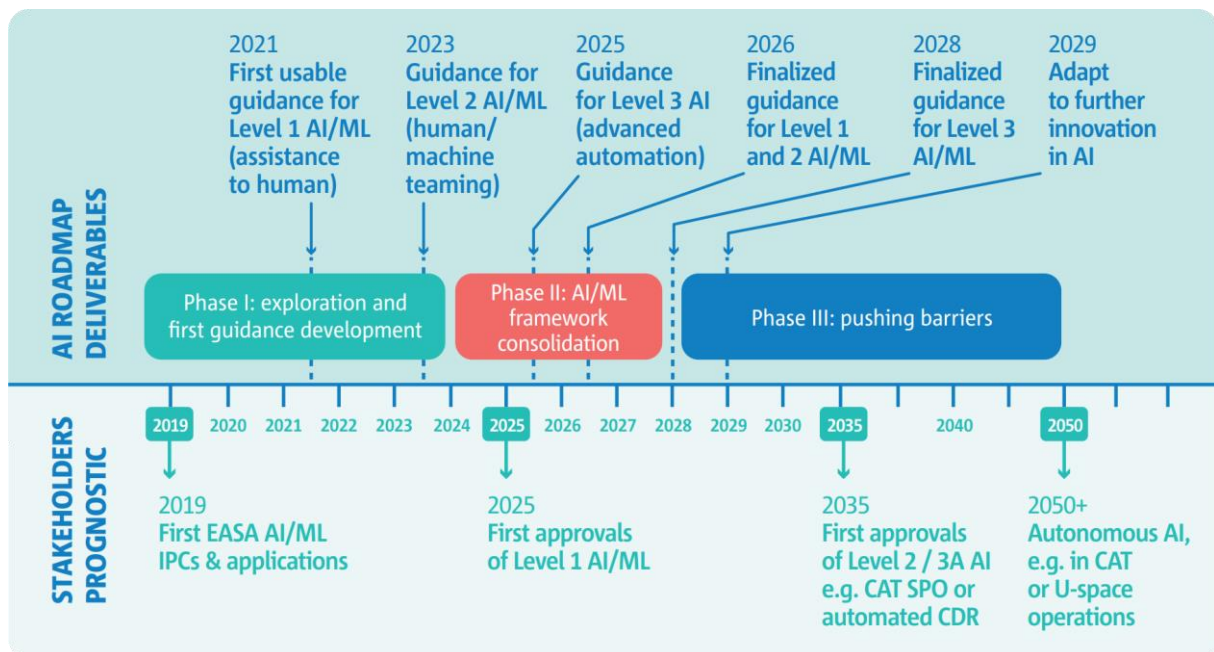


Fig. 2. EASA AI Roadmap 2.0 timeline

Source: EASA (2023)

The FAA takes a more gradual approach in its AI Roadmap. While acknowledging AI's potential benefits, the FAA applies the principle of the "safety continuum," encouraging innovation first in lower-risk areas such as unmanned aerial systems before extending it to commercial aviation. A key distinction is made between learned AI, which is trained offline and remains static, and learning AI, which adapts in real time. The former can be assessed under current certification systems, while the latter raises new safety issues requiring fresh regulatory tools. The FAA also stresses that AI should not be treated as a co-pilot or autonomous decision-maker. Accountability, it argues, must remain with designers, operators, and certificate holders, not with the AI itself (FAA, 2024).

Alongside regulators, the aviation industry has developed ethical frameworks to guide AI use. Rolls-Royce's Aletheia Framework sets out 32 practical principles across three dimensions: social impact, accuracy and trust, and governance. These principles address transparency, bias reduction, and accountability, with an emphasis that responsibility for outcomes always lies with organizations and their leadership—not with algorithms (Rolls-Royce, 2021). Similarly, the International Air Transport Association has explored AI in compliance-focused projects. For example, its AI and digital identity initiatives show how large language models can support documentation verification in cargo operations, reducing delays while improving regulatory compliance. This highlights AI's dual role in aviation: enhancing efficiency while strengthening safety and trust.

Ethical challenges go beyond compliance and certification. Transparency and explainability are vital in safety-critical settings, where human operators must be able to interpret AI outputs in real time. Bias and inclusivity are also major concerns, particularly for systems using biometric data or monitoring crew performance. Data governance and privacy represent another essential area, since AI relies on large volumes of personal and operational data, requiring strict protection under international standards. Across both regulatory and industry frameworks, one theme is consistent: human oversight must remain central, ensuring that ultimate accountability lies with qualified professionals rather than automated systems.

1.3. Types of artificial intelligence

Artificial intelligence covers a wide range of computational methods that aim to replicate, support, or extend human decision-making. In aviation—where safety, efficiency, and reliability are essential—only certain types of AI have shown practical value. These can be grouped into several main technical foundations.

One of the most widely used approaches is machine learning (ML), where algorithms learn patterns from large datasets and use them to make predictions. Both supervised and unsupervised learning are applied in aviation for tasks such as flight data monitoring, anomaly detection, and predictive maintenance. These methods reduce the need for manual checks and help detect faults at an earlier stage (Koul, 2025). A more specialized form, reinforcement learning (RL), is particularly relevant for dynamic environments. RL supports sequential decision-making, making it suitable for air traffic flow management, trajectory optimization, and adaptive control in uncertain conditions (Razzaghi et al., 2024).

Deep learning (DL) builds on these methods using multilayer neural networks that excel in recognizing complex patterns. Recent studies show DL to be effective in detecting defects during aircraft inspections, identifying anomalies in system behavior, and improving cybersecurity against increasingly advanced threats (Ahmed, 2025).

Another important field is natural language processing (NLP), which allows computers to interpret unstructured text and speech. In aviation, NLP is applied to transcribe air traffic control (ATC) communications, analyze pilot reports, and extract safety-related information from narrative databases. While promising, NLP still faces challenges with limited data availability and the difficulty of explaining model decisions (Nanyonga et al., 2025).

Beyond these data-driven methods, neurosymbolic AI is emerging as a hybrid approach that combines neural networks with symbolic reasoning. This method offers both adaptability and transparency, making it highly relevant for safety-critical domains such as Advanced Air Mobility (AAM), where explainability is crucial for certification (Acharya et al., 2025). Closely related is explainable AI (XAI), which focuses on making complex “black-box” models more transparent and auditable. The European Union Aviation Safety Agency (EASA) has already launched projects such as MLEAP to explore methods for ensuring that machine learning can be deployed in aviation in a trustworthy and certifiable way (EASA, 2023).

The working principles and aviation relevance of the main AI approaches are summarised in Table 1.

Table 1. Working principles of different types of AI

AI Type	Definition	Relevance to Aviation
Machine Learning (ML)	Algorithms that learn patterns from data through supervised, unsupervised, or reinforcement methods.	Basis for anomaly detection, predictive modeling, adaptive decision support.
Deep Learning (DL)	Subset of ML using multilayered neural networks for complex pattern recognition.	Applied in computer vision (e.g., aircraft inspection) and anomaly detection.
Natural Language Processing (NLP)	Techniques for interpreting and generating human language.	Used for ATC transcription, pilot reports, and safety data analysis.
Logic- & Knowledge-Based	Symbolic reasoning and rule-based systems using knowledge bases and inference engines.	Useful for expert systems, training, and rule-driven safety assessments.
Statistical Approaches	Traditional models such as regression, clustering, Bayesian estimation.	Still relevant in reliability analysis and demand forecasting, valued for interpretability.
Hybrid / Neurosymbolic AI	Integration of ML with symbolic reasoning or statistical models.	Provides adaptability with transparent reasoning, vital for Advanced Air Mobility (AAM).
Explainable AI (XAI)	Methods that improve transparency and interpretability of complex models.	Essential for regulatory approval, certification, and trust in AI-driven decisions.

Source: Adapted from Razzaghi et al., (2024); Koul, (2025); Ahmed (2025);Nanyonga et al. (2025);Acharya et al. (2025)

Figure 3 provides an overview of the AI technology categories included in EASA’s AI Roadmap 2.0.

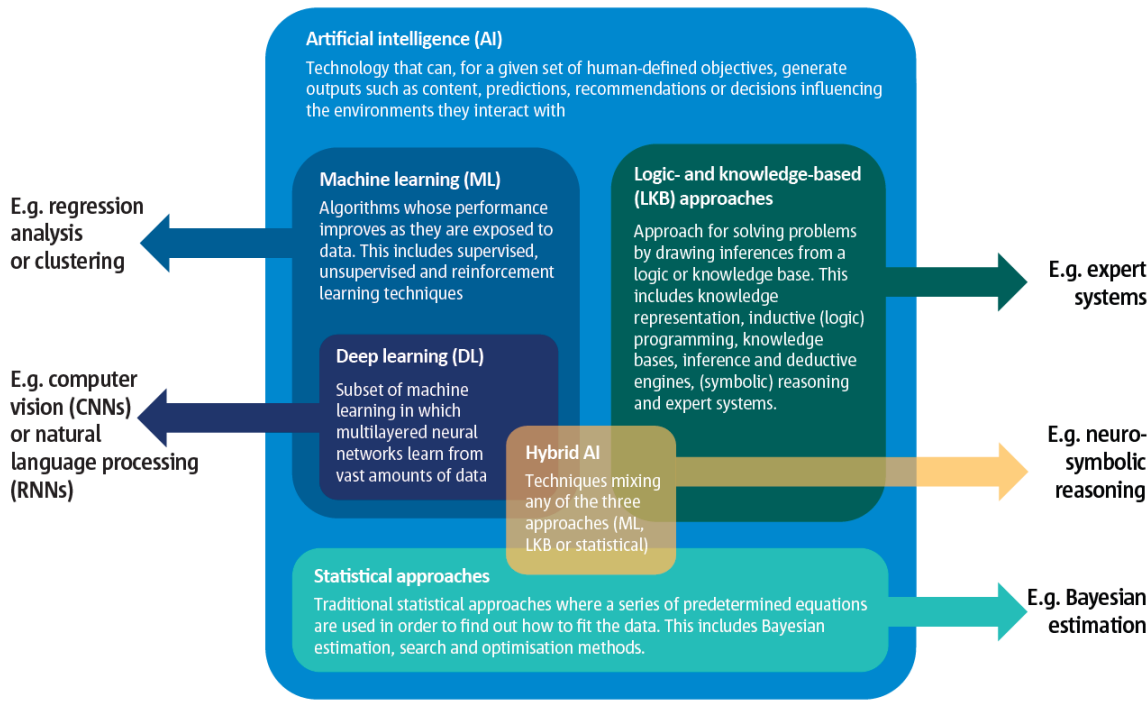


Fig. 3. AI technology covered by EASA AI Roadmap 2.0

Source: EASA (2023)

This distribution underscores the broad technical scope regulators must address.

1.4. Possible use cases of AI in aviation

Artificial intelligence is now applied across almost every domain of aviation, helping to make operations safer, more efficient, and more sustainable. Both the European Union Aviation Safety Agency and the Federal Aviation Administration identify AI as a transformative enabler, supporting functions from aircraft design and maintenance to passenger services and regulatory oversight. Some applications are already well supported by research and industry practice, while others are still in early development or remain mostly conceptual.

In aircraft design and operation, AI is being explored for flight profile optimization, adaptive flight control, and onboard decision-support systems. EASA highlights possible applications such as virtual copilots, camera-based traffic detection, and pilot assistance during periods of high workload (EASA, 2023). Research confirms the value of AI in trajectory optimization and performance modelling, including climb and descent optimization and engine thrust prediction (Le Clainche et al., 2023).

In production and maintenance, predictive maintenance and digital twins are among the most mature AI applications. EASA points to IoT-enabled production and AI-based health monitoring, while studies show that predictive models lower maintenance costs (Moghadasnian, 2025a) and improve fault detection accuracy. Airbus's AIRMAN platform demonstrates that AI-powered predictive maintenance is already operationally relevant.

AI also contributes to environmental sustainability. EASA highlights trajectory optimization for emission reduction and data-driven assessments of environmental impact. Research supports this with models for fuel consumption prediction (Degas et al., 2022) and optimization algorithms for eco-efficient operations. In air traffic management, both EASA and FAA emphasize AI for trajectory prediction, conflict detection, and controller decision support. Reinforcement learning and neural network models have achieved promising results in these areas (Wang et al., 2019), making ATM one of the most advanced fields of AI application.

At the airport level, AI addresses both safety and efficiency challenges. Examples include systems for detecting foreign object debris, preventing bird strikes with avian radar, and identifying unauthorized drones. Passenger-facing applications include automated security screening, optimized baggage handling, and passenger flow management. Studies confirm the effectiveness of AI in predicting airport surface movement and detecting anomalies (Shan et al., 2025). Looking forward, AI will also be central to drones, U-space, and advanced air mobility. EASA identifies AI as a prerequisite for detect-and-avoid, adaptive deconfliction, and autonomous navigation in GPS-denied environments. While reinforcement learning has shown

potential in drone separation and obstacle avoidance (Zhou et al., 2020), large-scale deployment is still limited.

Cybersecurity represents another important and emerging area. EASA notes that AI systems themselves can be vulnerable to adversarial attacks or data poisoning, but also highlights AI's ability to strengthen defences through adaptive intrusion detection and anomaly monitoring. Research supports this dual role, with AI models already tested on systems such as ADS-B networks and avionics data buses (Ahmed et al., 2024). AI also supports safety risk management by combining diverse data sources—including flight data, weather, and safety reports—to predict hazards and prevent accidents. Initiatives like EASA's Data4Safety and the FAA's AI for Safety framework illustrate this approach (EASA, 2023a); (FAA, 2024). Academic studies confirm the potential of AI for proactive hazard detection (Zhou et al., 2020).

In training and simulation, AI enables adaptive learning environments, intelligent tutoring systems, and more realistic simulators for pilots and maintenance staff. Early prototypes of AI-powered trainers exist (Paces & Insaurralde, 2021), though widespread use in certified training remains limited. On the commercial side, customer service is one of the most mature AI areas. Airlines already use chatbots and virtual assistants, while machine learning supports dynamic pricing, demand forecasting, and service personalization (Arfi et al., 2021). Passenger experience is further improved through biometric boarding, recommendation engines, and tailored services.

Finally, AI also shows potential in regulatory compliance and oversight. EASA highlights applications such as automated contract analysis, consistency checks in rulemaking, and data-driven auditing (EASA, 2023a). In practice, CAMO and MRO organizations could use AI to process maintenance records, check compliance with airworthiness requirements, and prepare for audits. While academic research in this area is limited, early natural language processing tools for aviation documentation suggest significant time savings and reduced regulatory workload.

Overall, these examples show that AI use cases cover the entire aviation ecosystem. Mature applications such as predictive maintenance, air traffic management, and customer service already deliver measurable value, while emerging areas like cybersecurity, advanced mobility, adaptive training, and compliance automation are still developing. Together, they demonstrate AI's cross-cutting role in aviation: improving efficiency, enhancing the passenger experience, and strengthening safety, sustainability, and regulatory adherence.

1.5. Challenges of implementing AI in aviation

The adoption of artificial intelligence in aviation is widely seen as a transformative opportunity, but it faces significant challenges. These obstacles are not only technical but also organizational, cultural, financial, and regulatory. Understanding them is essential to judge how realistic and sustainable AI adoption will be for airlines, airports, and other aviation stakeholders.

One of the biggest barriers is organizational and cultural transformation. Both airlines and airports report that their main challenge is not technology itself but the difficulty of adapting business processes and culture to digital ways of working. According to SITA's 2024 Air Transport IT Insights, 53% of airlines and 63% of airports see this as their top IT and data challenge, ahead of purely technical issues (SITA, 2024). Shifting from legacy systems and rigid structures to agile, data-driven operating models requires not just new tools, but also new management approaches and employee mindsets. Iansiti and Lakhani, in *Competing in the Age of AI*, explain that AI-driven firms operate on integrated digital cores, while traditional organizations remain stuck in silos, making adaptation particularly difficult (Davenport et al., 2023). Neeley and Leonardi, in *Developing a Digital Mindset*, add that successful digital transformation depends on employees learning to treat data, algorithms, and AI as part of everyday work rather than as abstract tools (Davenport et al., 2023). In aviation, where safety-critical procedures and traditional practices dominate, creating this mindset is especially complex.

Closely related are challenges with data quality, integration, and governance. AI relies on large, reliable datasets, but aviation still struggles with fragmented and inconsistent data. Airlines often face problems with data maturity, sharing, and integration across stakeholders. Airports are mostly in intermediate stages of data collection, with only a few already training AI models or deploying large language models. Weak or siloed data reduces prediction accuracy and limits scalability. As Harvard Business Review notes in *Getting AI to Scale*, AI cannot succeed if limited to small pilot projects—it needs standardized platforms and shared data architectures (Davenport et al., 2023). For aviation, legacy IT, varied regulations, and multiple stakeholders such as airlines, airports, air navigation providers, and regulators make such unified systems hard to achieve.

Cybersecurity and regulatory compliance are also pressing issues. As aviation becomes more digital, it becomes a prime target for cyberattacks. Airlines and airports now rank cybersecurity among their top priorities, with concerns ranging from protecting critical systems and passenger data to ensuring secure payment processes. AI systems themselves can also

become attack vectors, making resilience even more important. The use of third-party vendors adds risk, since vulnerabilities in the supply chain can affect entire operations. Regulatory requirements, such as International Civil Aviation Organization (ICAO) cybersecurity standards or the European NIS2 directive, further complicate the picture. As Iansiti and Lakhani argue, AI-driven firms must embed resilience and governance into their core operations rather than treating cybersecurity as an add-on (Davenport et al., 2023). For aviation, the challenge is to innovate while still meeting strict regulatory oversight.

Another obstacle is the shortage of skills and talent. Around one-third of both airlines and airports report problems in hiring and retaining IT and AI experts. Aviation competes not only within its sector but also against large technology companies that can offer more attractive opportunities. Beyond specialist roles, the broader workforce also needs reskilling to integrate AI into daily work. Neeley and Leonardi stress that AI success depends on digital fluency across the entire organization, not just a small group of experts (Davenport et al., 2023). Without this, aviation risks creating an isolated team of specialists disconnected from the wider workforce.

Financial and strategic barriers are equally significant. AI requires large investments in infrastructure, cloud services, data platforms, and analytics. For smaller airlines, regional airports, or public-sector organizations, these costs can be overwhelming. SITA reports that financing is a key barrier, with many organizations struggling to maintain legacy systems while funding digital upgrades (SITA, 2024). *Getting AI to Scale* warns that many companies spend heavily on pilots that never expand, wasting resources with little impact (Davenport et al., 2023). For aviation companies with thin margins and cyclical revenues, uncertainty about return on investment makes them cautious about large-scale AI adoption.

Finally, a persistent challenge is scaling AI initiatives beyond pilots. Many airlines and airports experiment with AI in areas like customer service, predictive maintenance, or passenger processing, but relatively few manage to embed these systems across entire organizations. SITA's survey shows most aviation stakeholders remain at intermediate stages of maturity, with only a minority moving to advanced deployments like large language models or fully integrated predictive platforms (SITA, 2024). Fountaine, McCarthy, and Saleh argue in *Getting AI to Scale* that AI has real impact only when it redefines entire business domains, not when it is confined to isolated use cases (Davenport et al., 2023). For aviation, fragmented governance, regulatory constraints, and international complexity make this kind of broad transformation especially hard.

In summary, while AI holds great promise for aviation, its implementation is slowed by organizational resistance, weak data ecosystems, cybersecurity risks, skills shortages, financial barriers, and difficulties in scaling. These challenges show that AI adoption is not just a

technical upgrade but a systemic transformation involving people, processes, and governance. Unless these obstacles are addressed, aviation organizations risk remaining stuck at the pilot-project stage, unable to realize the full potential of AI.

1.6. Research on using AI in aviation

The article "Artificial intelligence in aviation: A comprehensive review" provides an extensive overview of AI applications in aviation. The authors of this article examine various AI technologies, including machine learning, neural networks, and expert systems, and their integration into aviation operations such as air traffic management, predictive maintenance, and flight optimization. The study highlights significant benefits, including enhanced safety through real-time data analysis, improved operational efficiency via predictive algorithms, and cost reductions achieved by automating routine tasks. The authors conclude that AI has the potential to revolutionize the aviation industry by increasing safety, efficiency, and sustainability. (Ziakkas & Pechlivanis, 2023)

1.6.1 Safety enhancements

The study titled "Automated Scenario Generation from Operational Design Domain Model for Testing AI-Based Systems in Aviation" focuses on developing a framework to test AI-based aviation systems, particularly in collision avoidance scenarios. By utilizing Model-Based Systems Engineering (MBSE), the researchers created a highly automated process to generate and test synthetic data derived from the Operational Design Domain (ODD). Applying this framework to Airborne Collision Avoidance System (ACAS X) scenarios, they generated 1,800 Near Mid-Air Collision (NMAC) scenarios and executed them in the FlightGear simulation environment. The results demonstrated an efficient method for verifying system requirements and conducting automated testing based on ODD definitions, highlighting the potential of MBSE in managing complexity and ensuring safety in AI-based aviation systems. (Stefani et al., 2024)

The paper titled "Toward Mid-Air Collision-Free Trajectory for Autonomous and Pilot-Controlled Unmanned Aerial Vehicles" investigates the development of onboard detect and avoid (DAA) technology for unmanned aerial vehicles (UAVs) to enhance mid-air collision avoidance capabilities. The research emphasizes the integration of artificial intelligence techniques within advanced microcontrollers to enable UAVs to autonomously detect and avoid potential conflicts during flight. The results demonstrated that the proposed AI-driven DAA system significantly improved the success rate of collision avoidance manoeuvres, reducing

potential conflicts in complex airspace scenarios. The study highlights the increasing need for such technology in safety-critical systems, aiming to ensure safer airspace operations for both autonomous and pilot-controlled UAVs. (Kuru et al., 2023)

The chapter titled "Application of Grey Relational Analysis for Utilizing Artificial Intelligence in Aviation" explores the multifaceted benefits of AI integration within the aviation sector. The authors identify six critical factors influenced by AI: flight safety, customer satisfaction, employee acceptance, revenue growth, maintenance time, and maintenance cost. By employing Grey Relational Analysis (GRA), a method adept at handling complex interrelationships among multiple factors, the study evaluates the degree of influence each factor has on the successful implementation of AI in aviation. The analysis reveals that flight safety and customer satisfaction are the most significantly impacted by AI adoption, underscoring the technology's potential to enhance operational efficiency and service quality in the aviation industry. (Ivan et al., 2024)

The study titled "Deep Spatio-Temporal Neural Networks for Risk Prediction and Decision Support in Aviation Operations" focuses on enhancing aviation safety by developing a predictive model for aircraft trajectories during the approach phase. Utilizing a combination of convolutional neural networks (CNNs) and long short-term memory (LSTM) layers, the researchers created a model that forecasts an aircraft's ground speed at future points based on flight data parameters. The model achieved a relative root-mean-square error between 1.27% and 2.69%, indicating high accuracy in predicting ground speed. This advancement demonstrates the potential of AI-driven models to provide real-time decision support to aircrews, thereby enhancing safety during critical flight operations. (Lee et al., 2021)

The study titled "The Impact of Artificial Intelligence on Future Aviation Safety Culture" explores how the integration of AI into aviation operations impacts safety dynamics and culture. It identifies potential benefits such as AI's ability to enhance decision-making through intelligent assistance, predictive analytics, and real-time safety alerts. These capabilities could help prevent incidents by improving situational awareness and reducing human errors. However, the study also highlights challenges, such as potential over-reliance on AI, loss of human agency, and complexities in accountability when AI systems make incorrect decisions. To address these, the paper suggests implementing safeguards and emphasizing human-AI collaboration, ensuring that AI supports rather than replaces human judgment. These insights underscore the need for strategic integration of AI to strengthen safety practices without compromising the robust safety culture that aviation relies upon. (Kirwan, 2024)

1.6.2. Operational efficiency

The chapter titled "AI Solutions for Delay Reduction in the Civil Aviation Industry: A Comprehensive Review" examines the pivotal role of artificial intelligence in mitigating flight delays within the expanding global aviation network. The authors identify key factors contributing to delays, including adverse weather conditions, air traffic control congestion, and mechanical issues. Through a systematic review, the study highlights how AI-driven systems can enhance traffic flow management, reduce congestion, and improve operational efficiency, thereby elevating passenger satisfaction. Initial findings suggest that AI implementation leads to notable reductions in delays and operational enhancements. The chapter underscores AI's potential not only in addressing immediate operational challenges but also in contributing to long-term planning, safety improvements, and sustainable practices within the aviation ecosystem. (Vignesh & Parab, 2024)

The chapter titled "Transforming Aviation: The Role of Artificial Intelligence in Air Traffic Management" examines how AI integration is revolutionizing air traffic management by enhancing safety, efficiency, and overall operational effectiveness. The authors present quantitative outcomes demonstrating AI's impact, including a 15% reduction in average flight delays and a 20% increase in airspace capacity utilization due to AI-driven traffic flow management. Additionally, AI implementations have led to a 30% decrease in reported near-misses and a 25% reduction in aviation accidents, underscoring significant safety improvements. AI-enabled route optimization strategies have also resulted in a 12% decrease in fuel consumption and a 10% reduction in flight duration for long-haul flights, yielding substantial cost savings for the aviation industry. (Whig et al., 2024)

The study titled "Air Holding Problem Solving with Reinforcement Learning to Reduce Air Traffic Controller Workload" explores the application of reinforcement learning to optimize air holding patterns, aiming to alleviate air traffic controller workload and enhance operational efficiency. By employing RL algorithms, the researchers developed a system capable of learning from historical air traffic control decisions to suggest solutions that closely resemble those of professional controllers. This approach demonstrates the potential of AI-driven systems to support decision-making processes in air traffic management, thereby improving safety and efficiency in aviation operations. (Cruciol et al., 2015)

The study titled "Virtual Flight Deck Crew Assistance Utilizing Artificial Intelligence Methods to Interpret NOTAMs: A User Acceptance Study" investigates the integration of AI to enhance the usability of Notices to Airmen (NOTAMs) for pilots. Through semi-structured interviews with ten pilots, the research identifies challenges in the current NOTAM system, such as information overload leading to critical data being overlooked. The findings suggest

that AI-based methods can streamline and prioritize NOTAM information, making it more efficient and user-friendly for flight crews. Additionally, the study emphasizes the importance of addressing pilots' concerns regarding AI implementation, highlighting the need for effective human-machine collaboration to ensure safety and acceptance in aviation operations. (Dieter et al., 2024)

1.6.3. Sustainability

The chapter titled "Towards Smart Aviation with Sustainable Development: Artificial Intelligence Insights into the Airline and Advanced Air Mobility Industries" explores the potential of AI to revolutionize the aviation industry with a strong emphasis on sustainability. It highlights AI applications such as predictive maintenance, which minimizes resource wastage and enhances aircraft lifecycle management, and fuel consumption prediction systems, which significantly reduce greenhouse gas emissions by optimizing flight operations. Additionally, the text discusses AI's role in advanced air mobility, particularly with electric vertical take-off and landing (eVTOL) vehicles, which promote urban sustainability by decreasing road traffic congestion and associated fuel consumption. The research underscores AI's transformative potential to support sustainable aviation, not only by improving operational efficiency but also by addressing environmental concerns like carbon emissions and fuel efficiency. These insights affirm AI's critical role in steering the aviation industry toward a more sustainable future. (Lingrui & Xin, 2024)

1.6.4. Human-machine collaboration

The study titled "A Testbed for Investigating Task Allocation Strategies between Air Traffic Controllers and Automated Agents" introduces a simulation platform designed to explore optimal task distribution between human air traffic controllers and AI-driven automated systems. By employing mixed initiative approaches and multi-agent systems, the research aims to enhance decision-making processes and operational efficiency in air traffic management. Preliminary findings from pilot studies indicate that dynamic function allocation, where tasks are assigned based on real-time context, leads to qualitative improvements over static allocation methods. This underscores the potential benefits of adaptive human-machine collaboration in complex aviation environments. (Schurr et al., 2010)

1.7. Types of utility from AI implementation in aviation

When evaluating the benefits of Artificial Intelligence in aviation, it is essential to understand the concept of utility—the value created by implementing AI. In management and economics, utility refers to the usefulness or advantage an agent gains from an action or technology, often represented in decision theory through utility functions (Dan Hendrycks & Taylor & Francis, 2024). In aviation business management, utility must be considered across several dimensions, reflecting the perspectives of different stakeholders as well as operational outcomes.

Economic utility refers to cost savings, productivity improvements, and revenue generation. AI applications such as predictive maintenance, optimized scheduling, and dynamic pricing reduce operational costs and improve asset use. For example, frameworks that integrate technical, operational, economic, and regulatory elements help determine the feasibility of predictive maintenance, showing how economic benefits are closely linked with safety and technical considerations (Kabashkin et al., 2025).

Operational utility in aviation refers to the efficiency gains, workflow improvements, and enhanced resource management that result from applying AI-based systems. Recent systematic reviews show that AI is increasingly used in areas such as trajectory prediction, air traffic management, and airport operations, where machine learning models enable faster and more accurate decision-making, reduce delays, and optimize the flow of aircraft and passengers. These applications not only strengthen operational efficiency but also contribute to safety improvements by addressing challenges such as traffic congestion, delay forecasting, and fuel consumption optimization (Tafur et al., 2025).

Safety utility is a core priority in aviation. AI contributes through accident prevention, risk modeling, and human–AI teamwork. Advanced AI systems and intelligent assistants are studied for their ability to support human crews without compromising safety culture (Kabashkin et al., 2025). While economic and operational benefits are important, the industry’s traditionally cautious approach to new technologies shows that safety remains the leading criterion in decision-making (Ziakkas et al., 2022).

Strategic utility relates to long-term competitiveness, innovation, and organizational adaptability. AI enables airlines and airports to differentiate themselves through better services, predictive analytics, and scalable digital infrastructure. Although specific academic work in aviation is limited, the broader evidence from large-scale programs such as NextGen suggests that operational improvements can strengthen long-term strategic positioning (Moghadasnian, 2025b).

Social and environmental utility, though less explored in the literature, is increasingly important. AI supports sustainability by improving fuel efficiency and reducing emissions, helping aviation align with global climate goals (Ekici et al., 2023). At the same time, such initiatives strengthen public trust, social value, and the industry’s reputation for responsibility.

1.8. Make-or-buy decisions for AI in aviation

Adopting artificial intelligence in organizations is not only a technological issue but also a strategic one. A key question is whether to develop AI solutions internally (“make”) or obtain them from external providers (“buy”). This make-or-buy (MoB) dilemma has been long studied in manufacturing, IT, and outsourcing (Coase, 1995). However, the specific characteristics of AI—its need for large volumes of high-quality data, the “black box” nature of its decision-making, and the requirement for continuous retraining—make traditional MoB frameworks more complex when applied to aviation (Gräf et al., 2024).

Classical theories provide useful guidance. Transaction Cost Theory (TCT) argues that organizations should choose the option that minimizes production and transaction costs, considering uncertainty, asset specificity, and frequency of transactions (de Camargo Fiorini et al., 2018). In aviation, this means that if developing and maintaining an AI system is too costly or uncertain, buying from an external provider may be more efficient. On the other hand, if the AI system is highly asset-specific—such as predictive maintenance models tailored to a specific aircraft type—developing it internally may reduce risks of dependency on external suppliers. Resource-Based View (RBV) emphasizes that organizations should build AI capabilities internally when they strengthen core competencies and competitive advantage (Barney, 1991). For aviation, this may apply to AI systems used in fleet maintenance optimization, safety analysis, or operations scheduling, where retaining expertise in-house is strategically valuable.

More recent research expands these considerations. (Gräf et al., 2024) identified twelve factors influencing MoB decisions for AI in mobility and logistics organizations, many of which also apply to aviation. These include strategic importance, total cost of ownership, internal resources, complexity of the use case, intellectual property protection, long-term support, and data security. In safety-critical industries like aviation, data security and regulatory compliance are particularly decisive. Outsourcing may involve sensitive operational or passenger data that cannot easily be shared. Similarly, the opaque nature of AI makes certification more difficult, which can favor in-house solutions where transparency and explainability are required.

Flexibility and lifecycle management also play a role. AI systems in aviation must be regularly retrained with new operational data (e.g., new sensor readings, evolving traffic patterns, or regulatory changes). This creates long-term reliance on either internal data teams

or external vendors. Outsourcing can seem cost-effective but carries risks of vendor lock-in, especially if providers are small AI startups that may struggle to remain operational or compliant with aviation regulations (Gerbert Philipp et al., 2018). In-house development avoids such risks but demands ongoing investment in scarce AI expertise, which many aviation organizations lack.

Finally, not all AI applications require the same approach. Low-risk, low-strategic-value applications, such as chatbots for customer service or translation tools, can often be outsourced with minimal downside. In contrast, AI systems that directly affect airworthiness, predictive maintenance, or safety management may need to be developed internally to ensure compliance, protect critical knowledge, and support long-term strategic goals. This shows that MoB decisions for AI in aviation are case-specific and should be tailored to the importance and sensitivity of each application.

The key criteria informing AI make-or-buy choices are depicted in Figure 4.

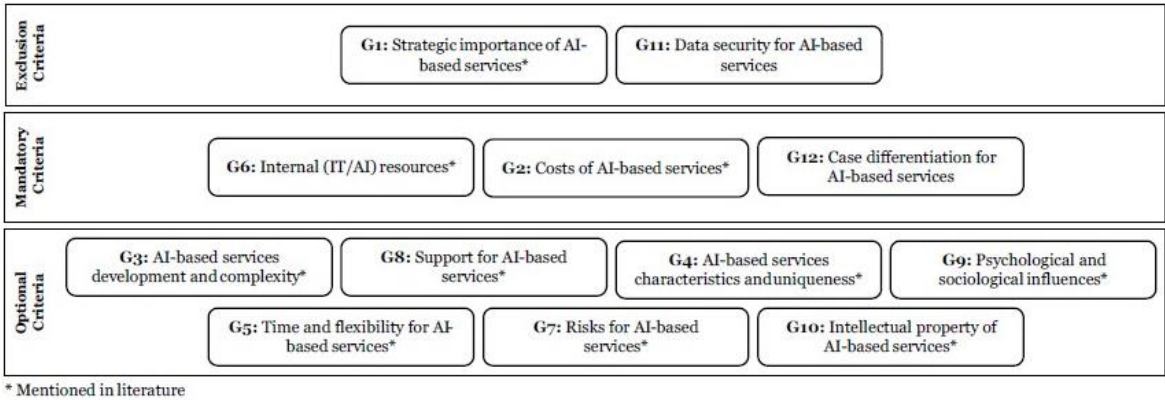


Fig. 4. Overview of the guidelines for MoB Decision making for AI based services

Source: Gräf et al. (2024)

In summary, the MoB decision is a pivotal determinant of how aviation organizations can harness AI effectively. While classical theories such as TCT and RBV provide a foundation for analysing costs, risks, and resources, contemporary research highlights additional AI-specific factors such as data security, black-box opacity, and continuous retraining requirements. For aviation, where safety, regulatory compliance, and strategic control are paramount, these considerations elevate the importance of carefully evaluating whether AI solutions should be developed in-house, procured externally, or pursued through hybrid strategies. By situating MoB within the broader AI adoption process, it becomes clear that this decision directly shapes the distribution of benefits, risks, and competitive advantage in the aviation sector.

1.9. Gaps in the literature

Although research on artificial intelligence in aviation has expanded quickly, important gaps remain that limit the ability to fully evaluate its benefits. Most existing studies focus on very specific technical applications—such as trajectory prediction, delay forecasting, or fuel consumption modelling—while offering limited insight into how these improvements translate into measurable benefits for organizations or stakeholders. As (Tafur et al., 2025) note, AI models often achieve high accuracy with controlled datasets, but their robustness in dynamic, real-world conditions is less certain. This methodological limitation makes it difficult to know whether benefits such as efficiency gains or safety improvements can consistently be realized in practice.

A first gap relates to domain coverage. Research has concentrated heavily on air traffic management, flight performance optimization, and weather forecasting. In contrast, areas such as Continuing Airworthiness Management Organizations, Maintenance, Repair, and Overhaul, ground handling, and regulatory oversight remain largely unexplored. These domains account for significant costs, safety responsibilities, and compliance demands. Yet, the lack of empirical studies means that possible benefits—such as better maintenance scheduling, fewer compliance errors, or faster documentation handling—are not fully evaluated. Without evidence from these areas, aviation companies have limited grounds to justify AI adoption in some of their most resource-intensive functions.

Another gap concerns explainability and trust. Many studies prioritize algorithmic accuracy over interpretability, overlooking the importance of explainable AI that professionals can trust in safety-critical operations (Habiba et al., 2025). Research rarely addresses human-AI collaboration, operator training, or trust-building measures. As a result, even effective AI models may face resistance from users or regulators, limiting their practical benefits.

There are also contextual and geographical gaps. Much of the literature focuses on large international hubs or national air navigation service providers. Smaller actors—such as regional airlines, small airports, and training organizations—receive little attention (Tafur et al., 2025). Yet these organizations often operate with tighter resources, meaning AI-driven efficiencies could provide especially high value. Without tailored studies, however, the return on investment for these stakeholders remains unclear, and adoption decisions risk being based on assumptions rather than evidence.

Finally, there is a lack of long-term and cross-domain evaluation. Few studies examine the lasting impact of AI adoption on safety, efficiency, sustainability, or costs across multiple domains. Comparative analyses between AI-based and traditional decision-making methods are

also scarce. This leaves open questions about scalability, cost-effectiveness, and regulatory acceptance, limiting the ability of companies and policymakers to make evidence-based decisions about where AI delivers the most value.

In summary, these gaps show that current literature provides only a fragmented view of AI's potential in aviation. Future research needs to integrate technical, regulatory, economic, and human factors to build a more holistic assessment of AI's strategic value across the aviation ecosystem.

1.10. Evaluation methods

Evaluating the benefits of artificial intelligence in aviation is complex because of the sector's multi-stakeholder environment, strict safety standards, and the mix of both quantitative and qualitative outcomes. Traditional single-criterion methods such as cost–benefit analysis (CBA) or return on investment have long been used in aviation project assessments. However, their strong financial focus makes them less suitable for capturing intangible but critical dimensions such as improved safety, reliability, or regulatory compliance. For this reason, researchers and practitioners increasingly rely on multi-criteria decision-making (MCDM) methods, which allow the simultaneous consideration of multiple, and often conflicting, criteria(Ardil, 2021).

MCDM provides structured tools for comparing alternatives across different dimensions, making it particularly well suited for aviation. Among these methods, the Analytic Hierarchy Process (AHP) is one of the most widely used because of its intuitive structure: complex problems are broken down into goal–criteria–alternatives, and pairwise comparisons generate weights for each criterion. A review of 166 studies from 2000 to 2018 across aviation subdomains—including airlines, airports, and air traffic management—found that evaluation was the dominant theme, about 50% of studies included fuzzy approaches, and around 40% applied AHP including fuzzy AHP (Dožić, 2019).

Other MCDM approaches extend these capabilities. The Analytic Network Process (ANP) handles interdependencies between criteria, which is common in aviation—for instance, when predictive maintenance affects both cost and safety. TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) ranks alternatives based on their closeness to an ideal solution, while methods like PROMETHEE, VIKOR, and TODIM provide preference-based rankings or compromise solutions. DEMATEL goes further by mapping cause–effect relationships among evaluation factors. Because expert judgments often involve uncertainty—especially when assessing AI systems with limited operational history—many of these methods have fuzzy versions. Increasingly, hybrid models are also used, such as combining AHP to

determine weights with TOPSIS to rank alternatives, to offset the weaknesses of any single technique.

Practical use of these methods in aviation has grown steadily. Dožić’s review confirms that MCDM is widely applied across airlines, airports, and air traffic management, with evaluation as the primary focus and AHP as the most common tool. For example, Aslan and (Aslan & Tolga, 2022) used a mix of VIKOR, TODIM, and AHP to show that predictive–preventive maintenance is the most suitable domain for AI in the maintenance, repair, and overhaul sector, and then selected the best AI tool among alternatives. More recently, (Kulakli & Şahin, 2023) applied fuzzy AHP and fuzzy TOPSIS to rank the ground operational performance of three Turkish low-cost carriers based on five main criteria and eighteen sub-criteria.

Despite their advantages, MCDM methods also have weaknesses. A well-known paradox is that applying different MCDM methods to the same problem can result in different rankings, raising questions about consistency and transparency. Sensitivity analysis and clear justification of the chosen method are therefore essential. Furthermore, effective AI evaluation should go beyond mathematical models: it requires validation through simulation, expert judgment, and continuous performance monitoring, which is particularly important given AI’s evolving and adaptive nature.

The synthesis of multi-criteria methods across aviation domains is presented in Table 2.

Table 2. Research on MCDM methods used in Aviation

Author(s) & Year	Domain / Context	Method(s) Used	Purpose / Key Finding
(Dožić, 2019)	Airlines, Airports, ATM	AHP (incl. fuzzy), various MCDM	Review of 166 studies; Evaluation most common; ~50% fuzzy; ~40% used AHP
(Aslan & Tolga, 2022)	MRO (Maintenance)	VIKOR, TODIM, AHP	Identified predictive/preventive maintenance as prime domain; selected optimal AI tool (avesis.gsu.edu.tr, ResearchGate)
(Kulakli & Şahin, 2023)	Low-cost carriers (Ground ops)	Fuzzy AHP, Fuzzy TOPSIS	Ranked performance of three LCCs on ground ops; structured evaluation criteria (MDPI, ResearchGate)

Source: designed by author

In summary, while no single method can be considered universally superior, the literature shows that MCDM provides a valuable toolkit for weighing the diverse benefits and risks of AI in aviation. The framework proposed in this thesis builds on these insights by

establishing a structured process to determine what to evaluate, where in the organization evaluation should take place, and when in the lifecycle it is most meaningful. At the same time, it allows each organization to choose the method—whether AHP, TOPSIS, VIKOR, or a hybrid—that best fits its decision-making culture, operational needs, and resources.

1.11. Literature review conclusions

The reviewed literature confirms that artificial intelligence is a transformative force in aviation, generating value across safety, operational efficiency, sustainability, customer service, and regulatory compliance. Mature applications such as predictive maintenance and air traffic management already demonstrate measurable benefits, while emerging areas—including cybersecurity, advanced air mobility, and compliance automation—remain under development. At the same time, significant challenges such as data fragmentation, regulatory uncertainty, organizational resistance, and difficulties in scaling beyond pilots continue to limit the full realization potential of AI.

Because AI generates multiple types of utility—economic, operational, safety, strategic, and social–environmental—its evaluation requires more than traditional single-criterion approaches. The literature highlights multi-criteria decision-making methods as particularly well suited for this task, as they allow organizations to balance diverse benefits, risks, and stakeholder perspectives in a structured and transparent way.

The review also reveals important gaps. While domains such as air traffic management and predictive maintenance are well studied, areas including Continuing Airworthiness Management, Maintenance, Repair, and Overhaul, ground handling, and human–AI collaboration remain underexplored. Long-term and cross-domain evaluations are likewise scarce, leaving the evidence base for AI in aviation incomplete. Addressing these gaps will be critical for future research. Nevertheless, the current body of knowledge already provides a strong foundation for developing robust evaluation frameworks and guiding the strategic adoption of AI in aviation.

2. AI BENEFIT EVALUATION FRAMEWORK

The literature review has shown that artificial intelligence generates benefits across multiple dimensions—economic, operational, safety, strategic, and social–environmental—while also introducing risks and organizational challenges. Capturing this complexity requires more than traditional financial measures alone. To address this, the thesis proposes a structured evaluation framework that guides decision-makers in identifying, comparing, and prioritizing AI applications within their domain.

The framework is intentionally designed to be flexible. It can be applied across different areas of aviation and allows organizations to adopt the decision-making methods that best fit their specific context. Its process begins with stakeholder priorities and expected benefits, incorporates risk and feasibility checks, and concludes with make-or-buy considerations and regulatory alignment. In doing so, it supports organizations in ensuring that selected AI applications are not only attractive in theory but also realistic, sustainable, and compliant in practice.

2.1. Framework structure

The proposed framework is organized as a sequence of stages that gradually narrow down a broad range of potential AI applications into a smaller set of options that are both beneficial and feasible for a given organization. It functions like a funnel: many possible use cases are considered at the beginning, and at each stage further analysis and filtering ensures that only realistic and valuable options remain.

The process begins with domain and stakeholder identification. Since the relevance of AI depends on the operational area and the perspectives of those affected, each organization must first clarify the domain in which it seeks to apply AI—such as CAMO, MRO, air traffic management, or passenger services—and identify the relevant stakeholders, including management, regulators, employees, and customers.

The second stage is the evaluation of benefits, which applies the five utility dimensions identified in the literature: economic, operational, safety, strategic, and social–environmental. Using multi-criteria decision-making methods, organizations assign weights to these criteria according to stakeholder priorities and then score the different AI applications. This produces an initial ranking of applications based on expected benefits.

The third stage introduces a risk assessment. Even highly beneficial applications may be unsuitable if they involve unacceptable risks, such as cybersecurity vulnerabilities, poor

explainability, immature data, or staff resistance. Risk assessment ensures that the evaluation accounts not only for opportunities but also for barriers and threats.

The fourth stage is the feasibility check, which acts as a practical filter. Here, the organization evaluates whether it has the data, infrastructure, budget, skills, and cultural readiness needed to implement the shortlisted applications. Feasibility reflects not only the balance of benefits and risks but also the organization's capacity to act at a given point in time.

For applications that pass this stage, the framework incorporates two further considerations. The make-or-buy decision determines whether the AI solution should be developed internally or sourced externally, based on factors such as strategic importance, asset specificity, data security, and vendor dependence. The regulatory acceptance check then evaluates whether the application is likely to meet certification and oversight requirements, avoiding investment in solutions that cannot be deployed in practice.

Finally, the framework concludes with the selection and monitoring stage. Here, decision-makers choose which applications to pursue, design pilot projects, and define key performance indicators for continuous monitoring. Since AI systems evolve and require regular retraining, this stage emphasizes that evaluation is not a one-off exercise but a cyclical process of reassessment and adjustment.

The overall structure of the proposed evaluation process is presented in Figure 5.



Fig. 5. Evaluation framework for AI applications in aviation

Source: designed by author

Through this structure, the framework offers a transparent and systematic pathway from the identification of potential AI applications to final implementation decisions. Each stage builds on the previous one, ensuring that selected solutions align with stakeholder priorities,

account for risks, are feasible within the organizational context, and remain consistent with both regulatory requirements and strategic objectives.

2.2 Application identification

Before defining evaluation criteria, the first step in the framework is to establish a list of AI applications relevant to the organization's domain. This stage ensures that decision-makers work with a concrete set of use cases that reflect both technological opportunities and domain-specific challenges, rather than evaluating AI in the abstract.

Applications can be identified from several sources. The literature review in Chapter 1 outlined a wide range of AI use cases across aviation, including predictive maintenance in MRO and CAMO, air traffic flow optimization in ATM, biometric identification in airports, and customer service chatbots for airlines. Regulatory roadmaps, such as EASA's Artificial Intelligence Roadmap 2.0 and the FAA's AI Strategy, also provide structured overviews of applications already under consideration by industry and regulators. In addition, organizations can draw on their own strategic priorities, benchmarking studies, or internal brainstorming workshops.

At this stage, the objective is not to evaluate or prioritize but to create a comprehensive longlist of candidate applications. This list should be broad enough to capture diverse possibilities while remaining specific to the organization's operational reality. For example, a CAMO organization might identify predictive maintenance, automated compliance documentation, and fleet-wide anomaly detection, while an airport operator may focus on passenger flow management and automated security screening.

The outcome of this stage is a domain-specific longlist of AI applications, which will later be filtered and prioritized using the evaluation criteria defined in the next step of the framework. This ensures that the evaluation begins with a relevant and structured set of alternatives rather than an unbounded or overly abstract set of possibilities.

2.3. Benefit evaluation

As established in the literature review, the benefits of artificial intelligence in aviation can be grouped into five utility dimensions: economic, operational, safety, strategic, and social–environmental. Within the framework, these dimensions form the basis for defining evaluation criteria. Rather than treating them as abstract categories, they are translated into measurable indicators that allow structured comparison of different AI applications.

For example, economic utility may be measured through indicators such as return on investment, cost savings per flight hour, or increased asset utilization. Operational utility can be assessed through improvements in turnaround time, reductions in delays, or higher capacity utilization. Safety utility may be reflected in predictive accuracy for anomaly detection, reduced incident probability, or enhanced situational awareness. Strategic utility can be linked to alignment with digital transformation goals, contributions to innovation, or long-term competitiveness. Finally, social and environmental utility may be expressed through CO₂ emissions avoided, noise reduction, or passenger satisfaction scores.

The exact criteria will vary by domain. For example, a Continuing Airworthiness Management Organization may prioritize safety and compliance, while in passenger services, customer satisfaction and efficiency may weigh more heavily. To ensure criteria reflect stakeholder perspectives, stakeholder involvement is essential. In practice, this means internal stakeholders—management, regulators, and operational staff—contribute directly to the weighting process, while customer perspectives are included indirectly through surveys, service quality data, or representation by customer experience teams. Research on multi-criteria analysis supports this approach, showing that incorporating stakeholder preferences increases both the legitimacy and acceptance of outcomes (Ruangpan et al., 2021).

Once criteria are defined, they must be weighted to reflect their relative importance. Multi-criteria decision-making methods such as the Analytic Hierarchy Process or Analytic Network Process are particularly suitable, as they allow structured pairwise comparisons and can combine both quantitative and qualitative judgments. In contexts of uncertainty, fuzzy extensions of these methods can capture expert hesitation and ambiguity. The outcome of this stage is a transparent, stakeholder-aligned set of weighted criteria that forms the foundation for evaluating AI applications in the next steps of the framework.

Although the framework emphasizes the five core utility dimensions, it does not assume they are exhaustive. Stakeholders may refine existing indicators or introduce additional ones that reflect their specific operational context. Structured approaches such as expert panels, Delphi surveys, or benchmarking studies can be used for this purpose. This flexibility ensures that the framework remains systematic yet adaptable, allowing organizations to respond to emerging challenges and domain-specific priorities without losing methodological consistency.

2.4. Risk assessment

In addition to evaluating benefits, the framework incorporates a structured assessment of risks. As outlined in the literature review, AI adoption in aviation faces challenges such as cybersecurity vulnerabilities, limited explainability, organizational resistance, and regulatory

uncertainty. These categories represent common risk dimensions, but the list is not exhaustive. Organizations can expand it with other risks relevant to their context, using structured methods such as expert panels or Delphi surveys to capture a comprehensive view.

To ensure transparency, risks can be assessed using a risk matrix that scores each factor by its likelihood and potential impact. This method, already well established in aviation safety management, helps decision-makers visualize and prioritize risks across different AI applications. Applications that fall into the “high likelihood / high impact” zone can either be excluded from further evaluation or downgraded in subsequent analysis.

Figure 6 illustrates a standardised risk matrix used within the framework.

Risk	Severity				
	A Catastrophic	B Major	C Moderate	D Minor	E Superficial
Very likely 5	High	High	High	Medium	Medium
Likely 4	High	High	Medium	Medium	Medium
Possible 3	High	Medium	Medium	Medium	Low
Unlikely 2	Medium	Medium	Medium	Low	Low
Very unlikely 1	Medium	Medium	Low	Low	Low

Fig. 6. Risk assessment matrix

Source: designed by author

It is important to distinguish this stage from the later feasibility check. Risk assessment considers the general risks inherent to an AI application or its operating environment—for example, that predictive maintenance requires high-quality data or that deep learning systems often lack explainability. Feasibility, by contrast, evaluates whether a specific organization has the resources and capabilities to manage those risks effectively in practice.

Within the framework, risks can be incorporated in two complementary ways. First, they may be included as criteria within the multi-criteria decision-making process, ensuring that higher-risk applications receive lower overall rankings. Second, they may serve as a filter, removing applications that exceed acceptable thresholds. Both approaches ensure that risk is integrated directly into the decision process rather than treated as an afterthought.

The outcome of this stage is a risk-adjusted shortlist of AI applications that balances potential benefits with uncertainties and barriers. This provides a more realistic foundation for the next stage of the framework, where organizational feasibility is assessed.

2.5. Feasibility check

Following the assessment of benefits and risks, the framework incorporates a feasibility check to determine whether shortlisted AI applications can realistically be implemented within a specific organizational context. Whereas the risk stage addresses the general uncertainties associated with a technology, feasibility focuses on the internal capacity of the organization to manage those risks and realize the anticipated benefits.

Feasibility can be considered across several dimensions. Technical feasibility concerns the maturity of data and IT infrastructure, including system interoperability and access to sufficient, high-quality datasets. Organizational feasibility reflects the availability of skills, cultural readiness to adopt AI, and alignment with existing workflows. Economic feasibility addresses whether financial resources are sufficient to cover investment, integration, and long-term maintenance costs. In addition, time and scalability considerations are relevant: some applications may be feasible as small pilots but not at the scale required for system-wide impact.

Assessment may be conducted using simple scoring scales or structured readiness models, with stakeholders rating the organization's current capacity in each dimension. For example, an AI solution requiring real-time data streams may be judged infeasible for an operator that still relies heavily on paper records, while a customer-facing chatbot may be feasible even in low-maturity settings because it requires relatively modest infrastructure.

The feasibility dimensions and representative indicators are summarised in Table 3.

Table 3. Feasibility dimensions and example indicators

Dimension	Description	Example Indicators
Technical feasibility	Availability and maturity of technological infrastructure and data required to support AI.	Data quality index; percentage of digital vs. paper records; system interoperability; real-time data access.
Organizational feasibility	Internal skills, cultural readiness, and process alignment with AI adoption.	Number of staff trained in AI/data analytics; survey of employee acceptance; integration with existing workflows.
Economic feasibility	Financial resources to cover initial investment, integration, and long-term operation.	Projected ROI; implementation cost vs. budget share; total cost of ownership.
Time feasibility	Ability to implement the solution within acceptable timelines.	Estimated time to pilot; deployment schedule; regulatory approval lead time.
Scalability feasibility	Potential for the AI solution to expand beyond pilots to organization-wide use.	Pilot-to-scale ratio; cloud/IT infrastructure capacity; adaptability across aircraft types or business units.

Source: Adapted from SITA (2024); Davenport et al. (2023); EASA, (2023)

As with benefits and risks, feasibility criteria should not be treated as fixed. Organizations may expand the list to include additional context-specific factors, using expert judgment, benchmarking, or readiness assessment tools. The outcome of this stage is a refined shortlist of AI applications that are not only beneficial and low-risk, but also realistic for implementation in the current organizational environment.

2.6. Make-or-buy decision

The final stage before regulatory assessment is deciding whether an AI application should be developed internally (“make”) or procured externally (“buy”). As outlined in the literature review, the make-or-buy dilemma has long been examined through theories such as Transaction Cost Theory (Coase, 1995) and the Resource-Based View (Barney, 1991). However, as shown in the case study by (Gräf et al., 2024) AI-based services introduce additional considerations. Their research confirmed many traditional MoB factors while also highlighting AI-specific concerns such as data security, vendor lock-in, and case differentiation.

Within this framework, the MoB stage integrates these insights into a structured decision point. Once an AI application has passed benefit evaluation, risk assessment, and feasibility checks, decision-makers apply MoB logic to identify the most suitable procurement pathway. For instance, if an AI application is strategically central, requires sensitive operational data, or depends on highly specialized knowledge, the framework suggests a stronger case for in-house development. Conversely, if the solution is standardized, non-critical, or available with reliable long-term vendor support, external sourcing may be the more efficient option.

The study by (Gräf et al., 2024) further demonstrates how organizations can prioritize decision factors hierarchically. Exclusion factors such as strategic importance and data security are considered first. These are followed by mandatory factors including costs, internal resources, and use-case complexity, and then refined with optional factors such as ongoing support, intellectual property rights, and cultural acceptance. Embedding this hierarchy into the framework ensures that MoB decisions are consistent, transparent, and aligned with organizational strategy.

In aviation, this stage is particularly important because AI solutions vary widely in scope and criticality. Standardized tools such as customer service chatbots may often be outsourced without risk, while highly safety-critical applications—such as predictive maintenance—may require in-house development to maintain control over sensitive data and processes. By embedding MoB as an explicit stage within the evaluation framework, organizations are guided not only in selecting the right AI applications but also in determining the most effective and sustainable way to implement them.

2.7. Regulatory acceptance check

Even if an AI application is beneficial, feasible, and supported by a suitable procurement pathway, it cannot be implemented in aviation unless it is acceptable to regulators. The regulatory acceptance check therefore forms the final filter before adoption. This stage does not create a new certification process within the framework but ensures that organizations explicitly account for whether a given AI solution can meet the requirements of authorities such as the European Union Aviation Safety Agency or the Federal Aviation Administration.

As highlighted in the literature review, regulatory agencies are developing guidance for AI integration that emphasizes trustworthiness, transparency, and human oversight. These principles mean that some AI applications, particularly adaptive systems or those with limited explainability, face longer or more uncertain approval pathways (EASA, 2023a). By contrast, applications in non-safety-critical areas—such as customer service or administrative processes—generally encounter fewer regulatory barriers.

Within the framework, the regulatory acceptance check serves two functions. First, it encourages organizations to differentiate between safety-critical and non-safety-critical domains, recognizing that certification feasibility is uneven across use cases. Second, it prompts decision-makers to consider timing and lifecycle issues: even if a solution cannot be certified today, it may be viable in the future as regulatory standards mature.

By incorporating this stage, the framework ensures that decision-making is grounded not only in internal evaluations of benefits, risks, and resources, but also in the external reality of oversight. For aviation organizations, this helps avoid investing in solutions that are strategically attractive yet regulatorily unattainable. Instead, resources can be directed toward AI applications with both high value and a realistic pathway to approval.

2.8. Selection and monitoring

The final stage of the framework is the selection of AI applications and the establishment of monitoring mechanisms to ensure that chosen solutions continue to deliver value over time. This stage acknowledges that AI projects are not static: models, data, and regulatory environments evolve, requiring continuous oversight. Selection therefore does not mark the end of evaluation but the start of an iterative cycle of adoption, monitoring, and re-evaluation.

Once applications have passed the benefit, risk, feasibility, make-or-buy, and regulatory checks, decision-makers select those with the strongest overall profile. Selection should be supported by a clear implementation roadmap, including pilot testing, timelines, and allocation

of responsibilities. Equally important is defining criteria for success in the form of key performance indicators (KPIs). Examples include predictive accuracy for maintenance applications, delay reduction in air traffic management, cost savings in operations, or customer satisfaction gains in service contexts.

Monitoring mechanisms then ensure that these KPIs are continuously tracked. Because AI models degrade over time as data and operating conditions change, monitoring must include both performance validation and risk reassessment. In safety-critical domains, this may involve ongoing verification of outputs against established benchmarks, while in customer-facing applications it may focus on satisfaction surveys and efficiency metrics. Monitoring should also cover compliance checks, ensuring that regulatory and data protection requirements remain satisfied as systems evolve.

The cyclical monitoring and re-evaluation process is depicted in Figure 7.

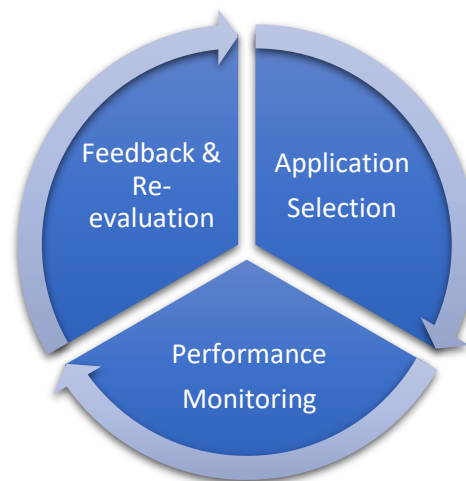


Fig. 7. Application selection and monitoring cycle

Source: designed by author

Finally, the framework emphasizes that monitoring must be connected to clear feedback loops. If KPIs consistently fall short, risks increase, or regulatory standards change, the application should be re-evaluated. In this way, the monitoring stage closes the loop with earlier stages of the framework, ensuring that the process remains dynamic rather than linear. This cyclical approach reflects the reality of AI in aviation: adoption is not a one-time decision but an ongoing process of aligning technology with organizational capabilities and regulatory oversight.

2.9. Methodological basis for framework validation

The purpose of the empirical analysis in this thesis is to validate the proposed AI benefit evaluation framework rather than to apply it to specific AI applications. Since the primary research objective is to develop a structured and logically coherent framework, the empirical stage is designed to assess whether the framework is understandable, complete, and aligned with the practical needs of aviation professionals. Conducting validation before any full application ensures that the framework is methodologically sound and suitable for future use in different operational contexts.

To achieve this, two complementary validation methods were selected: an expert survey and the Analytic Hierarchy Process. The expert survey provides qualitative and quantitative assessments of the framework's structure, clarity, and relevance. Experts evaluate whether each stage—benefit assessment, risk analysis, feasibility, make-or-buy decisions, regulatory acceptance, and monitoring—correctly reflects the decision-making logic required in aviation organizations. Their feedback indicates whether the framework captures all necessary considerations or whether any stages require refinement.

The AHP method is used exclusively to validate the weighting logic of the benefit evaluation stage. Experts conduct pairwise comparisons of the five benefit dimensions—economic, operational, safety, strategic, and social–environmental utility—to determine their relative importance. These weights are not used to evaluate actual AI applications but serve to confirm that the benefit structure embedded in the framework reflects expert judgement and industry priorities.

Taken together, the expert survey and AHP analysis validate the internal logic and practical suitability of the framework. They do not constitute a full implementation of the framework; instead, they ensure that the model is well-founded and ready for use in future studies or organisational decision-making processes. This validation-focused empirical approach is consistent with the research aim and scope of this thesis.

2.10. Expert selection criteria

To ensure that the validation of the proposed framework is based on informed and credible professional judgement, clear expert selection criteria were established. Because expert-based validation relies on the depth and relevance of participants' knowledge, the selection process followed principles commonly recommended in applied research and decision-science studies. According to (Fink, 2016), expert surveys are most effective when respondents possess substantial practical experience and direct exposure to the phenomena

being evaluated, enabling them to provide accurate, context-rich assessments. Similarly, (Lavrakas, 2008) notes that expert sampling is appropriate when the objective is to obtain informed evaluations rather than statistically representative population estimates, making it suitable for methodological validation in specialised fields such as aviation.

For the purposes of this thesis, an individual qualifies as an expert if they possess a minimum of five years of professional experience in the aviation industry. This threshold reflects the expectation that respondents have accumulated sufficient domain knowledge, operational exposure, and familiarity with digitalisation or safety-related processes to evaluate the framework meaningfully. Expert judgement is widely used in multi-criteria decision-making and technology assessment research, as experienced professionals can reliably identify relevant factors and evaluate structured decision models (Ishizaka & Nemery, 2013). Setting a minimum experience requirement therefore enhances the reliability of the feedback and supports the validity of the empirical findings.

Additional considerations were used to further ensure the relevance of expert input. Respondents were required to work—or to have previously worked—in aviation roles linked to operational decision-making, safety management, airworthiness, maintenance, or digitalisation initiatives. This is consistent with the recommendations of (Bougie & Sekaran, 2020), who argue that validity in methodological studies depends on selecting participants whose roles reflect the context in which the framework will be used. Experience in decision-making, involvement in innovation or digital transformation, or responsibility for safety-critical processes were therefore considered strong indicators of relevant expertise.

By applying these criteria, the study ensured that the framework was evaluated by practitioners with sufficient experience and domain-specific insight to assess its clarity, completeness, and practical applicability. This expert-based approach strengthens the credibility of the validation process and aligns with best practices in methodological and decision-science research.

2.11. Expert survey method

The expert survey represents the first empirical instrument used to validate the proposed AI benefit evaluation framework. Surveys are widely used in methodological and decision-making research to assess conceptual clarity, completeness, and practical relevance (Fink, 2016). In aviation and other safety-critical domains, expert surveys are particularly suitable because they allow researchers to capture informed professional judgement that cannot be obtained from general population samples (Lavrakas, 2008). The purpose of the survey in this

thesis is therefore to evaluate whether the framework's stages are understandable, logically connected, and aligned with real organisational decision-making processes.

The design of the survey follows established principles of structured questionnaire development. According to (DeVellis, 2017), well-constructed survey instruments must clearly differentiate between background information, evaluative items, and open-ended questions. Based on this guidance, the survey used in this thesis consists of three groups of questions: background questions describing the expert sample, Likert-scale statements evaluating specific aspects of the framework, and open-ended questions that allow respondents to elaborate on strengths, weaknesses, or missing elements. This combination of structured and exploratory questions is recommended when validating conceptual frameworks, as it provides both quantitative and qualitative evidence of validity (Bougie & Sekaran, 2020).

2.11.1 Background questions

Background questions were included to describe the professional characteristics of each respondent and ensure alignment with the expert selection criteria defined in Section 2.10. These questions captured the expert's role, operational domain, years of experience, organisation type, and organisational size. As noted by (Lavrakas, 2008), background information increases the interpretability of survey results by providing context and enabling analysis of differences across expertise profiles. The purpose of these questions is descriptive rather than analytical, but they help ensure that the expert sample reflects the diversity of roles where AI adoption and evaluation are relevant.

The background questions used in the expert survey are presented in Table 4.

Table 4. Background questions and their purpose

Question	Purpose
1. Main area of work	Identify the professional domain of the expert (e.g., CAMO, MRO).
2. Specific specialization/role	Understand the respondent's responsibilities and expertise.
3. Years of aviation experience	Ensure respondent meets the ≥ 5 -year expert criterion.
4. Type of organisation	Identify operational context (airline, MRO, CAMO, etc.).
5. Organisation size	Capture differences in adoption capacity and resources.

Source: designed by author

These background variables ensure that the expert sample is clearly defined and that subsequent evaluations can be interpreted in relation to each respondent's professional profile. Although these questions are not used directly in the analysis, they provide essential context for understanding the diversity and relevance of the expert group.

2.11.2. Framework evaluation questions

The central part of the survey consists of Likert-scale statements designed to evaluate the clarity, completeness, and perceived applicability of the proposed framework. Likert-scale items are widely used to measure attitudes and cognitive evaluations because they allow respondents to express varying degrees of agreement in a structured and quantifiable format (DeVellis, 2017). Such scales are particularly useful in framework validation, where the objective is to assess expert perceptions of structure, logic, relevance, and feasibility.

Table 5 provides the full list of framework evaluation statements.

Table 5. Framework evaluation questions and their purpose

Question	Purpose
6. The framework is clearly structured	Evaluate clarity and logical flow.
7. Terminology is understandable	Assess accessibility and technical wording.
8. Coverage of perspectives	Evaluate whether benefits, risks, feasibility, and regulatory aspects are captured.
9. Coverage of utility types	Check representation of operational, strategic, and social/regulatory utility.
10. Applicability in respondent's organisation	Assess organisational fit.
11. Availability of required data	Evaluate feasibility of data collection.
12. Decision quality improvement	Determine practical impact on decision-making.
13. Distinction between safety-critical and non-critical applications	Test whether the framework respects aviation safety logic.
14. Overall viability	Assess overall suitability for evaluating AI applications.
15. Recommendation potential	Determine whether experts would propose using the framework.
16. Sufficiency of feasibility dimensions	Evaluate completeness of feasibility evaluation.
17. Availability of feasibility evidence	Assess whether required feasibility data can be realistically collected.
18. Usefulness of make-or-buy step	Evaluate the relevance of the procurement decision step.
19. Usefulness of monitoring step	Test suitability of continuous evaluation after implementation.

Source: designed by author

The Likert statements in this thesis were formulated to cover all stages of the framework, including benefit evaluation, risk assessment, feasibility analysis, make-or-buy considerations, regulatory acceptance, and monitoring. This approach aligns with recommendations by (Bougie & Sekaran, 2020), who emphasise that validation instruments must reflect the full structure of the proposed conceptual model to ensure that all components are evaluated systematically.

To analyse the Likert-scale responses, descriptive statistics were applied. The arithmetic mean was calculated for each item to represent the central tendency of expert evaluations, while

the standard deviation (SD) was used to capture the degree of agreement among respondents. A lower SD indicates stronger consensus, whereas higher values suggest more diverse expert perceptions. Using mean and SD is consistent with established practices in applied survey research (Field, 2009) and provides a clear and interpretable summary of expert feedback.

2.11.3. Open-ended questions

The final part of the survey includes open-ended questions designed to capture more detailed insights into how experts perceive the usefulness, clarity, and completeness of the framework. Open-ended items are recommended when validating new conceptual models because they allow respondents to identify missing components, refine definitions, and highlight practical challenges that cannot be captured through fixed-response formats (Bougie & Sekaran, 2020). These qualitative data complement the quantitative evaluations and provide depth needed to interpret numerical results in context.

The open-ended survey items, designed to generate qualitative insights, are shown in Table 6.

Table 6. Open-ended questions and their purpose

Question	Purpose
20. Most useful aspect	Identify strengths of the framework.
21. Least useful aspect	Identify weaknesses or unclear parts.
22. Suggested improvements	Collect recommendations from experts.
23. Adoption challenges	Identify organisational barriers.

Source: designed by author

The combination of background information, Likert-scale assessments, and open-ended feedback ensures that the expert survey provides a comprehensive basis for evaluating the conceptual validity, structural integrity, and practical relevance of the proposed AI benefit evaluation framework.

2.12. Analytic hierarchy process

The Analytic Hierarchy Process, developed by Thomas L. Saaty, is applied in this thesis as a quantitative method to validate the weighting logic of the benefit dimensions included in the proposed evaluation framework. AHP is one of the most established and widely used multi-criteria decision-making (MCDM) tools, particularly suited for complex decisions involving both qualitative and quantitative factors (T. Saaty & Vargas, 2012). Its structured pairwise comparison approach enables experts to express relative preferences in a consistent and

mathematically interpretable form, making it especially appropriate for evaluating priority relationships among benefit dimensions in aviation.

AHP is widely applied in engineering, aviation, transportation, and technology evaluation contexts because it provides a transparent and replicable weighting process (Vaidya & Kumar, 2006). Unlike unstructured ranking or rating methods, AHP incorporates consistency checks that ensure expert judgments are coherent, thereby increasing the reliability of the results. This aligns with the needs of safety-critical industries, where decision-making must be explicit, rational, and traceable. As (Keeney & Raiffa, 1979) emphasize, weighting methods used in multi-criteria evaluation should reflect decision-maker priorities in a logically structured way—an attribute AHP directly fulfills.

In this thesis, AHP is not used to rank AI applications or evaluate alternatives. Instead, its purpose is limited to validating the internal structure of the framework by determining the relative importance of the five benefit dimensions—economic, operational, safety, strategic, and social–environmental utility. This targeted use ensures that the benefit evaluation stage of the framework is grounded in expert judgement and aligns with real-world aviation priorities.

2.12.1. AHP hierarchical structure

Following standard AHP procedures (T. L. . Saaty & Vargas, 2012), the evaluation problem is structured into a simple hierarchy. At the top of the hierarchy is the overall goal—determining the relative importance of the benefit dimensions. Below this are the five criteria representing the different types of value artificial intelligence can generate. Because the purpose of this stage is solely to validate the weighting logic rather than compare specific applications, no subcriteria or alternatives are included.

This streamlined hierarchy follows established MCDM guidance, which recommends limiting AHP structures to essential elements when the goal is validation rather than full decision-making (Ishizaka & Nemery, 2013). It ensures that experts can focus their judgments on the conceptual importance of each benefit type without distraction from downstream implementation considerations.

2.12.2. Criteria evaluation

Experts compare each benefit dimension with every other dimension using the Saaty scale, which ranges from 1 (equal importance) to 9 (extreme importance). The scale used is shown in Table 7.

Table 7. The Saaty scale

Value	Verbal Judgment	Explanation
1	Equal Importance	Two elements contribute equally to the objective.
2	Weak or Slight	A value between equal and moderate importance.
3	Moderate Importance	One element is moderately favored over the other.
4	Moderate Plus	A value between moderate and strong importance.
5	Strong Importance	One element is strongly favored over the other.
6	Strong Plus	A value between strong and very strong importance.
7	Very Strong or Demonstrated Importance	One element is very strongly favored over the other; its dominance is obvious.
8	Very, Very Strong	A value between very strong and extreme importance.
9	Extreme Importance	One element is favored to the highest degree possible.

Source: designed by author

Each pairwise judgement is placed into a pairwise comparison matrix. If criterion C1 is assigned a value n compared to criterion C2, then criterion C2 is assigned the reciprocal value $1/n$.

An example structure of a pairwise comparison matrix is shown in table 8:

Table 8. Example of a pair-wise comparison matrix

	C1	C2	C3
C1	1	3	5
C2	1/3	1	1/2
C3	1/5	2	1

Source: designed by author

After creating pair-wise comparison matrices based on each respondents' survey results, values of each matrix are compiled into aggregated pair-wise comparison matrix by averaging the values of all respondents.

When aggregated pair-wise comparison matrix is created the values in each column of the matrix are added together as shown in the equation 2.1.

$$C_j = \sum_{i=1}^n C_{ij} \quad (2.1)$$

where:

C_j – sum of the column values of the pair-wise matrix,

C_{ij} – pair-wise evaluation value.

After sums of each column values of the pair-wise matrix are calculated the normalized pair-wise matrix can be created by dividing each element in the matrix by its column total as show in the equation 2.2.

$$X_{ij} = \frac{C_{ij}}{\sum_{i=1}^n C_{ij}} \begin{bmatrix} X_{11} & X_{12} & X_{13} \\ X_{21} & X_{22} & X_{23} \\ X_{31} & X_{32} & X_{33} \end{bmatrix} \quad (2.2)$$

X_{ij} – normalized pair-wise matrix values

By dividing the sum of the normalized column of the matrix by the number of criteria used a weighted matrix is created as shown in the equation 2.3.

$$W_{ij} = \frac{\sum_{i=1}^n X_{ij}}{n} \begin{bmatrix} W_{11} \\ W_{12} \\ W_{13} \end{bmatrix} \quad (2.3)$$

where:

W_{ij} – weiged matrix value

n – number of criteria.

This weight represents the relative importance of each criterion.

2.12.3. Consistency analysis

Compatibility Analysis refers to evaluating the compatibility of alternatives or criteria within the Analytic Hierarchy Process framework. This ensures that the comparisons and priority weights derived are logical, consistent, and aligned with the decision-making objective.

The consistency analysis is started by multiplying the pair-wise comparison matrix with the weighted matrix as show in the equation 2.4.

$$Cv_{ij} = \begin{bmatrix} C_{11} & \cdots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{n1} & \cdots & C_{nn} \end{bmatrix} \cdot \begin{bmatrix} W_{11} \\ \vdots \\ W_{1n} \end{bmatrix} = \begin{bmatrix} Cv_{11} \\ \vdots \\ Cv_{1n} \end{bmatrix} \quad (2.4)$$

After the creation of the new matrix the principal eigenvalue of the matrix can be calculated as shown in the equation 2.5.

$$\lambda = \frac{Cv_{ij}}{W_{ij}} \quad (2.5)$$

where:

λ - the principal eigenvalue

Consistency index can be calculated as shown in the equation 2.6.

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (2.6)$$

where:

λ_{max} – maximum value of the principal eigenvalue

Consistency ratio can be calculated as shown in the equation 2.7.

$$CR = \frac{CI}{RI} \quad (2.7)$$

where:

RI – Random index (a standard value based on matrix size).

Random index required in equation 2.7 is a standard value based on matrix size. Values of which for matrix size not exceeding 12 are shown in table 9.

Table 9. Random index values

n	1	2	3	4	5	6	7	8	9	10
RI	0	0	0,58	0,9	1,12	1,24	1,34	1,41	1,45	1,49

Source: designed by author

If $CR < 0.1$, the matrix is considered consistent.

2.13. Data Collection Process

The data collection process was carried out in two separate stages to ensure that the framework was validated before applying the AHP method. In the first stage, the expert survey was distributed electronically to aviation professionals with at least five years of experience. This survey included background questions, Likert-scale evaluations of the framework, and open-ended questions. Its purpose was to confirm that the framework was clear, complete, and practically relevant. Collecting this feedback separately ensured that any missing elements or unclear stages could be identified before proceeding to benefit weighting.

After analysing the survey results and confirming that no structural changes were required, the second instrument—the AHP questionnaire—was distributed. This form consisted solely of pairwise comparisons of the five benefit dimensions and was completed by the same group of experts. Conducting AHP as a separate step ensured that experts evaluated the benefit dimensions using a framework they already understood and validated.

Both instruments were administered online, enabling participation from experts across different aviation domains. Responses were collected anonymously, and AHP matrices were later aggregated using the geometric mean, while qualitative comments from the survey were analysed to identify recurring themes. This sequential approach strengthened the reliability of the validation and ensured that benefit weights reflected informed expert judgement.

3. FRAMEWORK VALIDATION AND EMPIRICAL FINDINGS

This chapter presents the empirical validation of the AI benefit evaluation framework developed in Chapter 2. The purpose of this empirical stage is not to apply the framework to specific AI applications but to verify that the framework itself is logically structured, complete, and suitable for use in aviation organisations. To achieve this, the chapter follows the two-step validation approach described in the methodological section. First, a structured expert survey was conducted to assess the clarity, coherence, and practical relevance of each framework stage, ensuring that the proposed process reflects real operational decision-making constraints. Second, the Analytic Hierarchy Process was used exclusively to validate the weighting logic of the benefit dimensions included in the framework. Together, these methods provide a systematic basis for confirming the framework’s robustness and practical applicability, without extending into a full evaluation of individual AI solutions.

3.1. Expert Sample Description

The empirical analysis in this thesis is based on input from 20 aviation professionals, all of whom met the predefined requirement of having at least five years of industry experience. Experience was collected using categorical intervals (6–10 years, 10+ years), ensuring that only respondents with substantial professional backgrounds were included. This aligns with the expert selection criteria described in Chapter 2 and ensures that both the survey and AHP results reflect informed, practice-based judgement.

Experts were drawn from a variety of aviation domains relevant to the framework, including airworthiness and CAMO functions, maintenance and engineering roles in Part-145/MRO organisations, flight operations, safety and quality management, airport operations, IT/data functions, and flight training organisations. Their organisations also varied in size—from small specialised maintenance units to large airlines and airports—allowing perspectives shaped by different operational environments, resource levels, and technological maturity.

The composition of the expert sample is presented in Table 10.

Table 10. Expert respondent profiles

Expert	Main Area Q1	Specific Role Q2	Experience Q3	Organisation Type Q4	Org. Size Q5
1	Airworthiness CAMO /	Airworthiness Engineer	6–10 years	CAMO / Airworthiness Management	Medium
2		Continuing Airworthiness Specialist	10+ years	CAMO / Airworthiness Management	Large
3		Maintenance Programme Engineer	6–10 years	CAMO / Airworthiness Management	Medium
4		Reliability & Technical Data Analyst	6–10 years	Airline / Air Operator	Large
5		Airworthiness Review Staff	10+ years	CAMO / Airworthiness Management	Medium
6		Technical Records Supervisor	6–10 years	Airline / Air Operator	Large
7	Safety & Quality	Compliance Monitoring Auditor	10+ years	Regulatory Authority	Medium
8	Maintenance Engineering (MRO) /	Base Maintenance Planner	6–10 years	Part-145 / MRO	Medium
9		Line Maintenance Supervisor	10+ years	Part-145 / MRO	Large
10		Quality Engineer	6–10 years	Part-145 / MRO	Medium
11		Component Shop Engineer	6–10 years	Part-145 / MRO	Small
12		Production Planning Specialist	10+ years	Part-145 / MRO	Large
13		Senior Aircraft Technician	10+ years	Part-145 / MRO	Medium
14		Diagnostics & Reliability Technician	6–10 years	Part-145 / MRO	Medium
15	Flight Operations	Flight Operations Controller	10+ years	Airline / Air Operator	Large
16	Safety & Quality	Flight Safety Specialist	6–10 years	Airline / Air Operator	Large
17	Airport Operations	Airport Operations Coordinator	6–10 years	Airport / Ground Handling	Large
18	IT / Data / Innovation	Aviation Data Analyst	6–10 years	Airline Innovation Department	Large
19	ATO / Flight Training	Human Factors & Training Instructor	10+ years	ATO / FTO	Medium
20	Management / Operational Planning	Technical & Operational Planning Officer	10+ years	Airline / Air Operator	Large

Source: designed by author

The diversity of domains, operational responsibilities, and organisation types represented in the sample strengthens the credibility of the empirical findings. It ensures that

the validation of the framework and the weighting of benefit dimensions are influenced by a broad and realistic range of professional perspectives across the aviation industry.

3.2. Validation of Framework Structure

The first stage of empirical analysis involved evaluating the clarity, completeness, and practical relevance of the proposed framework through a structured expert survey. Respondents rated 19 statements on a five-point Likert scale, assessing whether the framework is understandable, comprehensive, feasible to apply in practice, and suitable for evaluating AI applications in aviation. The statements were grouped around the key aspects of the framework described in chapter 2.

Overall, the responses indicate strong agreement that the framework is well designed and suitable for potential use in aviation organisations. Experts evaluated whether the framework could be applied in practice—not whether it was applied during this study—and their feedback confirms that its structure, terminology, and coverage of evaluation dimensions are appropriate for future decision-making contexts. The results therefore validate the conceptual soundness and perceived practicality of the framework, without implying its operational implementation in this thesis.

Descriptive statistics for expert agreement levels are summarised in Table 11.

Table 11. Summary of Likert-scale expert evaluations

Question	Survey Statement	Mean	SD	Interpretation
Q6	The framework is clearly structured and easy to follow.	4.3	0.7	Strong agreement
Q7	The terminology used in the framework is understandable.	4.2	0.6	Strong agreement
Q8	The framework covers all necessary perspectives (benefits, risks, feasibility, regulatory acceptance, monitoring).	4.1	0.7	Strong agreement
Q9	The treatment of different utility types is sufficient.	4.0	0.8	Positive evaluation
Q10	The framework can be realistically applied in my organisation.	4.1	0.7	Strong agreement
Q11	The data required to use the framework is reasonably obtainable.	3.9	0.8	Positive evaluation
Q12	Using the framework would improve AI-related decision-making quality.	4.2	0.6	Strong agreement
Q13	The distinction between safety-critical and non-critical applications is appropriate.	4.3	0.7	Strong agreement
Q14	Overall, the framework is viable for evaluating AI applications.	4.3	0.6	Strong agreement
Q15	I would recommend using this framework in future AI-related decisions.	4.2	0.7	Strong agreement
Q16	The feasibility dimensions included in the framework are sufficient.	4.0	0.7	Positive evaluation

Q17	The evidence needed for feasibility evaluation is realistically obtainable.	3.8	0.9	Moderate–positive agreement
Q18	Including a make-or-buy stage is useful for AI decision-making.	4.2	0.6	Strong agreement
Q19	The monitoring stage would help detect performance issues or risks over time.	4.4	0.5	Very strong agreement

Source: designed by author

3.3. Qualitative insights from open-ended responses

These qualitative responses support the interpretation of the survey results by highlighting which aspects of the framework practitioners consider most relevant and well aligned with real decision-making processes. Experts also provided reflections on how the framework could function in practice, identifying strengths, potential areas of refinement, and contextual considerations that may influence future adoption.

A commonly identified strength was the framework’s comprehensive structure. Experts noted that the inclusion of benefits, risks, feasibility, make-or-buy considerations, and regulatory acceptance reflects real-world aviation decision-making processes, particularly for safety-sensitive technologies such as artificial intelligence. The step-by-step structure was frequently described as “logical,” “complete,” and “practically usable,” reinforcing the strong Likert-scale scores reported in the previous section. Several experts also highlighted the framework’s balanced view of utility, noting that it captures not only financial or operational advantages but also safety, regulatory, and strategic dimensions, which are often overlooked in traditional evaluation models.

Despite the overall positive assessment, a number of experts indicated areas where additional clarification could further strengthen the framework. The most common suggestion was to provide more detailed guidance on assessing feasibility, particularly regarding data availability and organisational readiness. Although the feasibility stage was generally considered sufficient, some respondents expressed uncertainty about how to evaluate less tangible aspects, such as cultural acceptance or the maturity of existing digital infrastructure. A few experts also recommended expanding examples or definitions within the framework to ensure consistent interpretation across different organisational roles.

Experts also proposed several actionable improvements. These included adding short explanatory notes or examples under each stage, developing optional checklists to support practical implementation, and simplifying terminology where possible. Some respondents suggested that the make-or-buy stage could benefit from clearer criteria or illustrative scenarios, as procurement decisions for AI solutions often depend heavily on data ownership, supplier reliability, and long-term support considerations.

Finally, experts identified several organisational challenges that may affect the adoption of the framework in practice. These included limited availability of AI expertise, organisational resistance to digital transformation, fragmented data systems, and constrained financial resources in smaller organisations. While these challenges do not reflect weaknesses of the framework itself, they highlight the broader context in which AI evaluation takes place and point to areas where aviation organisations may need additional support or capability development.

Overall, the qualitative insights reinforce the survey findings by confirming that the framework is viewed as complete, well-structured, and relevant to real aviation contexts. The suggestions received were primarily aimed at improving clarity and ease of use rather than modifying the underlying structure, indicating that the framework is sufficiently robust for use in the subsequent AHP analysis.

3.4. AHP Results

Before presenting the results, it is important to note that the AHP method in this thesis serves exclusively to validate the weighting logic of the framework's benefit dimensions. It does not rank or evaluate specific AI applications.

Following the validation of the framework's structure, the Analytic Hierarchy Process was applied to determine the relative importance of the five benefit dimensions: safety, operational, economic, strategic, and social–environmental utility. Although 20 experts participated in the survey, only 10 experts completed the AHP pairwise comparison. Their matrices were aggregated using the geometric mean, in line with standard AHP procedures. The resulting group matrix reflects the consolidated judgement of these 10 respondents.

3.4.1. Aggregated pairwise comparison matrix

Table 12 presents the aggregated pairwise comparison matrix derived from the geometric mean of the 10 individual expert matrices. Values greater than 1 indicate that the row criterion is preferred over the column criterion.

Table 12. Aggregated pairwise comparison matrix

Criteria	Economic	Operational	Safety	Strategic	Social–Environmental
Economic	1.00	0.64	0.34	1.76	2.28
Operational	1.57	1.00	0.62	2.44	5.28
Safety	2.93	1.61	1.00	4.10	5.26
Strategic	0.57	0.41	0.24	1.00	1.70
Social–Environmental	0.44	0.19	0.19	0.59	1.00

Source: designed by author

These values indicate, for example, that compared to economic utility, safety utility is on average judged approximately three times more important (2.93), and operational utility is judged moderately more important (1.57).

3.4.2. Normalised matrix and weight calculation

Each column of the comparison matrix was normalised and row averages were calculated to determine the weight of each benefit dimension. The resulting weights are presented in Table 13.

Table 13. Normalised weights of benefit dimensions

Benefit Dimension	Weight
Safety utility	0.408
Operational utility	0.269
Economic utility	0.157
Strategic utility	0.101
Social–environmental utility	0.064

Source: designed by author

The weights show that safety is considered the most important benefit dimension, followed by operational efficiency and economic gains. Strategic and social–environmental benefits, while relevant, are evaluated as less influential in AI-related decision-making.

3.4.3. Consistency Analysis

To ensure the reliability of the aggregated judgements, the consistency of the pairwise matrix was tested. The weighted sum vector was calculated, followed by λ -values for each criterion. The average produced:

$$\lambda_{max} = 5.030$$

The Consistency Index was computed as:

$$CI = \frac{5.030 - 5}{4} = 0.0074$$

With the Random Index for $n = 5$ (RI = 1.12), the Consistency Ratio is:

$$CR = \frac{0.0074}{1.12} = 0.0066$$

Consistency Ratio = 0.0066 (< 0.1) indicates that the aggregated expert judgements are highly consistent and reliable.

3.4.4. Interpretation of Results

The AHP results reveal a clear prioritisation pattern consistent with established aviation values. Safety utility received the highest weight (0.408), reflecting the industry's strong safety-centric culture and regulatory expectations. Operational utility (0.269) ranked second, indicating the significance of efficiency, reliability, and optimisation in day-to-day operations. Economic utility (0.157) was evaluated as moderately important, suggesting that financial considerations matter but do not outweigh operational or safety factors.

The remaining two dimensions—strategic utility (0.101) and social–environmental utility (0.064)—received lower weights. This indicates that long-term positioning, sustainability, and social value are acknowledged but are less dominant drivers compared to safety and operational performance. The results align with the literature review and validate the benefit structure incorporated into the proposed evaluation framework.

3.5. Implications for AI evaluation in aviation

These findings have direct implications for how the proposed framework could be applied in future organisational settings. They clarify which types of benefits aviation professionals prioritise most when evaluating AI initiatives and therefore confirm the logical foundation of the framework's benefit evaluation stage.

The high weight assigned to safety utility confirms that safety considerations remain the primary driver in aviation-related decisions, regardless of an organisation's size, domain, or operational context. This aligns with long-established industry norms and regulatory

expectations, and it reinforces the need for AI projects to demonstrate clear safety improvements or, at a minimum, no negative impact on established safety margins. For organisations considering AI adoption, the results suggest that safety-related arguments will be the most persuasive in securing stakeholder support and regulatory acceptance.

The strong emphasis on operational utility highlights the growing importance of efficiency, reliability, and process optimisation in modern aviation. AI initiatives that streamline workflows, reduce maintenance burden, enhance predictability, or improve resource utilisation are therefore likely to be viewed favourably. This is particularly relevant in environments experiencing labour shortages, increasing traffic complexity, or high pressure to reduce turnaround times. Operational gains may also indirectly support safety, which further increases their perceived value.

The moderate weight assigned to economic utility indicates that financial considerations matter, but they are not the dominant factor. This contrasts with many other industries where cost savings may outweigh qualitative benefits. In aviation, financial arguments appear to play a complementary rather than decisive role. This implies that organisations applying the framework should treat economic benefits as one important component of a larger evaluation rather than the sole justification for AI investments.

The lower importance placed on strategic and social–environmental utility suggests that while these benefits are recognised, they are less immediate or less tangible in the eyes of practitioners. Strategic benefits such as innovation, competitive positioning, or digital transformation may require longer time horizons to materialise and therefore receive less weight in short-term operational decision-making. Social and environmental considerations—such as emissions reduction or stakeholder impact—are increasingly emphasised in policy discussions, but their perceived direct value to day-to-day operations remains limited. Nevertheless, their presence in the weighting structure ensures they are not overlooked, especially as sustainability expectations continue to rise.

Taken together, these findings confirm that the framework’s five-dimensional benefit structure reflects real expert priorities and can guide organisations toward more informed and balanced evaluations of AI applications. The framework helps decision-makers focus on the areas that matter most—safety and operational improvements—while still accounting for economic, strategic, and social–environmental factors. By integrating these weighted priorities into the evaluation process, aviation organisations can more effectively compare AI initiatives, allocate resources, and justify adoption decisions both internally and to external stakeholders.

3.6. Summary of empirical findings

The empirical analysis in this chapter confirmed that the proposed framework is conceptually sound, clearly structured, and aligned with the practical expectations of aviation professionals. The expert survey demonstrated strong agreement regarding the clarity, completeness, and logical sequencing of the framework's stages, with no major modifications required. Descriptive statistics from the Likert-scale items showed consistent evaluations across experts, while qualitative comments provided additional insights that helped interpret these results and highlighted minor areas where practical guidance could enhance usability. The subsequent AHP analysis—used exclusively to validate the weighting logic of the five benefit dimensions—produced consistent and reliable priority weights, indicating that safety and operational considerations are perceived as most influential in AI-related decision-making. Together, these findings validate the internal logic and practical relevance of the framework, confirming its suitability for future application in aviation organisations without constituting a full evaluation of specific AI applications within this study.

3.7. Practical application of the AI benefit evaluation framework

The empirical results confirmed that the proposed evaluation framework is clear, logically structured, and aligned with the decision-making logic used in aviation organisations. Building on these findings, this subchapter provides practical guidance on how the framework shown in Figure 8 can be applied in operational environments such as CAMO, MRO, flight operations, airport management, and safety or quality departments.

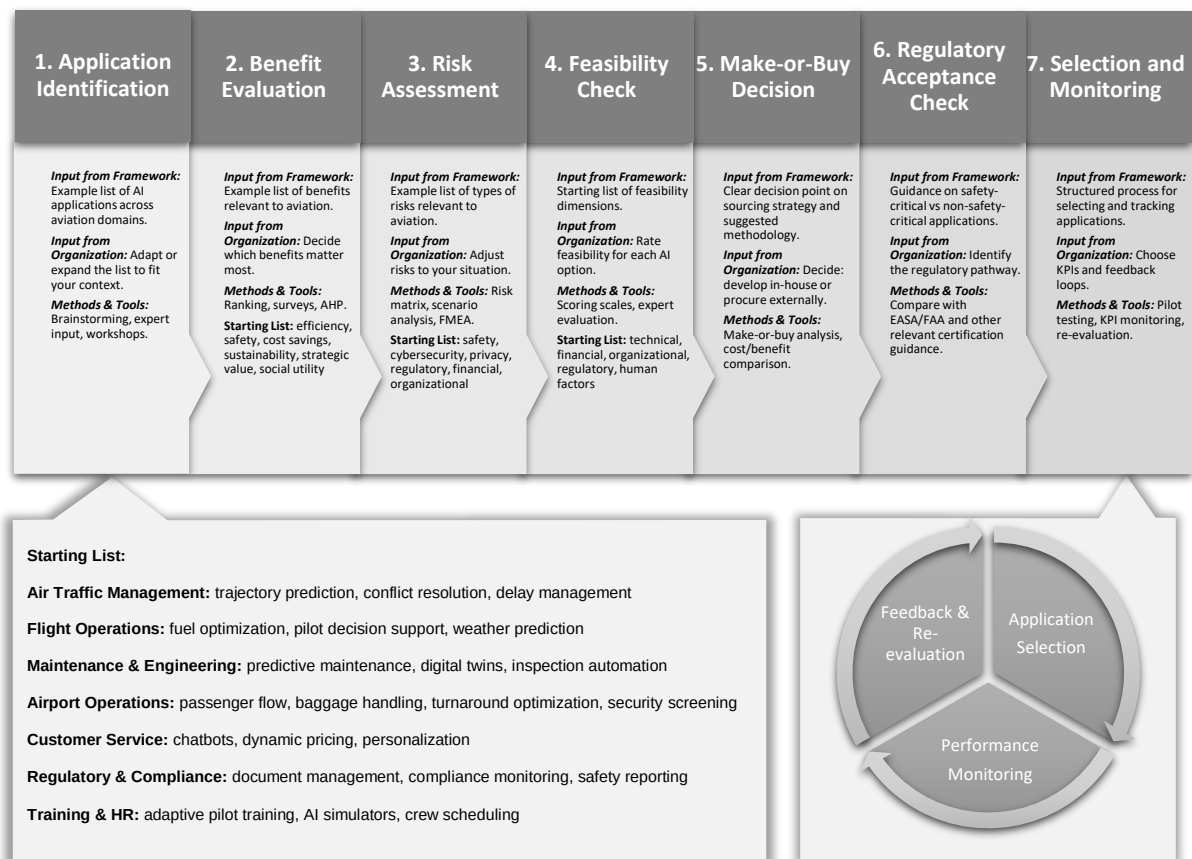


Fig. 8. Practical workflow for applying the AI evaluation framework in aviation

Source: designed by author

The purpose of this section is to demonstrate how aviation organisations can use the framework to prioritise AI initiatives, evaluate feasibility, ensure regulatory compliance, and ultimately increase the efficiency and effectiveness of business operations. The instructions below outline a step-by-step process that can be integrated into existing decision-making, project management, or digital transformation workflows.

3.7.1. Preparation and organisational scoping

The first step involves defining the operational domain, stakeholders, and problem context. Organisations should identify where AI adoption is being considered (e.g., predictive maintenance in MRO, documentation automation in CAMO, passenger flow optimisation at airports) and determine which stakeholders will be involved—typically operational managers, safety personnel, regulatory compliance teams, IT/data departments, and, when needed, external partners. During this step, organisations should also assess their current digital maturity, available data sources, and strategic priorities. Establishing this context ensures that the evaluation process is aligned with actual operational needs, resource constraints, and regulatory obligations.

3.7.2. Benefit assessment procedure

Once the scope is defined, the organisation evaluates the potential benefits of candidate AI applications using the five utility dimensions validated in this study—safety, operational, economic, strategic, and social–environmental utility. The organisation may adopt the weighting values obtained from the AHP analysis in this thesis or derive its own weights through an internal expert workshop. For each AI application under consideration, evaluation teams should rate expected impacts using quantitative indicators (e.g., reduction in delays, predicted maintenance cost savings, anomaly detection accuracy) or qualitative judgements where quantitative data are unavailable. This stage produces a structured comparison of applications based on what aviation professionals consider most important: safety enhancement, operational efficiency, and measurable improvements in reliability and performance.

3.7.3. Risk assessment

Following benefit evaluation, organisations assess risks using a structured matrix such as the one presented in Figure 6. Each AI application should be evaluated for risks related to cybersecurity, explainability, data integrity, operational disruption, staff acceptance, and potential unintended impacts on safety. Applications falling into the “high likelihood / high impact” category should be flagged for redesign, mitigation planning, or exclusion. This step helps organisations maintain a balanced perspective, ensuring that expected benefits are interpreted alongside potential threats. For aviation organisations operating under strict safety regimes, this step reinforces alignment with risk-based oversight principles used by EASA and national authorities.

3.7.4. Feasibility evaluation

The feasibility assessment determines whether the organisation has the practical capability to implement the AI solution. Using the criteria presented in Table 3—technical, organisational, economic, time-related, and scalability feasibility—the organisation evaluates internal readiness. This can be conducted through workshops, scoring exercises, or interviews with domain experts. Common elements assessed at this stage include data quality, IT infrastructure maturity, staff skills, availability of financial resources, and compatibility with existing workflows. If the feasibility score for an application is low, the organisation may choose to delay implementation, initiate a pilot study, or invest in capability-building before

proceeding further. Only applications that meet minimum feasibility thresholds should move to the next stage.

3.7.5. Make-or-buy decision

Once benefits, risks, and feasibility have been assessed, organisations must decide whether to develop the AI solution internally or procure it from external vendors. This decision is guided by factors such as strategic importance, data sensitivity, required customisation, dependence on external providers, and long-term lifecycle costs. In-house development may be more appropriate for predictive maintenance models requiring access to sensitive operational data, while outsourcing may be suitable for standardised tools such as chatbots, document summarisation services, or passenger-facing applications. The criteria identified in the literature—particularly from AI make-or-buy studies—may be adapted into internal checklists to support consistent decision-making across projects.

3.7.6. Regulatory acceptance check

Before committing to implementation, organisations must ensure that the AI solution aligns with regulatory expectations, particularly those outlined in EASA’s AI Roadmap 2.0. This includes verifying that the system provides sufficient transparency, supports human oversight, and can be validated according to aviation safety standards. Applications operating in non-safety-critical areas (e.g., administrative or customer service functions) typically require minimal regulatory involvement, while solutions affecting flight safety, airworthiness, or operational decision-making require detailed review and documentation. By integrating a regulatory check into the evaluation process, organisations reduce the risk of investing in solutions that cannot be certified or used operationally.

3.7.7. Selection, implementation, and monitoring

After satisfying all previous criteria, organisations select the AI application(s) to proceed with. This step involves defining pilot projects, implementation timelines, and key performance indicators. Examples of KPIs include model accuracy, reduction in delays, time saved in documentation processes, or improvements in predictive maintenance reliability. Continuous monitoring, as illustrated in Figure 7, ensures that the solution remains effective over time and adapts to changes in data, regulations, or operational environments. Monitoring should include performance validation, feedback from operational staff, periodic risk reassessment, and alignment checks with safety and regulatory requirements. This cyclical process enables continuous improvement and long-term sustainability of AI adoption.

3.7.8. Example of framework application in CAMO operations

To demonstrate practical use, consider a Continuing Airworthiness Management Organisation evaluating the adoption of an AI-based document processing system for aircraft maintenance records. The organisation would begin by identifying stakeholders: airworthiness engineers, quality auditors, IT specialists and clarifying objectives such as reducing manual workload and improving compliance accuracy. Benefits would be assessed by estimating reductions in processing time, improvements in error detection, and potential safety enhancements due to more consistent documentation. Risks would focus on data integrity, cybersecurity, and potential misinterpretation of records by the AI model. Feasibility would examine data availability, integration with existing record systems, and staff readiness. A make-or-buy evaluation would determine whether internal development is necessary due to sensitive data, or whether a commercial solution can be adapted. Regulatory checks would assess whether automated documentation tools are acceptable under continuing airworthiness rules. Finally, performance metrics such as accuracy rates, time savings, and audit findings would be monitored continuously.

This example illustrates how the framework guides structured, transparent decision-making across all stages of AI adoption in a safety-critical aviation environment.

CONCLUSIONS

1. The literature review provided a comprehensive overview of artificial intelligence technologies, their applications, and the benefits and challenges of AI adoption in aviation. It showed that AI can enhance safety, operational efficiency, maintenance performance, and sustainability, but its scalability is limited by issues such as data fragmentation, regulatory uncertainty, and uneven organisational readiness. The analysis also revealed a lack of structured, multi-dimensional evaluation tools tailored specifically to aviation, confirming the need for a systematic decision-support framework capable of guiding organisations in prioritising AI initiatives.
2. To address these gaps, the thesis developed a multi-stage AI benefit evaluation framework integrating five utility dimensions, risk assessment, feasibility analysis, make-or-buy decisions, regulatory checks, and monitoring. The framework aligns with aviation safety logic, EASA oversight principles, and operational realities in CAMO, MRO, flight operations, airports, and regulatory environments. Its sequential structure enables transparent comparison of AI applications and supports resource prioritisation, while remaining flexible enough for practical adoption across different organisational contexts.
3. A mixed empirical methodology was designed to validate the framework's clarity and internal logic. A structured expert survey evaluated the completeness and applicability of each framework stage, and the AHP was used exclusively to establish the relative importance of the benefit dimensions. This approach follows established practices in decision-science research and ensured that both qualitative professional judgement and quantitative weighting informed the validation. The aim was to verify the framework itself rather than assess specific AI applications, ensuring that the model is conceptually sound before practical use.
4. Empirical findings confirmed that the developed framework is coherent, practically relevant, and aligned with aviation industry expectations. Experts expressed strong agreement regarding the clarity, completeness, and applicability of each evaluation stage, while the AHP analysis produced consistent weighting results that reflect the sector's safety-centric priorities. Safety and operational utility emerged as the most influential dimensions, reinforcing the model's suitability as a decision-support tool in safety-critical environments. Based on these outcomes, organisations can apply the framework to systematically assess and prioritise AI initiatives, compare alternative technological options, evaluate implementation risks and feasibility, and ensure compliance with aviation regulatory requirements. By integrating the model into digital transformation programmes

or technology evaluation workflows in CAMO, MRO, flight operations, and airport management, companies may improve the consistency, transparency, and efficiency of AI-related decision-making. Nevertheless, the study is limited by the size and composition of the expert sample and by the fact that the framework was validated conceptually rather than tested through real-world AI implementation cases. Future research could therefore examine the performance of the framework in practical organisational settings, expand the expert base to include additional stakeholder groups, incorporate quantitative operational data, or explore the interaction between the framework and emerging regulatory or certification requirements as AI technologies evolve.

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REFERENCES

- Acharya, K., Sharifi, I., Lad, M., Sun, L., & Song, H. (2025). *Integrating Neurosymbolic AI in Advanced Air Mobility: A Comprehensive Survey*. <https://arxiv.org/pdf/2508.07163>
- Ahmed, W. (2025). Artificial Intelligence in Aviation: A Review of Machine Learning and Deep Learning Applications for Enhanced Safety and Security. *Premier Journal of Artificial Intelligence*. <https://doi.org/10.70389/PJAI.100013>
- Ahmed, W., Anwar Bhatti, N., Masood, A., A. K. Alharbi, A., & Alotaibi, S. (2024). *Advancements in ADS-B Security: A Comprehensive Survey of Vulnerabilities, Mitigation Strategies, System Requirements, and Emerging Research Trends*. <https://doi.org/10.20944/PREPRINTS202405.0586.V1>
- Airbus. (2025). *Airbus Annual Report 2024*.
- Ardil, C. (2021). *Airline Quality Rating Using PARIS and TOPSIS in Multiple Criteria Decision Making Analysis*. <https://orcid.org/0000-0003-2457-7261>
- Arfi, W. Ben, Nasr, I. Ben, Kondrateva, G., & Hikkerova, L. (2021). The role of trust in intention to use the IoT in eHealth: Application of the modified UTAUT in a consumer context. *Technological Forecasting and Social Change*, 167, 120688. <https://doi.org/10.1016/J.TECHFORE.2021.120688>
- Aslan, M. E., & Tolga, A. C. (2022). Evaluation of Artificial Intelligence Applications in Aviation Maintenance, Repair and Overhaul Industry via MCDM Methods. *Lecture Notes in Networks and Systems*, 504 LNNS, 822–830. https://doi.org/10.1007/978-3-031-09173-5_94
- Barney, J. (1991). Firm Resources and Sustained Competitive Advantage. *Journal of Management*, 17(1), 99–120. <https://doi.org/10.1177/014920639101700108>
- Bougie, Roger., & Sekaran, Uma. (2020). *Research methods for business : a skill-building approach*. John Wiley & Sons, Inc.
- Bughin, J., Brussels, |, Seong, J., Shanghai, |, Manyika, J., Francisco, S., Chui, M., Joshi, R., & Stockholm, |. (2018). *NOTES FROM THE AI FRONTIER MODELING THE IMPACT OF AI ON THE WORLD ECONOMY*. www.mckinsey.com/mgi.

- Coase, R. H. (1995). The Nature of the Firm. In *Essential Readings in Economics* (pp. 37–54). Macmillan Education UK. https://doi.org/10.1007/978-1-349-24002-9_3
- Cruciol, L. L. B. V., Weigang, L., De Barros, A. G., & Koendjibiharie, M. W. (2015). Air holding problem solving with reinforcement learning to reduce airspace congestion. *Volume 49, Issue 5, Pages 616 - 633, 49(5), 616–633*. <https://doi.org/10.1002/atr.1293>
- Dan Hendrycks, & Taylor & Francis. (2024). *Introduction to AI Safety, Ethics and Society*.
- Davenport, T. H. ., & Mittal, Nitin. (2023). *All in on AI : how smart companies win big with artificial intelligence*. Harvard Business Review Press.
- Davenport, T. H., Iansiti, Marco., Neeley, Tsedal., & Agrawal, Ajay. (2023). *HBR's 10 Must Reads on AI (with bonus article "How to Win with Machine Learning" by Ajay Agrawal, Joshua Gans, and Avi Goldfarb)* . Harvard Business Review Press.
- de Camargo Fiorini, P., Roman Pais Seles, B. M., Chiappetta Jabbour, C. J., Barberio Mariano, E., & de Sousa Jabbour, A. B. L. (2018). Management theory and big data literature: From a review to a research agenda. *International Journal of Information Management, 43*, 112–129. <https://doi.org/10.1016/j.ijinfomgt.2018.07.005>
- Degas, A., Islam, M. R., Hurter, C., Barua, S., Rahman, H., Poudel, M., Ruscio, D., Ahmed, M. U., Begum, S., Rahman, M. A., Bonelli, S., Cartocci, G., Di Flumeri, G., Borghini, G., Babiloni, F., & Aricó, P. (2022). A Survey on Artificial Intelligence (AI) and eXplainable AI in Air Traffic Management: Current Trends and Development with Future Research Trajectory. *Applied Sciences 2022, Vol. 12, Page 1295, 12(3), 1295*. <https://doi.org/10.3390/APP12031295>
- Deloitte. (2025). *Generative artificial intelligence (AI) initiatives return on investment rate worldwide in 2024*.
- DeVellis, R. F. . (2017). *Scale development : theory and applications*. SAGE.
- Dieter, M., Sprenger, E., Pasnicu, O., Staudt, J., & Ellenrieder, N. (2024). Virtual flight deck crew assistance utilizing artificial intelligence methods to interpret NOTAMs: a user acceptance study. *Volume 15, Issue 4, Pages 1137 - 1144*. <https://doi.org/10.1007/s13272-024-00767-1>
- Dožić, S. (2019). Multi-criteria decision making methods: Application in the aviation industry.

- EASA. (2023). *ARTIFICIAL INTELLIGENCE ROADMAP 2.0 Human-centric approach to AI in aviation Human-centric approach to AI in aviation*.
- Ekici, S., Balli, O., Dalkiran, A., & Stiebe, M. (2023). Stakeholder Perceptions on Sustainability Challenges and Innovations in General Aviation. *Sustainability* 2023, Vol. 15, Page 16505, 15(23), 16505. <https://doi.org/10.3390/SU152316505>
- Eurostat. (2024). *Use of artificial intelligence in enterprises Statistics Explained Enterprises using artificial intelligence technologies*. <https://ec.europa.eu/eurostat/statisticsexplained/>
- FAA. (2024). *Roadmap for Artificial Intelligence Safety Assurance*.
- Field, Andy. (2009). *Discovering statistics using SPSS : (and sex and drugs and rock “n” roll)*. SAGE Publications.
- Fink, A. & B. (2016). *How to Conduct Surveys: A Step-by-Step Guide*. Sixth Edition. SAGE Publications Ltd (CA), December 2015, 244349.
- Gerbert Philipp, Duranton Sylvain, Steinhäuser Sebastian, & Ruwolt Patrick. (2018, January 4). *The Build-or-Buy Dilemma in Artificial Intelligence | BCG*. <https://www.bcg.com/publications/2018/build-buy-dilemma-artificial-intelligence>
- Gräf, M., Mehler, M., & Ellenrieder, S. (2024). *Association for Information Systems Association for Information Systems AI Strategy in Action: A Case Study on Make-or-Buy for AI-based AI Strategy in Action: A Case Study on Make-or-Buy for AI-based Services Services*. https://aisel.aisnet.org/pacis2024/track01_aibussoc/track01_aibussoc/8
- Habiba, U. E., Habib, M. K., Bogner, J., Fritzsche, J., & Wagner, S. (2025). How do ML practitioners perceive explainability? an interview study of practices and challenges. *Empirical Software Engineering*, 30(1). <https://doi.org/10.1007/S10664-024-10565-2>
- IATA. (2023). *Generative AI and Aviation Finding crossroads for future implementation 2 Generative AI and Aviation*.
- IATA. (2025). *Exploring Artificial Intelligence and Digital Identity Use Cases in Aviation*.
- Ishizaka, Alessio., & Nemery, Philippe. (2013). *Multi-criteria decision analysis : methods and*

software. Wiley.

- Ivan, B., Olga, B., Oksana, H., Roman, P., Marta, S., & Khrystyna, K. (2024). Application of Grey Relational Analysis for Utilizing Artificial Intelligence Methods in Aviation Management. In *Volume 515, Pages 113 - 123* (Vol. 515, pp. 113–123). Springer Science and Business Media Deutschland GmbH. https://doi.org/10.1007/978-3-031-48479-7_11
- Kabashkin, I., Fedorov, R., & Perekrestov, V. (2025). Decision-Making Framework for Aviation Safety in Predictive Maintenance Strategies. *Applied Sciences* 2025, Vol. 15, Page 1626, 15(3), 1626. <https://doi.org/10.3390/APP15031626>
- Keeney, R. L., & Raiffa, H. (1979). Decisions with Multiple Objectives: Preferences and Value Trade-Offs. *IEEE Transactions on Systems, Man and Cybernetics*, 9(7), 403. <https://doi.org/10.1109/TSMC.1979.4310245>
- Kirwan, B. (2024). The Impact of Artificial Intelligence on Future Aviation Safety Culture. *Future Transportation*, 4(2), 349–379. <https://doi.org/10.3390/FUTURETRANSP4020018>
- Koul, P. (2025). A review of machine learning applications in aviation engineering. *Advances in Mechanical and Materials Engineering*, 42, 16–40. <https://doi.org/10.7862/rm.2025.2>
- Kulakli, A., & Şahin, Y. (2023). A Combined Multi-Criteria Decision Making Approach for Improvement of Airlines' Ground Operations Performance: A Case Study from Türkiye. *Systems*, 11(8). <https://doi.org/10.3390/SYSTEMS11080421>
- Kuru, K., Pinder, J. M., Watkinson, B. J., Ansell, D., Vinning, K., Moore, L., Gilbert, C., Sujit, A., & Jones, D. (2023). Toward Mid-Air Collision-Free Trajectory for Autonomous and Pilot-Controlled Unmanned Aerial Vehicles. *Volume 11, Pages 100323 - 100342*, 11, 100323–100342. <https://doi.org/10.1109/ACCESS.2023.3314504>
- Lavrakas, P. J. . (2008). *Encyclopedia of survey research methods*. SAGE Publications.
- Le Clainche, S., Ferrer, E., Gibson, S., Cross, E., Parente, A., & Vinuesa, R. (2023). Improving aircraft performance using machine learning: A review. *Aerospace Science and Technology*, 138, 108354. <https://doi.org/10.1016/J.AST.2023.108354>
- Lee, H. K., Puranik, T. G., & Mavris, D. N. (2021). Deep Spatio-Temporal Neural Networks for Risk Prediction and Decision Support in Aviation Operations. *Volume 21, Issue 4*.

<https://doi.org/10.1115/1.4049992>

- Lingrui, L., & Xin, W. (2024). Towards smart aviation with sustainable development: artificial intelligence insights into the airline and advanced air mobility industries. *Decision Support Systems for Sustainable Computing*, 187–204. <https://doi.org/10.1016/B978-0-443-23597-9.00009-3>
- Moghadasnian, S. (2025a). *AI-Powered Predictive Maintenance in Aviation Operations*. <https://www.researchgate.net/publication/389711075>
- Moghadasnian, S. (2025b). *Strategic Leadership in AI-Enhanced Aviation: Balancing Financial and Environmental Goals Through Differentiated Search*. <https://www.researchgate.net/publication/390286358>
- Nanyonga, A., Joiner, K., Turhan, U., & Wild, G. (2025). *Applications of natural language processing in aviation safety: A review and qualitative analysis*. <https://arxiv.org/pdf/2501.06210>
- Paces, P., & Insaurralde, C. C. (2021). Artificially Intelligent Assistance for Pilot Performance Assessment. *AIAA/IEEE Digital Avionics Systems Conference - Proceedings, 2021-October*. <https://doi.org/10.1109/DASC52595.2021.9594487>
- Razzaghi, P., Tabrizian, A., Guo, W., Chen, S., Taye, A., Thompson, E., Bregeon, A., Baheri, A., & Wei, P. (2024). *A Survey on Reinforcement Learning in Aviation Applications*. <https://doi.org/10.1016/j.engappai.2024.108911>
- Rolls-Royce. (2021). *The Aletheia Framework*.
- Ruangpan, L., Vojinovic, Z., Plavšić, J., Doong, D. J., Bahlmann, T., Alves, A., Tseng, L. H., Randelović, A., Todorović, A., Kocic, Z., Beljinac, V., Wu, M. H., Lo, W. C., Perez-Lapeña, B., & Franca, M. J. (2021). Incorporating stakeholders' preferences into a multi-criteria framework for planning large-scale Nature-Based Solutions. *Ambio*, 50(8), 1514–1531. <https://doi.org/10.1007/S13280-020-01419-4/FIGURES/6>
- Saaty, T. L. ., & Vargas, L. G. . (2012). *Models, methods, concepts & applications of the analytic hierarchy process*. Springer.
- Saaty, T., & Vargas, L. (2012). Models, methods, concepts & applications of the analytic hierarchy process. ... *-Driven Demand and Operations Management Models*, 1–20.

<https://doi.org/10.1007/978-1-4614-3597-6>

- Schurr, N., Good, R., Alexander, A., Picciano, P., Ganberg, G., Therrien, M., Beard, B. L., & Holbrook, J. (2010). A testbed for investigating task allocation strategies between air traffic controllers and automated agents. *Volume 3, Pages 1839 - 1845, 3*. <https://doi.org/10.1609/aaai.v24i2.18822>
- Shan, J., Miccinesi, L., Beni, A., Pagnini, L., Cioncolini, A., & Pieraccini, M. (2025). A Review of Foreign Object Debris Detection on Airport Runways: Sensors and Algorithms. *Remote Sensing 2025, Vol. 17, Page 225, 17(2), 225*. <https://doi.org/10.3390/RS17020225>
- SITA. (2024). *SITA 2024-air-transport-it-insights*.
- Stefani, T., Christensen, J. M., Giriya, A. A., Gupta, S., Durak, U., Köster, F., Krüger, T., & Hallerbach, S. (2024). Automated scenario generation from Operational Design Domain model for testing AI-based systems in aviation. 2024 . <https://doi.org/10.1007/s13272-024-00772-4>
- Tafur, C. L., Camero, R. G., Rodríguez, D. A., Rincón, J. C. D., & Saenz, E. R. (2025). Applications of artificial intelligence in air operations: A systematic review. In *Results in Engineering* (Vol. 25). Elsevier B.V. <https://doi.org/10.1016/j.rineng.2024.103742>
- Vaidya, O. S., & Kumar, S. (2006). Analytic hierarchy process: An overview of applications. *European Journal of Operational Research, 169(1), 1–29*. <https://doi.org/10.1016/J.EJOR.2004.04.028>
- Vignesh, U., & Parab, Y. (2024). AI solutions for delay reduction in the civil aviation industry: A comprehensive review. In *Pages 41 - 59 (pp. 41–59)*. IGI Global. <https://doi.org/10.4018/979-8-3693-1954-3.ch003>
- Wang, Z., Li, H., Wang, J., & Shen, F. (2019). Deep reinforcement learning based conflict detection and resolution in air traffic control. *IET Intelligent Transport Systems, 13(6), 1041–1047*. <https://doi.org/10.1049/IET-ITS.2018.5357>
- Whig, P., Kasula, B. Y., Yathiraju, N., Jain, A., & Sharma, S. (2024). Transforming aviation: The role of artificial intelligence in air traffic management. In *Pages 60 - 75 (pp. 60–75)*. IGI Global. <https://doi.org/10.4018/979-8-3693-1954-3.ch004>
- Zhou, D., Zhuang, X., Zuo, H., Wang, H., & Yan, H. (2020). Deep Learning-Based Approach

for Civil Aircraft Hazard Identification and Prediction. *IEEE Access*, 8, 103665–103683.
<https://doi.org/10.1109/ACCESS.2020.2997371>

Ziakkas, D., & Pechlivanis, K. (2023). Artificial intelligence applications in aviation accident classification: A preliminary exploratory study. *Decision Analytics Journal*, 9, 100358.
<https://doi.org/10.1016/J.DAJOUR.2023.100358>

Ziakkas, D., Plioutsias, A., & Pechlivanis, K. (2022). Artificial Intelligence in aviation decision making process. The transition from extended Minimum Crew Operations to Single Pilot Operations (SiPO). *Artificial Intelligence and Social Computing*, 28.
<https://doi.org/10.54941/AHFE1001452>

APPENDICES

Appendix 1. Certificate of attendance



CERTIFICATE

This is to certify that

Giedrius Paulauskas

participated in the 28th Conference for Young Researchers

**“SCIENCE – FUTURE OF LITHUANIA.
ECONOMICS AND MANAGEMENT“**

that took place on October 21, 2025, at Vilnius Gediminas Technical
University at the Faculty of Business Management

and delivered a presentation

EVALUATION OF THE BENEFITS OF USING ARTIFICIAL INTELLIGENCE
IN AVIATION

Vice-Dean for Research of the Faculty of Business Management

Assoc Prof Dr Paulius Šūmakaris