Artificial Intelligence Technologies for Aircraft Maintenance: A Systematic Literature Review

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Abstract

Effective aircraft maintenance is crucial in ensuring safety, reliability, and cost-effectiveness in the aviation industry. Recent research and industry developments in artificial intelligence (AI) raise the potential to transform various aspects of aircraft maintenance, including predictive maintenance, fault diagnosis, and aircraft health monitoring and management. This paper presents a systematic literature review of AI technologies such as Automated Reasoning and Deep Learning in aircraft maintenance, highlighting its challenges and prospects. An extensive literature search resulted in a final dataset of 696 publications, covering the 40-years period from 1984 till 2024 and describing AI applications in airworthiness management, aircraft health monitoring, and maintenance, repair, and overhaul operations. These publications were analyzed to identify key AI technologies and related aircraft maintenance processes, identifying trends, popular research venues, and underexplored areas. The review concludes with insights into AI adoption in aircraft maintenance and its potential implications for researchers, practitioners, educators, and other stakeholders.

1. Introduction

Strong and strict safety regulations, high operational costs, and the crucial importance of timely maintenance are the essential features of Aircraft Maintenance (AM) processes. Regular AM practices often rely on scheduled inspections, which are planned in operator-approved maintenance programs and maintenance planning documents and are frequently based on the reactive repair strategy. This strategy can lead to inefficiencies, downtime, and increased operational costs. However, with the emergence of artificial intelligence (AI) technologies, there is a potential shift towards predictive and proactive maintenance strategies, aimed at minimizing downtime, reducing maintenance operation costs, and enhancing safety. AM is experiencing a revolutionary transformation with the adoption of AI for predictive maintenance (PdM). PdM utilizes advanced technologies, such as data analytics, machine learning, and sensor-based monitoring, to predict potential equipment failures before they occur (Dibsdale, 2020). The vast amount of data generated by numerous sensors embedded in aircraft components has made predictive maintenance one of the most advanced strategies. Analysis of this data using modern AI techniques such as machine learning algorithms has significantly enhanced maintenance reliability and improved its cost efficiency (Mallioris et al., 2024). Although the predictive strategy and health management are widely considered beneficial, their efficiency highly relies on data analysis techniques. Thus, AI advances such as deep learning models and computer vision algorithms have a huge potential for aircraft maintenance (Ranasinghe et al., 2022).

Due to the high research attention to the application of AI in aircraft maintenance, the number of related publications has significantly grown. At the same time, a comprehensive understanding of AI applications across AM processes and challenges remains lacking. Existing reviews are often limited in scope, focusing on specific AI technologies, subdomains, or methodologies without providing a holistic view of the field. This creates a critical need for systematic literature reviews that consolidate knowledge, identify emerging trends, and highlight research gaps to guide future studies. This review addresses these needs by analyzing AI technologies applied in AM. By examining a large systematically selected representative set of publications, this study aims to answer the following research questions:

- **RQ1:** What are the emerging AI technologies currently being explored in AM research and practice?
- **RQ2:** How has the application of AI in AM evolved historically from industrial operations and technological progress prospectives, and what are the current trends?
- **RQ3:** In which specific AM processes have AI technologies been successfully applied?

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We provide a structured synthesis of AI applications in AM, offering insights into the historical evolution, current state, and future directions of AI technologies' adoption for ensuring aviation safety and reliability.

2. RESEARCH SCOPE AND RATIONALE

2.1. Aircraft Maintenance Scope

Aircraft maintenance is a complex and highly regulated technical activity that includes servicing, inspection, testing, repair, and overhaul or modification activities on every aircraft in service. AM processes are affected by the maintenance strategies that evolved from reactive to proactive and predictive. Table 1 represents the evolution of maintenance strategies from reactive to predictive maintenance (Kabashkin et al., 2025).

Strategy	Principle	Training and competence	Investment
Reactive	Waiting for failure, then repair	Required a lower level of competence and smaller training	No specific investment is required
Proactive	Looking for faults and removing them to improve performance	Required specific knowledge and a good understanding	An average level of investment is required
Predictive	Using sensor data and data analysis techniques to forecast the aircraft reliability	Required deep understanding and a higher level of competence	A high level of investment is required

Table 1. Comparison of the AM strategies

The strategy employed by operators significantly influences the number of failures and the maintenance cost (Fig. 1). The cost optimization challenge has driven the aviation industry's increasing interest in AI-powered predictive maintenance solutions. Applying AI-based algorithms to analyze sensor data, maintenance logs, and operational parameters, airlines can transition from traditional calendar-based maintenance schedules to condition-based and predictive maintenance strategies. This shift not only reduces maintenance costs but also improves aircraft availability, enhances safety outcomes, and supports regulatory compliance – factors that explain the exponential growth in AI research for aviation maintenance applications observed in recent years. Going deeper into the AM processes, the three main strategies mentioned above are based on different maintenance philosophies (IATA, 2022): Hard Time (HT), On-Condition (OC), and Condition Monitoring (CM). Table 2 summarizes these philosophies (Kinnison & Siddiqui, 2013).

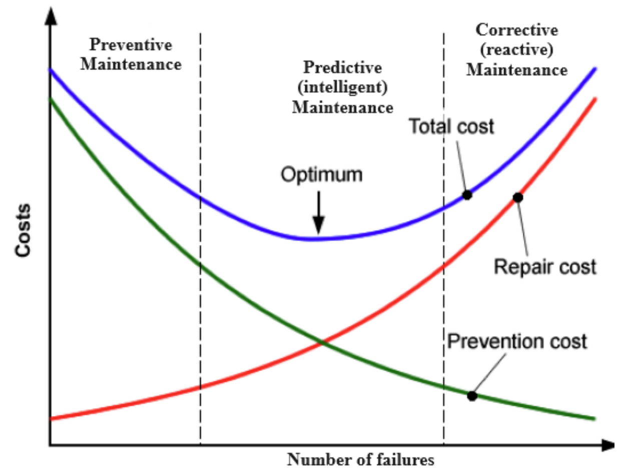

Fig. 1. Comparison of AM strategies (Tchakoua et al., 2014)

Philosophy	Description	Example components
Hard Time	A preventative process whereby the maintenance actions carried out at time-related periods limit the known deterioration of an item to an acceptable level. The prescribed action normally includes servicing, overhaul, and replacement.	Landing gear, emergency equipment
On-Condition	A preventative process, but the inspection actions are carried out at specified periods to determine whether it can continue in service. The fundamental purpose of the process is to remove an item before it fails in service.	Lubrication and oil samples, magnetic chip detector debris
Condition Monitoring	A proactive/predictive process where data collection and analysis allow the portrayal of information upon which judgments relating to the safe condition of the airplane can be made. It is a statistically controlled process.	Engine Health Monitoring (EHM) and Structural Health Monitoring (SHM)

Table 2. Comparison of AM philosophies

The following key players implement the maintenance strategies and philosophies:

- Continuing Airworthiness Management Organizations (CAWM): CAWM's main function is to maintain the airworthiness of the aircraft by monitoring the technical records, reliability reports, results of OC analysis, prognostic trend analysis, and control of remaining useful life (RUL).

- Maintenance Repair and Overhaul / Operations Organizations (MRO): MRO holds the ultimate responsibility for the diagnostic, detection, and analysis of the failures. In certain unusual cases, MRO can request assistance from CAWM to complete the assessment.
- Health Monitoring/Management: EHM and SHM are engine and structural condition control, using a variety of advanced sensor technology and flight data parameters control to reduce/avoid accidental failure of the aircraft and its systems.

The AM process classification used in this review is based on the involved players and related AM processes.

2.2. Artificial Intelligence Scope

Recently, the European Aviation Safety Agency (EASA) proposed a roadmap for addressing the challenges and opportunities of AI in aviation and highlighted the growing importance of AI for aircraft maintenance processes. The scope of AI technologies, covered by the EASA roadmap, is presented in Fig. 2 and includes logic- and knowledge-based (LKB) techniques, statistical approaches, and machine learning (ML) and deep learning (DL) algorithms.

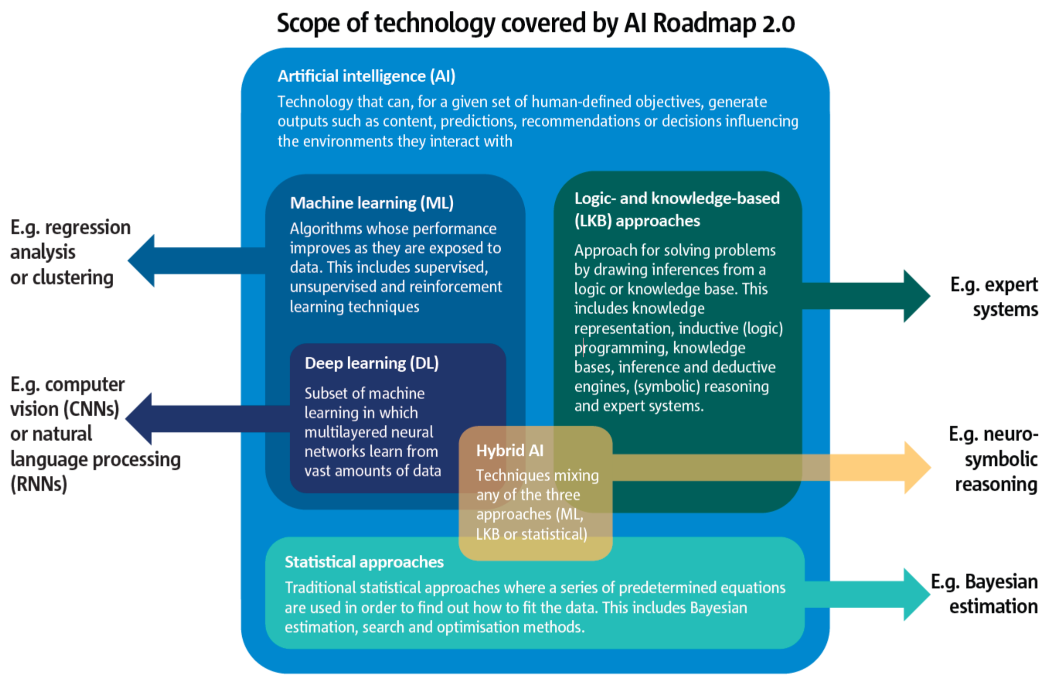

Fig. 2. Technologies enclosed by EASA AI Road map (EASA, 2023)

The presented EASA roadmap classifies the AI technologies following the proposal for the EU AI Act (European Commission, 2021), which differs from the final version of the EU AI Act entered into force in 2024 (European Commission, 2024). The EU AI Act only distinguishes ML/DL and LKB approaches, and this review will follow the latest Act's AI scope definition.

2.3. Research Rationale

For identifying the rationale of the systematic literature review (SLR) on AI in aircraft maintenance, the authors conducted a preliminary literature search for review papers, focused on artificial intelligence in aircraft engineering. The initial selection from Scopus, ScienceDirect, and IEEE Xplore was manually reviewed and filtered, resulting in a sample of 26 review papers. These papers were published from 2012 to 2024 (7 of them – in 2024), covering different aspects of AI in aircraft maintenance. The review papers were classified by:

- Subarea of aircraft maintenance – PdM, visual inspection, SHM, etc.
- Review domain – AM-focused or multi-domain.
- Review focus – methods, applications, etc.
- Type – systematic, SLR (e.g., conducted under PRISMA statement (Page et al., 2021)) or not.

The classification of existing literature reviews is presented in Table 3. Seven of the 25 existing reviews (e.g., (Kwakye et al., 2024; Rodríguez et al., 2024)) mention AI in the recent trends and provide a limited overview of related technologies. Another subset of the reviews provides information about AI technologies as a part of method descriptions in different subareas – predictive maintenance (Xu et al., 2023; Zuo et al., 2012), visual inspection (Böyük et al., 2021; Yasuda et al., 2022), spare parts logistics (Feng et al., 2021), resource planning (del Olmo & Domingo, 2022), and fault diagnosis (Liu et al., 2024). Four reviews are directly focused on specific AI branches – machine learning (Le Clainche et al., 2023; J. Li et al., 2023) and deep learning (Cha et al., 2024; Y.-F. Li et al., 2024). Also, it is worth noting that only 5 reviews can be classified as systematic.

Review paper	AM Subarea	Review domain	Review focus	SLR
AM subarea: PdM				
Zuo et al. (2012)	PdM	AM-focused	Methods	No
Khan et al. (2021)	PdM	AM-focused	Recent trends	No
Karaoğlu et al. (2022)	PdM	AM-focused	Methods	Yes
Bisanti et al. (2023)	PdM	AM-focused	Digital twins	Yes
Xu et al. (2023)	PdM	AM-focused	Methods	No
Zhong et al. (2023)	PdM	Multi-domain	Recent trends	No
Mallioris et al. (2024)	PdM	Multi-domain	Applications	Yes
AM subarea: Visual Inspection				
Böyük et al. (2021)	Visual inspection	AM-focused	Methods	No
Yasuda et al. (2022)	Visual inspection	AM-focused	Methods	Yes
Rodríguez et al. (2024)	Visual inspection	Multi-domain	Recent trends	No
AM subarea: Fault Diagnosis				
Li et al. (2023)	Fault diagnosis	AM-focused	Machine learning	No
Tang et al. (2023)	Fault diagnosis	AM-focused	Knowledge graphs	No
Liu et al. (2024)	Fault diagnosis	AM-focused	Methods	No
AM subarea: SHM				
Ranasinghe et al. (2022)	SHM	AM-focused	Recent trends	No
Khalid et al. (2023)	SHM	AM-focused	Recent trends	No
Kwakye et al. (2024)	SHM	AM-focused	Recent trends	No
Cha et al. (2024)	SHM	Multi-domain	Deep learning	No
Li et al. (2024)	SHM	Multi-domain	Deep learning, GPT	No
AM subarea: Other operations				
Agustian and Pratama (2024)	Wide-scope	AM-focused	Methods, data sources	Yes
Palmarini et al. (2018)	Operations	Multi-domain	Augmented reality	Yes
Ezhilarasu et al. (2019)	Health management	AM-focused	Reasoning	No
Feng et al. (2021)	Spare parts logistics	AM-focused	Methods	No
del Olmo and Domingo (2022)	Resource planning	AM-focused	Methods	No
Le Clainche et al. (2023)	Aircraft performance	AM-focused	Machine learning	No
Raoofi and Yasar (2023)	Airworthiness	AM-focused	Recent trends	No

Table 3. Review papers

Summarizing the analysis of the existing reviews, we conclude the absence of a systematic literature review that covers all aspects of AI applications in the area of aircraft technical maintenance and continuing airworthiness processes. Considering the persistent importance of aviation safety and reliability improvement and special attention to the preparation and certification of aviation maintenance engineers, a comprehensive understanding of the landscape of related AI technologies becomes critically important. The wide scope of the review will make it valuable for informing research. First, it is essential for educational purposes, particularly for researchers entering this interdisciplinary field. Aircraft maintenance encompasses multiple domains, each potentially benefiting from different AI approaches. Second, the wide scope enables trend prediction and identification of emerging patterns that would be invisible in narrowly focused reviews. A broad review provides researchers with the conceptual map that is necessary to understand how these domains interconnect and where AI applications have emerged, addressing a critical gap in aviation maintenance education and professional development. These conclusions provide a clear rationale for this wide-scope review.

The added value of this review is strengthened by its systematic approach to the hierarchical classification of existing studies according to AI technologies and AM operations, rather than merely enumerating them. This hierarchical classification provides readers with a comprehensive overview of the broader landscape of AI technologies and AM operations.

3. LITERATURE SELECTION

3.1. Methodology of Literature Review

Our SLR was conducted following the PRISMA 2020 Statement (Page et al., 2021) and consists of the stages, presented in Fig. 3. The literature search was performed in two digital databases: Scopus and IEEE Xplore. These databases contain a good index of publications in engineering science, and, although some papers can be missed, we believe that our search is representative of the overall trends and popularity of AI technologies.

The exclusion of gray literature – industry technical reports, white papers, government publications, and proprietary research from aviation manufacturers and maintenance organizations – may limit the completeness of our findings. Given that AI implementation in aviation maintenance often occurs through industry-led initiatives and practical applications documented in non-peer-reviewed sources, this exclusion potentially overlooks valuable insights from practitioners and industry experts. While this limitation aligns with the PRISMA methodology's emphasis on systematic and replicable search procedures, it should be acknowledged that the rapidly evolving nature of AI applications in aviation maintenance may be better reflected in gray literature sources that provide more immediate documentation of technological developments and real-world implementations. Future research could benefit from incorporating a complementary gray literature search to provide a more complete picture of AI adoption and effectiveness in aviation maintenance practices.

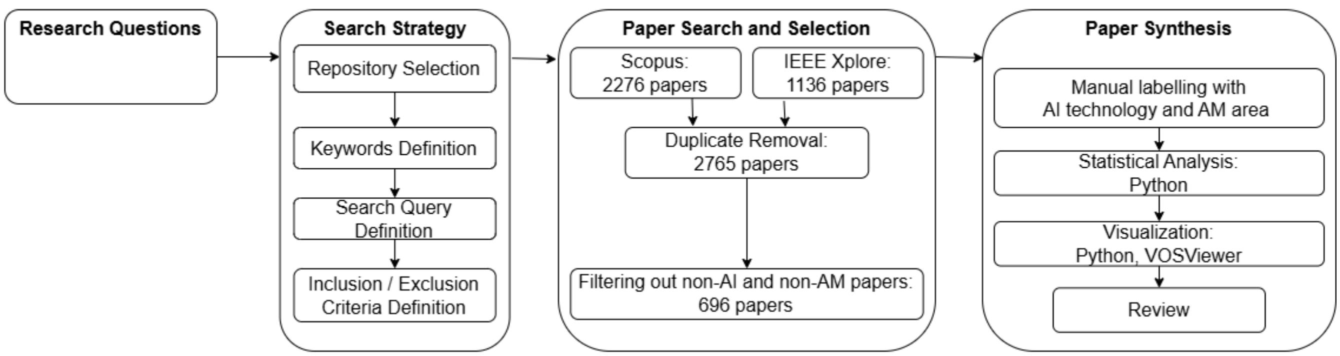

Fig. 3. Main stages of the literature review

The search keywords were defined to cover the research topic as broadly as possible:

- Aviation maintenance keywords: “maintenance” AND ("aircraft" OR "aviation"). The scope will cover papers on aviation-assisted maintenance (like maintenance of bridges, using data from drones), which will be filtered out manually.
- Artificial intelligence keywords: “artificial intelligence”, “computer vision”, “machine learning”, “deep learning”, “neural network”, “knowledge represent*”, “symbolic*”, “reinforcement learning”, “generative”, “statistic*”, “data mining”, “intelligent*”. The scope will cover most techniques, commonly associated with artificial intelligence. The inclusion of the “statistical” approaches leads to a large number of papers that utilize traditional statistical analysis and will be filtered out manually.

After preliminary searches, it was decided to add the exclusion keywords “solar” and “pavement” to automatically filter out papers on aviation-assisted maintenance of solar power plants and road pavement states. Additionally, the search was limited to papers in English and original studies (surveys, systematic literature reviews, and mappings were excluded). The resulting queries for Scopus and IEEE Xplore databases are presented in Table 4.

Database	Query	Papers
Scopus	TITLE-ABS-KEY (("aircraft" OR "aviation") AND "maintenance" AND ("artificial intelligence" OR "computer vision" OR "machine learning" OR "deep learning" OR "neural network" OR "knowledge represent*" OR "symbolic*" OR "reinforcement learning" OR "generative" OR "statistic*" OR "data mining" OR "intelligent*")) AND NOT "solar" AND NOT "pavement" AND (LIMIT-TO (LANGUAGE, "English")) AND (LIMIT-TO (DOCTYPE, "cp") OR LIMIT-TO (DOCTYPE, "ar") OR LIMIT-TO (DOCTYPE, "ch"))	2276
IEEE Xplore	("aircraft" OR "aviation") AND "maintenance" AND ("artificial intelligence" OR "computer vision" OR "machine learning" OR "deep learning" OR "neural network" OR "knowledge represent*" OR "symbolic*" OR "reinforcement learning" OR "generative" OR "statistic*" OR "data mining" OR "intelligent*") AND NOT "solar" NOT "pavement"	1136

Table 4. Queries on digital databases

The literature search was conducted on January 1, 2025, and included all publications until 2024 (several early publications of 2025 were excluded). Bibliographic information, including abstracts, of all papers was extracted from Scopus and IEEE Xplore, and duplicates were removed, resulting in 2765 papers. Additionally, one retracted paper was removed from the selection.

The initial queries are designed to minimize the probability of false negatives (automated exclusion of relevant papers), which increases the likelihood of false positives (automated inclusion of irrelevant papers). Thus, the abstract-based exclusion criteria play an important role. The exclusion criteria are summarized in Table 5.

#	Exclusion criteria description
Papers that are excluded as not directly related to the scope of aircraft maintenance, in particular, papers focused on:	
AM1	- maintenance of non-aircraft objects (e.g., wind turbines, power plants, constructions, etc.)
AM2	- maintenance of non-aircraft specific components (e.g., batteries)
AM3	- software development
AM4	- workforce optimization
AM5	- spare parts logistics
AM6	- maintenance process scheduling, routing, or other type of optimization
AM7	- aircraft design, testing, or improvement
AM8	- behavior analysis of aircraft maintenance engineers, including pose or movement recognition
AM9	- health of aircraft maintenance engineers
AM10	- regulation compliance
Papers that are excluded as not directly related to the scope of artificial intelligence, in particular, papers focused on:	
AI1	- application of methodologies, not associated with artificial intelligence (expert-based decision-making, classical and evolutionary optimization, etc.)
AI2	- exploratory statistical data analysis
AI3	- statistical inference (point and interval parameter estimation, hypothesis testing)
AI4	- statistical estimation of trends
AI5	- statistical models, not focused on prediction, decision-making, or reasoning

Table 5. Exclusion criteria

The exclusion process was independently conducted by two authors and all disparities were discussed and resolved. It was decided to keep papers on digital twins and augmented reality (AR) within the scope of the review, even if exact AI-based techniques are not mentioned in their abstracts. Frequently, digital twins and AR implementation require AI technologies under the hood. A comprehensive review of various aspects of digital twins in aircraft maintenance is presented by Bisanti et al. (2023).

Following the refined exclusion rules, the selection of 2765 papers was reduced to 696 papers, related to artificial intelligence in aviation maintenance.

3.2. Preliminary Results

The number of publications by year is presented in Fig. 4. The plot confirms the emerging interest in applying artificial intelligence in aircraft maintenance.

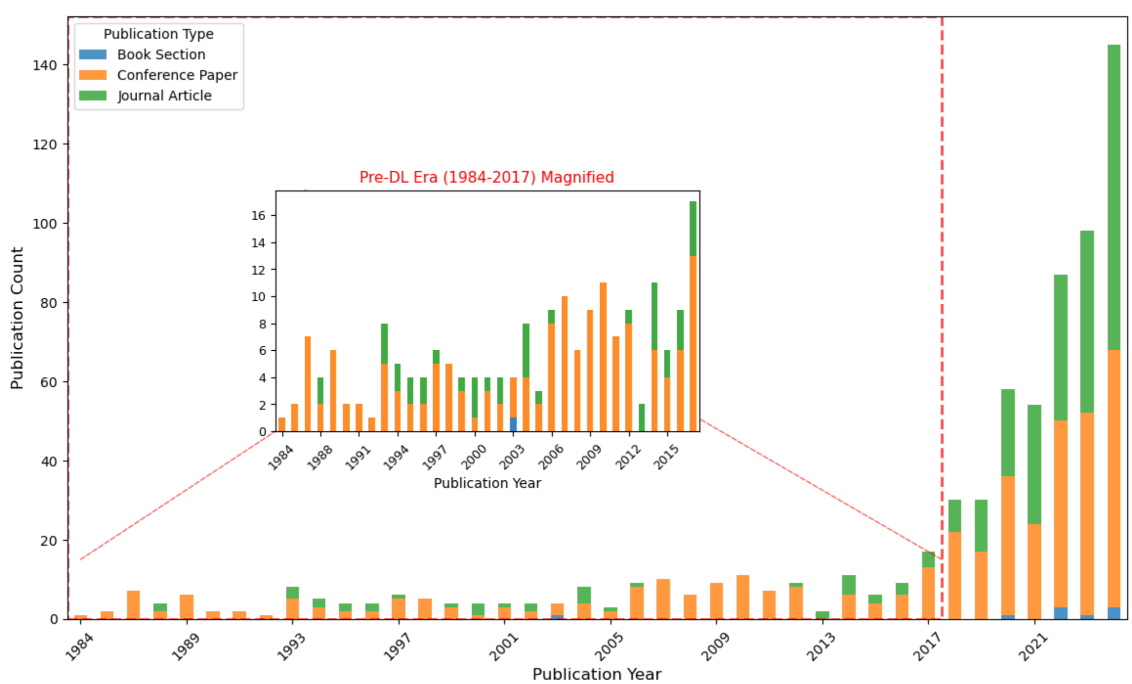

Fig. 4. Dynamics of related publications

From 1984 to 2014, the overall number of publications remained relatively low. However, a noticeable increase began in 2016 and accelerated after 2018, continuing to 2024. As demonstrated in subsequent sections, this acceleration corresponds to the raise of deep learning (DL) applications. The beginning of the DL era is commonly attributed to 2012, when several critical factors converged: algorithmic advances, enhanced computational power, and the maturation of big data technologies. However, the adoption of emerging technologies varies significantly across industries. Furthermore, scientific publications typically have temporal delays due to the conservative peer-review processes of top journals and conferences. Consequently, within the aviation maintenance domain, the substantial increase in publications employing intensive DL methodologies occurred in 2018. To accurately capture this shift in our subsequent analysis, we established a temporal division comprising two distinct periods: the Pre-DL Era (1984-2017) and the DL Era (2018-ongoing).

The overall growth is supplemented by the growing number of journal publications, which can be interpreted as a gradual shift from novel proposals, presented as conference papers, to more comprehensive and practically significant studies published in journals.

Additionally, a reduction in publications in 2021 is observed. This reduction can be associated with the negative effects of the COVID-19 pandemic on the aviation industry, but this hypothesis requires additional validation.

The most popular publication venues are presented in Table 6. Some inferences from popular journals and conferences are presented in the Discussion section.

Journals	Publications	Conferences	Conference papers
IEEE Access	14	SPIE International Society for Optical Engineering	18
Reliability Engineering and System Safety	13	AUTOTESTCON	11
Applied Sciences (Switzerland)	10	ASME Turbo Expo	10
Aerospace	9	IEEE Aerospace Conference	10
IEEE Transactions on Instrumentation and Measurement	6	AIAA SciTech Forum	10
Expert Systems with Applications	6	Annual Conference of Prognostics and Health Management Society	7
IEEE Sensors	6	Annual Reliability and Maintainability Symposium	6
Measurement Science and Technology	6	IEEE International Conference on Prognostics and Health Management	6
Mechanical Systems and Signal Processing	6	International Workshop on Structural Health Monitoring	6

Table 6. Popular publication venues

The overall distribution of citations of selected bibliographic sources is regular and follows Zipf's law (an exponential distribution with few frequent and many rare items (Fedorowicz, 1982)) for citation frequencies with an estimated exponent of 1.33 (1.59 for conference papers and 1.18 for journal articles) for cited papers. The overall share of cited papers is relatively small and equals 45%, which can be explained by many recent publications with a small number of citations. The three most cited publications are presented in Table 7.

Authors	Title	Year	Publication venue	Citations
Wu et al. (2018)	Remaining useful life estimation of engineered systems using vanilla LSTM neural networks	2018	Neurocomputing	648
Tamilselvan & Wang (2013)	Failure diagnosis using deep belief learning-based health state classification	2013	Reliability Engineering and System Safety	638
Yuan et al. (2016)	Fault diagnosis and remaining useful life estimation of aero engine using LSTM neural network	2016	IEEE/CSAA Conference on Aircraft Utility Systems	366

Table 7. Most cited papers

As anticipated, the first applications of AI algorithms received significant attention and were frequently cited (e.g., Yuan et al.(2016) and Wu et al. (2018) with their first application of LSTM in aircraft maintenance). Thus, the recent AI technologies that have not been applied in aircraft maintenance yet are presented in the Discussion section and can be mentioned as potential research directions.

The preliminary analysis of the paper database was conducted using title-and abstract-based clustering (k-means algorithm, VOSViewer). The resulting clusters are presented in Fig. 5.

Three main clusters can be associated with:

- fault identification and knowledge-based systems – red cluster (“fault”, ”knowledge”, “tool”, “expert system”)
- inspection and structural health monitoring – blue cluster (“structure”, “damage”, “inspection”, “detection”)
- predictive methodologies – green cluster (“RUL”, “prediction”, “dataset”, “feature”, ”prognostic”)

In terms of AI, knowledge-based technologies (expert systems, case-based reasoning) are concentrated in the red cluster (*fault*), machine-learning technologies (deep learning, neural networks) in the green cluster (*RUL*), and convolutional neural networks (CNN) are the only representatives of AI near the blue cluster (*Inspection*).

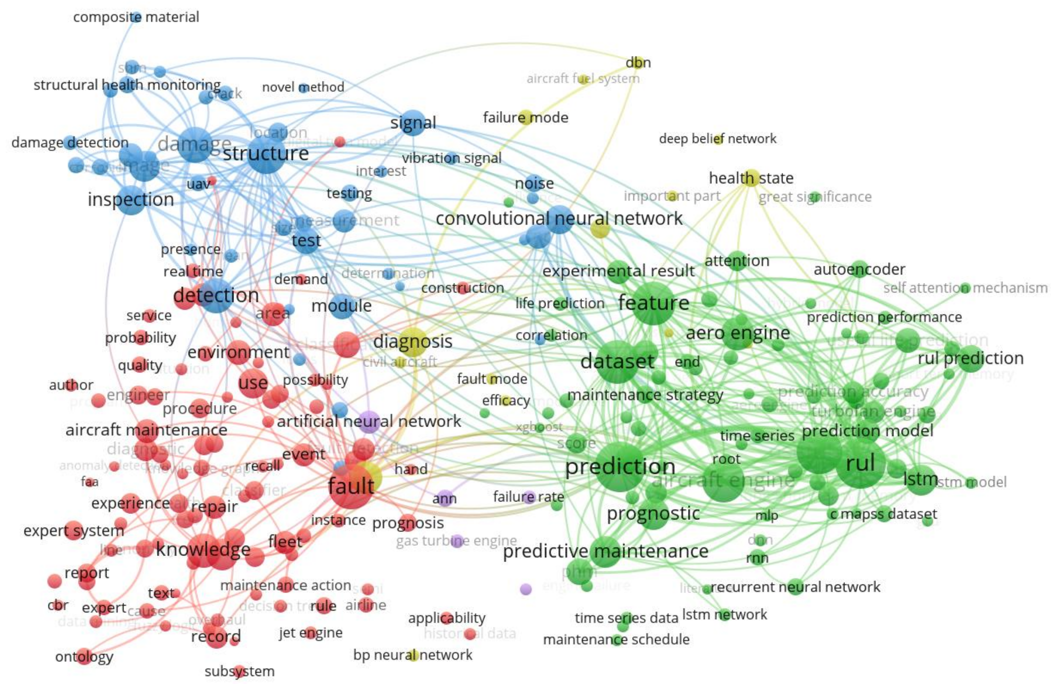

Fig. 5. Publication clusters

4. EMPIRICAL RESULTS

4.1. Classification of publications

The next step in the literature analysis involved manually labeling the papers. This labeling process was based on the titles and abstracts of the publications and was conducted along two dimensions:

- utilized AI technology.
- related AM processes.

Within every dimension, the bottom-up approach was applied – the paper was labeled by the most specific technology (e.g., You Only Look Once version 8 network), and further grouped into more general classes (e.g., CNN-based models). The classes in both dimensions are not mutually exclusive, so one paper could be associated with different classes if it utilizes several AI technologies or is related to several AM processes. A class was included in the final hierarchy if it contained at least three papers. The resulting hierarchies of AI technologies and AM processes are presented in Table 8 (number of papers in each class is provided in brackets). The hierarchies are visualized in Fig. 6 and Fig. 7.

Hierarchy of AI technologies	Hierarchy of AM processes
1. Logic/Knowledge (145)	4. Continuing Airworthiness Management, CAWM (300)
1.1. Knowledge-based (65)	4.1. Condition Monitoring (27)
1.1.1. Expert systems (28)	4.2. On Condition (10)
1.1.2. Semantic Models (3)	4.3. Residual useful life (158)
1.2. Reasoning (78)	4.4. Prognostic (80)
1.2.1. Case-based Reasoning (13)	4.4.1. Prognostic: Engine (46)
1.2.2. Bayesian Reasoning (25)	4.4.2. Prognostic: Airframe (16)
1.2.2.1. Bayesian Belief Network (3)	4.4.3. Prognostic: Aircraft Systems (15)
1.2.3. Fuzzy Logic (29)	4.5. Reliability (42)
1.2.4. Markov Models (8)	4.6. Maintenance Optimization (35)

Hierarchy of AI technologies	Hierarchy of AM processes
2. Machine Learning, ML (515)	5. Maintenance, Repair, and Overhaul (208)
2.1. Conventional ML (234)	5.1. Fault detection (72)
2.1.1. Feed-forward neural network, FFNN (131)	5.2. Fault Analysis (34)
2.1.2. Support vector machine, SVM (42)	5.2.1. Failure analysis: Engine (10)
2.1.3. Random Forest (13)	5.2.2. Failure Analysis: Airframe (3)
2.1.4. Decision Tree (16)	5.2.3. Failure Analysis: Aircraft Systems (8)
2.1.5. Self-organizing map, SOM (6)	5.3. Fault Diagnosis (118)
2.2. Deep Learning (297)	5.3.1. Failure Diagnosis: Engine (38)
2.2.1. Convolutional neural network (95)	5.3.2. Failure Diagnosis: Airframe (16)
2.2.1.1. You Only Look Once, YOLO (11)	5.3.3. Failure Diagnosis: Aircraft Systems (31)
2.2.2. Generative adversarial network, GAN (13)	5.4. Fault Isolation (7)
2.2.3. Recurrent neural network, RNN (112)	6.Health Monitoring / Management (257)
2.2.3.1. Long short-term memory neural network, LSTM (89)	6.1. Health Monitoring: Engine (57)
2.2.3.2. Gated recurrent unit, GRU (18)	6.2. Health Management Structure (73)
2.2.4. Deep belief network, DBN (9)	6.3. Predictive maintenance, PdM (133)
2.2.5. Autoencoder (25)	6.3.1. PdM: Engine (71)
2.2.6. Transformer (17)	6.3.2. PdM: Airframe (27)
2.2.7. Transfer learning (6)	6.3.3. PdM: Aircraft Systems (26)
2.2.8. Ensemble model (31)	7. Training (14)
2.2.8.1. Boosting (21)	
2.3. Reinforcement learning (10)	
3. Digital Representation Technologies (33)	
3.1. Augmented Reality (10)	
3.2. Digital Twin (23)	

Table 8. Hierarchy of publication classes

Note that the sum of papers across subcategories does not equal the total in higher-level categories due to two factors: (1) subcategories are not mutually exclusive, allowing papers to be classified under multiple subcategories, and (2) subcategories with fewer than three papers were excluded from the analysis. For instance, the *Logic/Knowledge* category contains 145 papers total. Within this category, the *Knowledge-based* subcategory includes 65 papers and the *Reasoning* subcategory includes 78 papers. The distribution is as follows: 62 papers are exclusively Knowledge-based, 75 are exclusively Reasoning, 3 papers belong to both subcategories, and 5 papers utilize specific approaches not covered by the included subcategories. Similarly, the *Machine Learning* category encompasses 515 papers, distributed among subcategories as follows: 234 papers are classified as *Conventional Machine Learning*, 297 as *Deep Learning*, and 10 as *Reinforcement Learning*. Twenty-nine papers employ both conventional and deep learning techniques and are therefore included in both relevant subcategories. The primary objective of Table 8 and Fig. 6-7 is to present the total number of papers within each subcategory. Thus, for clarity and simplicity, intersections between subcategories are not explicitly represented in these visualizations.

The first level of the hierarchy of AI technologies includes Machine learning (ML), Logic- and Knowledge-based (LKB) algorithms, and Digital Representation Technologies. ML and LKB correspond to the classes of AI technologies, defined in the EU AI Act. Digital Representation Technologies aggregate papers on Digital twins and Augmented/Virtual reality, frequently requiring AI technologies such as computer vision, generative AI, and optimization algorithms. The ML class of publications is divided to Conventional ML (FFNN, SVM, SOM, DT, RF) and Deep Learning (all multi-layer ANN architectures such as CNN, LSTM, and transformers). The LKB class of publications is split into knowledge-based models such as expert systems and different reasoning approaches such as case-based and Bayesian models. For the AM dimension, CAWM accounts for 312 publications, with “Remaining Useful Life” (169 publications) as the dominant subclass. Other notable applications include “Prognostic” (81), “Reliability” (42), and "Maintenance Optimization" (35). MRO encompasses 224 publications and prioritizes diagnostics and failure management. Fault diagnosis (127 papers), detection (74), and analysis (36) are the central themes, with engines being the most analyzed aircraft component. Health Management/Monitoring, comprising 273 publications, focuses on condition tracking through “Engine Health Monitoring” (62), “Structure Health Monitoring” (75), and broader predictive maintenance (142). Predictive maintenance applications mostly focus on engines with less emphasis on airframes, and systems. Training (14) is the least explored application area, suggesting that AI applications in training for aviation maintenance are still in their early stages or represent a less prioritized area compared to diagnostics and prognostics.

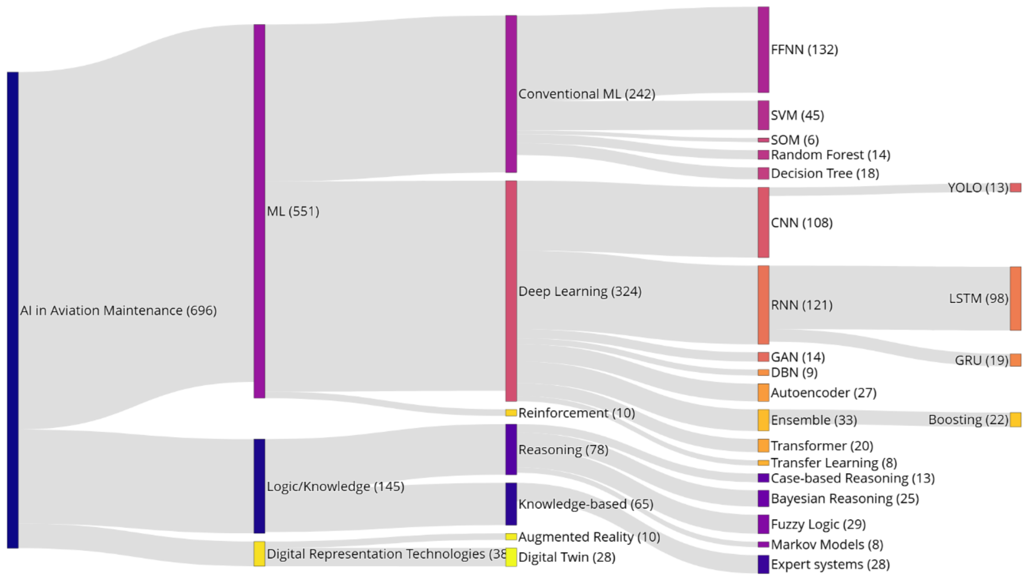

Fig. 6. Hierarchy of AI applications by the AI technology

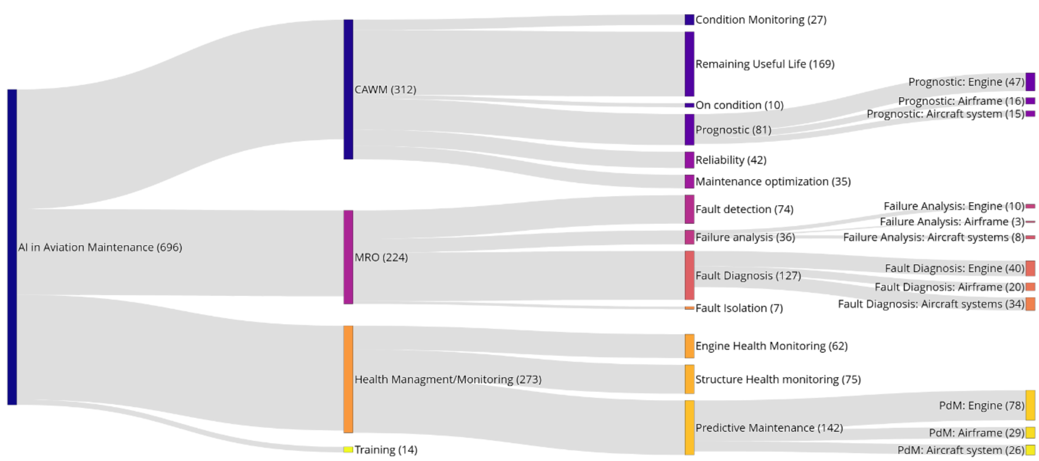

Fig. 7. Hierarchy of AI applications by the AM process

4.2. Trend identification

The specific research question (RQ2) is associated with the historical trends of AI technologies in aircraft maintenance. Fig. 8 illustrates the trends in the application of second-level AI technologies of the hierarchy, explained in Table 8, in aircraft maintenance over the years. In the earlier decades, knowledge-based systems and reasoning approaches dominated, with relatively low annual publication counts. From the mid-1990s onwards, conventional machine learning began to grow steadily, and after 2015 there is a significant increase in total publications, primarily driven by deep learning. Digital representation technologies appear only in recent years with comparatively lower counts. Overall, the figure highlights a marked shift from knowledge-based paradigms toward data-driven approaches, particularly deep learning, accompanied by a rapid expansion of research output.

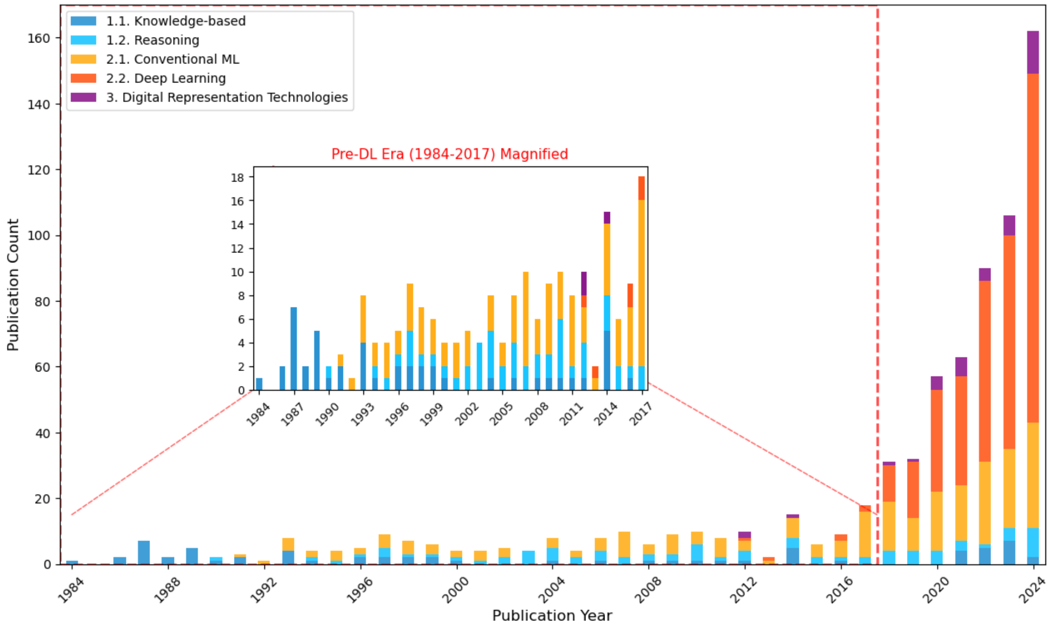

Fig. 8. Dynamics of AI applications by the AI technology

Fig. 9 illustrates the trends in the application of AI technologies for different AM processes. Early years show low publication counts with only sporadic contributions across categories. From the mid-2000s onwards, the number of papers gradually increases, and after 2015 there is a surge, particularly in condition monitoring, predictive maintenance, remaining useful life estimation, and fault diagnosis. Other topics such as engine and structural health monitoring, maintenance optimization, and training appear more recently with smaller but growing contributions. Overall, we observe the rapid expansion and diversification of research in maintenance and reliability over the past decade.

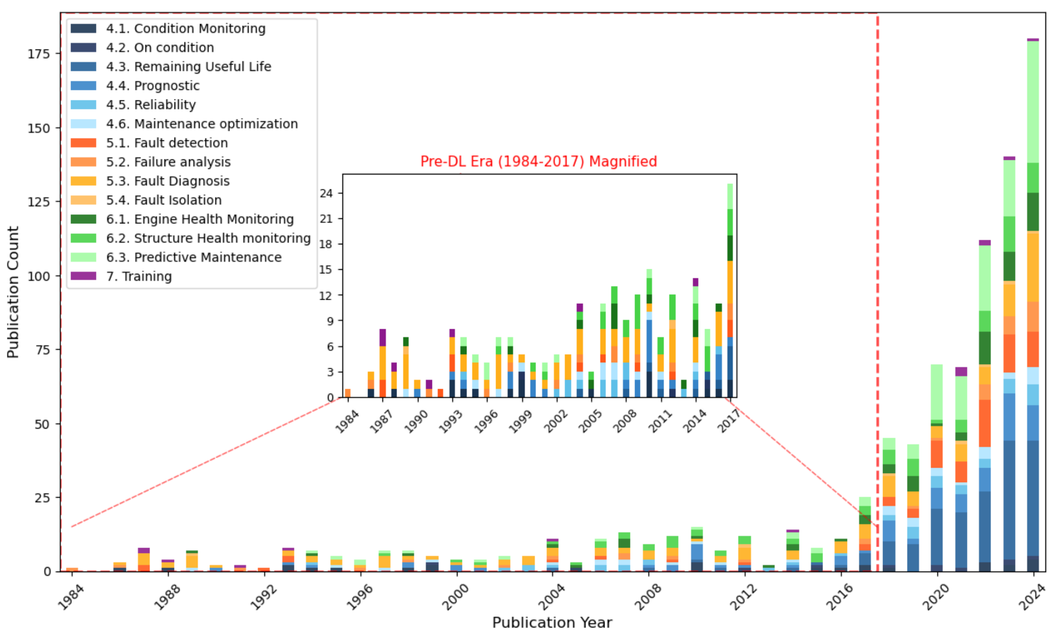

Fig. 9. Dynamics of AI applications by the AM process

4.3. Contingency tables

Finally, we obtained the crosstab results of the AI technologies and AM processes to cover the research question RQ3. The contingency tables of second-level classes are visualized in Fig. 10. The sizes of the circles in Fig. 10 and the values inside represent the number of publications. Colors represent a relationship between normalized row and column share: red colors correspond to larger column share (larger importance of the AI technology for a specific AM process), blue colors correspond to larger row share (larger focus of a specific AI technology on the AM process), violet colors correspond to similar row and column share.

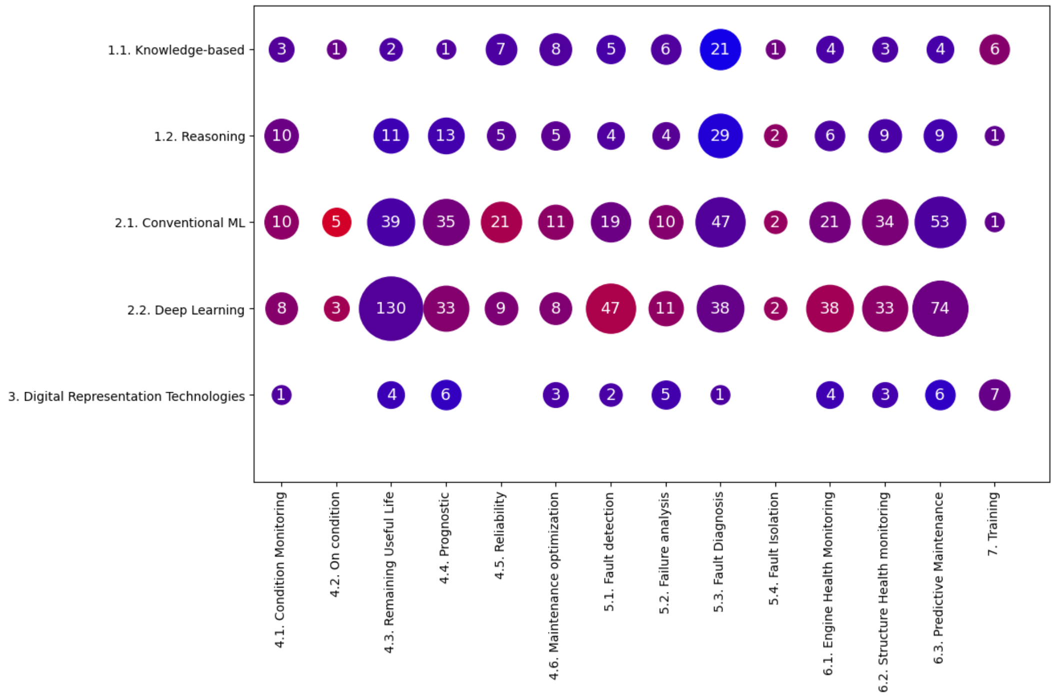

Fig. 10. Contingency table of AI technologies and AM processes.

The largest violet circles correspond to Deep Learning, particularly in RUL prediction (130), PdM (74), and Fault Diagnosis (38). This indicates that DL plays a crucial and highly targeted role in these areas. The large dark-red circle for DL in "Fault Detection" (47) illustrates the high importance of DL for this AM process.

Conventional ML has consistently large circles across several research problems, particularly in PdM (53) and Fault Detection (47). This suggests that conventional ML is a versatile technology applicable to various AM problems.

Knowledge-based systems are used across many research problems but with a smaller intensity. Larger blue circles indicate the high focus of knowledge-based algorithms and reasoning algorithms on Fault Diagnosis (21 and 29 papers respectively), which may reflect the necessity of explainable solutions for understanding and resolving system faults.

Digital Representation Technologies are applicable across the AM processes, but their role is limited up to 2024.

5. Discussion

The growing use of AI in research on aircraft maintenance is evidenced by Fig. 4 and corresponds to the overall tendency for successful AI applications. Further, we formulate several more specific insights from the obtained results.

Multidisciplinary journals, domain-specific conferences

The only journal among the most popular publication venues (Table 6) that is specifically focused on the aviation industry is *Aerospace*. The other journals are multidisciplinary, covering applications of AI technologies across various domains (*IEEE Access*) or focusing on methodological advancements (*Expert Systems with Applications*). Potentially, this lack of specialization could create an obstacle for access to recent AI advances for specialists, working purely in aircraft maintenance. On the other hand, the majority of conference publications are domain-specific and focused on maintenance, prognostic, and health management.

Fall and rise of knowledge-based technologies

Applications of AI technology classes (ML and LKB) in aircraft maintenance correspond to the regular patterns of AI development. Historically, knowledge-based expert systems were the primary AI tool (Fig. 8), and, starting from Bedoya and Keller (1984), several papers report about the successful application of expert systems in aircraft maintenance. Despite the attractive properties of expert systems like transparency, interpretability, and domain-specific precision, they were widely acknowledged as too expensive to maintain. In the history of AI, the difficulties of expert system maintenance led to the slowdown of their practical applications, frequently referred to as one of AI winters (Wooldridge, 2021). The same process is visible for AI use in aircraft maintenance. In 1990-2000 the interest within LKB was shifted to reasoning techniques such as case-based reasoning (Magaldi, 1994) or Bayesian reasoning (Allen, 1990), but remained low until 2023. Recently, the number of papers significantly increased (10 papers from the logic/knowledge-based branch published in 2023 and 11 – in 2024). We explain this growth with the general trend toward explainability in AI, where researchers try to better understand and explain processes inside the "black box" of machine-learning models, providing more interpretable results. Thus, several papers proposed a combination of LKB and ML techniques (Meng et al., 2024), raising interest in classical reasoning approaches. We expect that this trend will continue in the next years.

Rise of deep learning

Deep learning (DL) techniques are rapidly coming into practice in all areas, including aircraft maintenance. Tamilselvan et al. publications (2012; 2013) were the first applications of DL (more specifically, deep belief networks) for aircraft engine health diagnosis, enabling further applications and DL techniques and collecting more than 600 citations. Further, we observe (Fig. 8) the explosive growth of DL applications in aircraft maintenance, resulting in 106 publications in 2024 (73% of all related papers, published in 2024). These research advances are expected to enable daily use of DL tools.

Most popular models

Although there is evidence of applications of different types of DL models in aircraft maintenance, two models can be classified (Fig. 6) as the mainstream ones – convolutional neural network, CNN (108 papers, 15.5% of all publications, 37 of them – in 2024), and long short-term memory neural network, LSTM (98 papers, 14.0% of all publications, 28 of them – in 2024).

CNNs are designed to adaptively learn spatial hierarchies of features from input images through the use of convolutional layers, which apply filters to capture local patterns like edges, textures, and shapes. The structure of CNNs allows them to excel at tasks like image classification and object detection, by learning complex features at deeper layers. In aircraft maintenance, CNNs are primarily used for visual inspection tasks (Doğru et al., 2020) such as crack identification and damage and corrosion detection. Although traditional CNNs are mostly based on the processing of two-dimensional image data, there are a couple of examples where CNNs are applied for one-dimensional signal processing (Rajagopalan et al., 2024) and text processing (F. Jiang et al., 2024).

LSTMs are a type of recurrent neural network architecture designed to effectively learn and model sequences of data, particularly when long-term dependencies are crucial. LSTMs use specialized memory cells with gates that control the flow of information and allow LSTMs to retain or forget information over long sequences, making them highly effective for tasks like time-series prediction. In aircraft maintenance, time-series prediction is usually associated with RUL prediction, where LSTMs play the primary role (Yuan et al., 2016).

CNN and LSTM models are considered workhorses in aircraft maintenance, making it highly beneficial to incorporate their foundational concepts into education and training programs in this field.

Speed of adoption of new AI models

Although aircraft maintenance is widely acknowledged as a very conservative process, the adoption of recent DL models in related research is going relatively fast (Fig. 6). Generative adversarial networks were introduced in 2014 and applied in aircraft maintenance for the first time in 2019 (Ducoffe et al., 2019), the YOLO architecture was introduced in 2016 and applied in aircraft maintenance in 2020 (A. Jiang & Liu, 2020), transformers were introduced in 2018 and applied in aircraft maintenance in 2022 (Yang et al., 2022), therefore it typically takes 4-5 years for new AI model adoption. Thus, we expect to see the application of MLP-Mixer (Tolstikhin et al., 2021), normalizer-free networks (Brock et al., 2021), and other modern architectures in aircraft maintenance shortly.

Another potential direction for growth is associated with the application of pre-trained models. Transfer learning has already been adopted in aircraft maintenance (Gong et al., 2020), while other modern approaches like fine-tuning foundation models have not been applied yet.

Weak reinforcement

Another class of AI technology, under-utilized in aircraft maintenance, is reinforcement learning (10 papers, Fig. 6). Reinforcement learning is a type of machine learning where an agent learns to make decisions by interacting with an environment and receiving rewards or penalties based on its actions. These models are widely adopted for solving scheduling and planning problems (including aircraft maintenance, see exclusion criteria AM4 and AM5 in Table 5), but are rarely applied to other maintenance tasks. Existing examples (Lee & Mitici, 2023; Wei et al., 2024) suggest the integration of reinforcement learning techniques with regular maintenance tasks like RUL prediction to improve their economic performance. Authors foresee the growth of interest in the application of hybrid AI models with reinforcement learning components.

Steady utility of conventional machine-learning

Despite the explosive growth of DL models, the "conventional" machine-learning models (feed-forward neural networks, support vector machines, decision trees, random forests, and self-organizing maps) demonstrate steady utility in aircraft maintenance. The number of papers has been stable over the last years (25 in 2022, 24 in 2023, and 32 in 2024), which supports the status of conventional ML models as well-established AI tools.

Emergence of digital representation technologies

We observe the growing links between digital representation technologies (virtual reality, augmented reality, digital twins) and AI tools. Although such digital technologies do not fall into the primary scope of this review and are not specifically covered by the literature search strategy, the number of papers referring to AI technologies is significant (38 papers overall, 13 in 2024). Usually, AI technologies like deep learning or Bayesian reasoning are utilized for the internal implementation of digital twins (Selvarajan et al., 2024; Zhou & Dong, 2024), while computer vision-related techniques (e.g., CNNs) are intensively applied for augmented reality applications (Hu et al., 2023; D. Li et al., 2023).

Dominant AI application areas

Prognostic and Predictive Maintenance stand out as the most published areas of AI applications, particularly in the last decade. This trend indicates a prioritization of technologies and methodologies that focus on preventing failures rather than reacting to them. PdM utilizes AI algorithms to analyze historical maintenance data, sensor readings, and other relevant parameters to predict the likelihood of component failures before they occur. Airlines and maintenance providers can identify potential issues early on and proactively prevent costly breakdowns and disruptions (Bemani & Björsell, 2022; Dangut et al., 2021; Liao et al., 2020). AI already plays a key role in PdM, assisting in analyzing big datasets generated by aircraft systems and equipment. Although AI use has a significant potential, this implementation has significant challenges and requires numerous considerations from the industry. One of the important factors that must be considered is the regulatory framework as all maintenance processes are strongly regulated by the Federal Aviation Administration (FAA) and EASA.

AI importance in MRO

AI-powered fault diagnosis systems employ advanced algorithms to analyze sensor data and detect anomalies indicative of potential faults or malfunctions in aircraft systems. The number of reviewed publications focused on MRO is surprisingly large – 224 papers (32% of all publications). Many of these articles were published in 2023-2024, thus, the citation rate is low at the review moment, except for some articles such as (Zhang et al., 2020) and (Bouarfa et al., 2020). In the last decade, aircraft construction and design have been characterized by the essential integration of electronics technology within aircraft microgrids. This has led to complex relationships between aircraft systems and made fault diagnosis much more difficult for technicians using traditional methods. Integration of health management into newly designed aircraft provided a lot of capabilities required for transformation from condition-based maintenance into predictive maintenance (Li et al., 2023). This trend highlights the recognition of workforce development as a critical factor in realizing the potential of AI technologies in MRO.

Fault Detection: Steady but Secondary Focus

While the use of AI in processes like fault detection and isolation has shown steady growth over the years, they remain less prominent compared to broader themes (Nyulászi et al., 2018). This could suggest that while they are critical components of maintenance strategies, they are often integrated into more comprehensive systems like condition monitoring and diagnostics, leading to a less isolated research focus.

AI Expansion in Health Monitoring/Management

The use of AI for Engine Health Monitoring and Structure Health Monitoring/Management has gained significant attention in recent years. This trend likely reflects the growing complexity of modern engineering systems, such as aircraft and infrastructure, where tailored monitoring solutions are crucial for ensuring safety and operational efficiency. Across all categories, engines receive the most attention, particularly in diagnostics (40 publications, 31.5% in fault diagnosis and 46, 57.5% in prognostics) and predictive maintenance (78 publications, 53.4% in PdM), e.g., (Peng et al., 2019). This highlights the critical importance of engine performance and reliability in aviation maintenance workflows. Despite its potential, condition monitoring has only 27 cases have been identified under CAWM, a relatively small number compared to other subcategories such as RUL prediction. This may point to an opportunity to expand condition-monitoring applications for real-time assessment and immediate feedback on system health.

Maturity of AI technologies in AM

After the critical analysis of the research literature, we propose the following classification of maturity levels of AI technologies in AM (Table 9).

Table 9 summarizes typical applications and estimated maturity levels expressed as Technology Readiness Levels (TRLs). It should be noted that these classifications are subjective assessments based on available literature, and vary depending on the operational context, data availability, and regulatory environment.

AI technology	Typical AM applications	Maturity, TRL	Status
Logic/Knowledge-based	Assistance, Troubleshooting	High (8-9)	Widespread
Predictive ML	RUL prediction, fault prediction	Medium (6-8)	Selective use
Computer vision ML	Visual inspection	Medium (5-7)	Pilot projects
Reinforcement learning	Process optimization	Low (3-5)	Research
Digital Representation	Engine monitoring	Medium (5-7)	Selective use

Table 9. Maturity of AI technologies in AM

Barriers and Enablers of AI Adoption

The maturity levels presented in Table 9 reflect not only technological readiness but also the interplay of regulatory, workforce, economic, and integration factors that either accelerate or hinder practical adoption:

- Regulatory challenge. Existing AI guidelines (FAA and EASA) and many research papers highlight the compliance complexities and necessities for standardized AI deployment frameworks (EASA, 2023; FAA, 2024). The challenge lies in balancing AI system explainability with regulatory transparency demands, while the opportunity exists in developing AI systems that can provide auditable decision trails.
- Workforce challenge. Re-training maintenance personnel represents a significant organizational challenge (IATA, 2025). Conversely, adoption of modern AI-based digital representation technologies creates opportunities for workforce upskilling and new job categories in AI-augmented maintenance.
- Economic challenge. Organizations face significant upfront investments in AI infrastructure and data systems. However, industry reports (e.g., results of Delta's advanced predictive engine program (Delta Air Lines, 2024)) demonstrate substantial return on investments through reduced unscheduled maintenance, optimized parts inventory, and extended component lifecycles. The challenge involves justifying initial investment against long-term operational savings.
- Integration challenge. AM organizations typically operate with established legacy systems and processes. The operational challenge involves integrating AI solutions with existing maintenance management systems and enterprise resource planning platforms without disrupting critical operations(Credence Research Europe, 2025)

LKB systems achieve high maturity largely because they align with existing regulatory frameworks. The FAA and EASA strongly regulate all maintenance processes, and transparency and interpretability of knowledge-based systems make them attractive for compliance documentation. However, these systems are known as too expensive to maintain, creating an economic barrier that limited their expansion despite regulatory acceptance. The workforce enabler is strong here as technicians can understand, trust, and follow rule-based recommendations, facilitating adoption. The recent publications reflect the general trend toward explainability in AI, suggesting that hybrid approaches combining LKB transparency with ML performance may overcome maintenance cost barriers.

Predictive ML for RUL and fault prediction and computer vision-based visual inspection are currently associated with selective use, constrained primarily by data availability and integration challenges. Successful deployment of these systems requires careful integration with existing predictive maintenance and inspection workflows. The barrier here is less about technology capability and more about operational logistics, including standardizing data pipelines, validating models across application types, and establishing regulatory acceptance protocols. AI-based visual inspection demonstrates the highest short-term promise for advancement within the next 2-5 years. The technology includes well-established model architectures (e.g., LSTM, CNN), available data from maintenance operations, and clear return on investments through maintenance costs and labor cost reduction. The progression appears achievable as regulatory frameworks increasingly accommodate AI systems, and pre-trained models reduce development.

RL remains at low maturity primarily due to regulatory and safety concerns. RL agents learn through interaction with environments and receiving penalties, but AM cannot afford trial-and-error learning in operational contexts. The barrier is fundamental: safety-critical systems require deterministic, explainable decisions. The long-term track for RL adoption likely involves hybrid architectures that combine domain knowledge from LKB components and applied in non-safety-critical maintenance tasks. We foresee a 5–7-year timeline for meaningful maturity advancement of RL.

Digital representation technologies also face integration complexity as their primary barrier. AI technologies, utilized for internal implementation of digital twins, require stable data flow from physical assets to digital models. The economic enabler is substantial but implementation costs and data infrastructure requirements are significant. Integration of health management into newly designed aircraft provided capabilities required for transformation, suggesting that enablers strengthen for newer aircraft while legacy fleet integration remains a barrier.

Summary

Seven key findings and their potential implications are summarized in Table 10.

#	Key finding	Description	Potential Implications
1	Publications in multidisciplinary journals	The majority of papers are published not in aviation-specific journals, but in multidisciplinary journals	Researchers and practitioners who focus on emerging AI techniques in AM should monitor multidisciplinary journals. Applying modern AI-based assistants for publication monitoring becomes more important.
2	Rise of Deep Learning	The explosive growth of DL applications in AM, especially CNN and LSTM	Researchers and practitioners should develop expertise in Deep Learning (DL) architectures such as CNNs and LSTMs, as they are becoming integral to AM.
3	Speed of adoption of new AI models	It typically takes 4-5 years for the adoption of new AI models in AM research practice	Collaboration between academia and industry should be accelerated to shorten the gap between AI research breakthroughs and their practical implementation in AM.
4	Steady importance of conventional machine learning	The "conventional" machine-learning models (FFNN, SVR, DT, RF) demonstrate steady utility in aircraft maintenance.	Training programs for AM professionals should include case studies and practical applications of ML in diagnostics, predictive maintenance, and fault detection.
5	AI importance in MRO	Intensive research on AI applications in MRO processes like fault diagnosis, isolation, and analysis.	Complex relationships between aircraft systems made fault diagnosis much more difficult for technicians using traditional methods. AI-focused workforce training and development is a critical factor in realizing the potential of AI technologies in MRO.
6	Dominant AI application areas	Prognostic and Predictive Maintenance stand out as the most published topics. Their dominance highlights the importance of AI for these proactive strategies for ensuring system reliability and reducing downtime.	FAA and EASA strongly regulate maintenance processes, thus, implementing AI will require a huge effort from the industry to adapt regulatory orders to align with new technologies.
7	AI expansion in Health Management / Monitoring	AI provides a shorter path to expand condition-monitoring applications for real-time assessment and immediate feedback on system health.	AI will support and stimulate a switch to proactive strategies in AM practice.

Table 10. Key findings and their implications

6. CONCLUSION

This systematic literature review highlights how modern AI technologies are applied in the research and practice of AM. It indicates key trends, research gaps, and promising future directions in the application of AI to AM processes. AI techniques are already widely applied and their roles in AM are increasingly significant. Deep learning demonstrates great potential in predicting remaining useful life, diagnosing faults, and enabling predictive maintenance. Meanwhile, traditional ML models and knowledge-based systems remain versatile tools for solving various AM challenges.

The analysis of publication trends reveals steady growth in AI research within AM, with a notable increase in studies since 2018. This recent surge suggests a move toward more impactful, practical applications. One of the critical challenges is making AI models more explainable, particularly in fault diagnosis, where understanding the reasons behind system faults is crucial. While predictive maintenance for engines is well-studied, areas like airframes and auxiliary systems receive less attention. Emerging technologies like digital twins and augmented reality also show potential, though their use in AM is still in the early stages. Additionally, the role of AI in training maintenance engineers is underexplored.

This review underlines the importance of the collaboration of AI and AM specialists to address these challenges and unlock the full potential of AI in AM. Future research should prioritize improving AI explainability, expanding applications to less-studied areas, and integrating AI into cutting-edge technologies like digital twins.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used GrammarlyGO and gpt-4o large language models in order to improve the readability and language of the manuscript. After using these tools, the authors reviewed and edited the content as needed and take(s) full responsibility for the content of the published article.

CRediT author statement

Dmitry Pavlyuk: conceptualization, methodology, formal analysis of artificial intelligence aspects, data curation, visualization, writing; **Iyad Alomar**: conceptualization, formal analysis of aircraft maintenance aspects, data labeling, writing. Both authors reviewed and approved the final version of the manuscript.

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