Chapter 4

Digital Transformation of Aviation Maintenance: Artificial Intelligence-Enabled Approaches

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Abstract

Aircraft maintenance is a cornerstone of flight safety, operational continuity, and cost-effectiveness in the aviation industry. Traditional maintenance approaches, relying on scheduled inspections and corrective actions, face limitations in flexibility and efficiency due to their dependence on human intervention. In recent years, artificial intelligence has revolutionized the sector by shifting maintenance management from reactive methods to predictive and data-driven strategies. This transformation has enabled innovative solutions in digital twins, structural health monitoring, automated visual inspections, foreign object debris detection on runways, decision-support systems, and spare parts logistics optimization.

AI-powered predictive maintenance leverages sensor data and deep learning algorithms to estimate the remaining useful life of critical components, minimizing unplanned downtime and improving operational reliability. Digital twin technology creates virtual replicas of aircraft to enable real-time monitoring and proactive maintenance planning. Moreover, automated visual inspection systems reduce technicians' workload while enhancing inspection accuracy and quality standards.

However, challenges such as data integrity, explainable artificial intelligence, regulatory compliance, and effective human–machine collaboration remain critical to ensuring the safe and sustainable implementation of these technologies.

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https://doi.org/10.58830/ozgur.pub1093.c4350

This chapter highlights how artificial intelligence contributes to improved safety, efficiency, cost reduction, and sustainability in aircraft maintenance. It also provides a forward-looking perspective on the development of human-centric, ethical, and regulation-compliant maintenance ecosystems, outlining how these emerging technologies will shape the future of aviation maintenance practices.

1. Introduction

The aviation sector has a structure that differs from other sectors due to its complex nature, which requires the highest level of safety standards and a high degree of technical knowledge and experience (Okine et al., 2025). Maintenance activities in the aviation sector are not only an operational necessity but also one of the fundamental parameters of safety, economic sustainability, and legal compliance. Considering the complex structure of the systems that make up aircraft, their exposure to environmental conditions, and their high frequency of use, a regular and effective maintenance process has become mandatory (Żyluk et al., 2025). The International Civil Aviation Organisation highlights maintenance activities as one of the most important parameters of flight safety. It has made it mandatory for maintenance activities to be supervised by national authorities (Shelton-Mur, 2025). Aircraft are integrated systems consisting of thousands of component parts. Any malfunction in any component of these integrated systems can cause large-scale failures through a chain reaction and even lead to accidents that threaten flight safety. Planned maintenance activities performed on aircraft are critical not only for repairing faults but also for preventing them from occurring in the first place (Stolzer et al., 2023). In addition to safety and continuity, the economic aspect of maintenance is also very important for airline operators. Maintenance costs constitute a large portion of airline operators' annual expenses (Kinnison & Siddiqui, 2013). For airline operators, this situation reveals that maintenance activities are not only technical but also a strategic planning element. Effective maintenance strategies reduce aircraft downtime, optimise spare parts management, and prevent indirect costs. The proper documentation of maintenance activities and full compliance with regulations are essential for maintaining aircraft operability and certification compliance. Any deficiencies or errors in maintenance records can lead not only to legal sanctions but also to a loss of corporate reputation (Stolzer et al., 2023). When evaluated in all these aspects, maintenance activities in aviation are a multidimensional element that protects human life, makes operations sustainable, and builds sectoral trust. In today's aviation, the importance of maintenance continues to grow not only at the technical level but also at the managerial, economic, and strategic levels (Truong & Lee, 2025).

Maintenance activities also play a significant role in ensuring operational continuity for airlines (Kabashkin et al., 2025). The situation where an aircraft is grounded due to an unintended malfunction (AOG – Aircraft on Ground) causes both financial losses and programme disruptions for airlines. Preventing programme disruptions is directly related to the proactive and predictive implementation of maintenance. Particularly with the use of artificial intelligence-supported systems today, maintenance processes are now data-driven, time-sensitive, and capable of predicting systemic risks in advance (MoghadasNian, 2025).

The integration of artificial intelligence into maintenance processes in recent years has brought about a significant transformation in the sector. Artificial intelligence-based algorithms analyse sensor data, particularly in aircraft engines and critical components, to predict remaining useful life (RUL), thus enabling the prediction of failures before they occur (Khan et al., 2025). This contributes significantly to reducing both AOG events and unexpected downtime (Alomar & Nikita, 2025). The integration of artificial intelligence in aviation maintenance processes stands out as a versatile tool that not only provides safety and continuity but also enables cost optimisation, operational efficiency, and strategic decision support. In the coming years, it is anticipated that artificial intelligence will be more widely used in maintenance processes and become a standard practice in maintenance management (Moghadasnian and Rajol, 2025).

2. Traditional Maintenance Approaches and Challenges

Aircraft maintenance is one of the most critical activities in aviation, playing an indispensable and crucial role in terms of the aircraft's safety, security, cost and continuity (Ram et al., 2019). These aircraft maintenance activities exhibit a multidisciplinary structure through the simultaneous use of different engineering, planning, and operational processes and are of great importance in all steps of aviation (Marais and Robichaud, 2017). Traditional maintenance has been implemented in the aviation sector for many years in accordance with standardised procedures and specific criteria set by authorities (SKYbrary, n.d.). Traditional maintenance approaches generally consist of two main elements: scheduled maintenance and post-failure maintenance. While scheduled maintenance involves inspecting the aircraft at predetermined intervals or according to the aircraft's flight hours, post-failure maintenance is applied after any problem or issue is detected in the aircraft (Tsang et al., 2020). These elements have provided a safety and security-centred structure for many years and have contributed to the establishment of standards in training and inspection processes for aircraft personnel (Gonçalves et al., 2018). However, these traditional approaches and methods also bring different challenges. Considering the cost dimension of aircraft maintenance operations , replacing parts before the end of their service life causes significant financial loss (Marais and Robichaud, 2017). Such situations increase operating costs and reduce the efficiency of the parts used. On the other hand, traditional maintenance approaches are reactive, meaning intervention is only possible after a problem has occurred. This, in turn, leads to undesirable problems such as operational disruptions, flight delays and cancellations. These problems also give rise to undesirable negative situations such as reduced customer satisfaction (Tsang et al., 2020). In addition, human factors in maintenance processes are another risk factor. The high probability of maintenance personnel making mistakes due to fatigue, time pressure, and stress directly affects the quality of maintenance (Latorella and Prabhu, 2000). Furthermore, the rigidity of traditional maintenance procedures has been observed to lack sufficient flexibility in unprepared and unexpected situations and to be unable to produce quick solutions (SKYbrary, n.d.). Traditional aircraft maintenance practices are mostly based on a manual inspection, visual control, and technician experience approach. This approach limits maintenance reliability due to its susceptibility to human error (Latorella and Prabhu, 2000). The adverse effects of human error on flight and ground safety have long been discussed in the literature, and it has been noted that measures taken to prevent errors, particularly in traditional aircraft maintenance systems, are insufficient (Gonçalves et al., 2018). Although traditional aircraft maintenance approaches have laid very solid foundations in terms of continuity and safety, they face significant challenges in terms of cost, flexibility, and the human factor in today's advancing and changing aviation field. For this reason, the transition to a more innovative, data-driven, and proactive maintenance style in the aviation field is accelerating with each passing day (Ram et al., 2019).

3. The Role of Artificial Intelligence Technologies in Maintenance

The aviation industry is undergoing a significant and accelerating transformation by integrating artificial intelligence technologies into aircraft maintenance processes in its quest to enhance operational reliability, safety, and cost-effectiveness. At the heart of this transformation is the shift from traditional reactive or periodic maintenance to predictive maintenance, which anticipates potential failures and optimises maintenance actions (Kabashkin and Perekrestov, 2024). One of the fundamental roles of artificial intelligence is its ability to detect abnormal patterns and impending failures by analysing sensor data, flight records, and historical maintenance data, particularly using machine learning and deep learning algorithms (Akbari et al., 2023). Real-time data collected by Internet of Things devices, combined with the analytical power of artificial intelligence, creates an ecosystem that monitors aircraft health and generates actionable insights (Kabashkin & Perekrestov, 2024). This synergy enhances flight safety by predicting potential problems before they arise, significantly reducing the risk of unexpected failures. According to Patibandla's comprehensive research, the implementation of sophisticated predictive analytics engines in major airlines has achieved fault prediction accuracy ranging from 87.6% to 93.2% in critical aircraft components, resulting in significant reductions in unplanned maintenance events (Patibandla, 2024). In this context, AI-powered systems enable the planning of part replacements at the most appropriate time by accurately predicting the remaining useful life (RUL) of components. For example, using complex hybrid data preparation and optimisation models, the number of aircraft equipment failures can be predicted with high success, minimising maintenance costs by preventing unnecessary part replacements while reducing flight delays and cancellations (Uyar, 2024).

Artificial intelligence is not limited to failure prediction but optimises the entire range of Maintenance, Repair and Overhaul (MRO) operations. Reinforcement Learning (RL) algorithms are used to optimise decision-making processes such as maintenance scheduling and resource allocation. These algorithms continuously improve their ability to predict the optimal times for part replacement, repair planning, and workforce allocation by learning from interactions with the environment and receiving feedback based on the results obtained (Patibandla, 2024). Furthermore, artificial intelligence plays a key role in reducing human error and increasing operational efficiency by analysing large amounts of structural and operational data, providing technicians with faster and more accurate decision support systems during maintenance and troubleshooting processes. The Genetic Algorithm (GA)-based optimisation method proposed in the work of Kabashkin and Perekrestov has been shown to offer significant reductions in total life cycle costs by providing a dynamic maintenance schedule that adapts to real-time component health data (Kabashkin and Perekrestov, 2024).

However, the integration of artificial intelligence into aviation maintenance also presents significant challenges. One of the most critical challenges is data quality and availability. Machine learning algorithms require high-quality, accurate, and consistent data to be effective. Compatibility issues with existing legacy systems and incomplete/inconsistent data can reduce the accuracy and reliability of e predictions (Patibandla, 2024). Another important problem is algorithmic transparency (explainable AI - XAI) and model drift. In a high-risk field such as aviation, it must be understandable why AI predicts a failure or recommends an action. Model drift, defined as the model's performance declining over time and producing incorrect predictions, poses a significant safety risk requiring continuous monitoring and updating (Patibandla, 2024). To overcome these challenges, a structured AI governance framework integrated with aviation safety standards and certification methods is required. In summary, artificial intelligence is moving aviation maintenance towards a safer, more economical and sustainable future, but fully realising this potential depends on the balanced management of technology, regulation and human expertise.

4. Predictive Maintenance

Thanks to advances in artificial intelligence, machine learning, and big data analytics, predictive maintenance systems have begun to play an effective role in the aviation industry's aircraft maintenance systems. Unlike traditional maintenance strategies, predictive maintenance systems have the ability to predict potential failures by analysing real-time monitoring and historical data through corrective or planned preventive maintenance systems. By providing warnings before potential failures occur in aircraft, they offer the opportunity to reduce unplanned downtime, thereby enhancing operational efficiency and safety, which are of critical importance in aviation. (Khan et al., 2025). Modern aircraft are equipped with numerous sensors to enhance flight safety and security. These sensors have the capability to continuously generate large amounts of data for the protection of aircraft engine health, structural integrity, and improved avionics performance. Using this collected data, predictive maintenance systems can be implemented in aviation maintenance systems for the estimated material wear time of parts that will reach the end of their service life. In predictive maintenance systems, the collected data is analysed using artificial intelligence-based algorithms to detect anomalies. For example, deep learning techniques have successfully analysed turbofan engine data and demonstrated high accuracy in predicting engine failures (Kabashkin et al., 2025). The use of predictive maintenance systems in the aviation sector provides many advantages for the industry. Maintenance practices and the maintenance of aircraft by maintenance personnel are of great importance in aviation and play a significant role in aircraft accident incidents (Truong and Lee, 2025). Predictive maintenance systems make it possible to prevent such incidents using data provided by maintenance personnel. Furthermore, the International Civil Aviation Organisation (ICAO) has stated that predictive maintenance is one of the important parameters for improving flight safety and optimising global maintenance inspection programmes (Shelton-

Mur, 2025). Despite these advantages, the implementation of predictive maintenance involves challenges such as data standardisation, integration between heterogeneous aircraft systems, and the legal approval requirements for artificial intelligence-based tools. However, increasing research and industrial adoption make it clear that predictive maintenance will become a fundamental part of aviation maintenance practices over the next decade (MoghadasNian, 2025).

5. Image Processing and Autonomous Inspections

In recent years, artificial intelligence and, in particular, deep learning architectures have been frequently used in three key areas of aircraft maintenance processes: condition monitoring and predictive maintenance (PHM/PdM), visual inspection automation, and runway foreign object debris (FOD) detection. This transformation directly contributes to the safety, cost and continuity objectives of maintenance by enabling the scalable processing of sensor data and images. AI-based PdM approaches enable pre-failure intervention by estimating the remaining useful life (RUL) of engines, landing gear, and structural subsystems, thereby reducing delays and AOG risks (Fu et al., 2023). Complementing this, the quantitative validation of fault detection reliability in fibre optic, piezoelectric, and accelerometer-based SHM architectures using probability-based methods (Probability-of-Detection, POD) has become a critical requirement for regulatory compliance and certification (Galasso et al., 2024). Finally, in MRO fields, CNN-based perception and detection models are increasingly replacing human-eye-based visual inspection, reducing labour costs while increasing reproducibility (Yasuda et al., 2022; Ali et al., 2025). Predictive maintenance (PdM) and PHM. Post-2020 academic literature addresses PdM using data-driven (CNN, LSTM, Transformer), physics-based, and hybrid approaches, emphasising fleet-scale generalisation capability through multimodal sensor fusion (vibration, temperature, acoustic emission, fibre-optic strain) and online learning. The value proposition of PdM is quantified through prediction accuracy (RUL), false alarm rate, and maintenance window optimisation. However, explainable artificial intelligence (, XAI), data access/labelling, and domain shift in distribution are reported as the main barriers to industrial-scale deployment (Fu et al., 2023). In SHM, PoD-based reliability analysis and quantitative proof of detection performance under field conditions serve as a bridge in the certification journey of artificial intelligence models (Galasso et al., 2024). Automation of visual inspection. The use of artificial intelligence in the optical inspection of aircraft exterior surfaces (skin), rivet lines, paint/coating, and composite repair areas provides pixel-level defect detection, repeatability, and time savings compared to previous labour-intensive manual processes. Systematic reviews indicate that single-stage detectors such as the YOLO family and RT-DETR excel in real-time performance in this field; however, data imbalance, rare defects, and imaging variables such as lighting/reflection remain challenging (Yasuda et al., 2022). In the most recent field applications, it is stated that deep learning-based fault detection on images obtained by unmanned aerial vehicles achieves meaningful accuracy even under noise/emission variation and geometric diversity and can be integrated into maintenance cycles (Ali et al., 2025). Runway FOD detection directly threatens take-off and landing safety and requires rapid clearance. Post-2020 studies show that lightweight and attention-mechanism-enhanced YOLO/DETR derivatives, which focus on small object detection, deliver high mAP and FPS values despite background noise such as runway texture and oil stains. Using dual-mode cameras (visible and infrared) for day/night robustness and multi-scale feature fusion has yielded significant gains in detecting small FODs (Mo et al., 2024). A comprehensive recent review emphasises that integrating radar/LiDAR, optical, and AI-based methods into combined architectures adapted to airport conditions is the most promising approach for scalability and environmental robustness (Shan et al., 2025). Field experiments indicate that the probability of missing small-scale FODs increases with range in fixed camera-based systems; therefore, the need for perspective/distance compensation and multi-sensor fusion is evident (Noroozi et al., 2023).

In terms of open issues and research directions, airports are heterogeneous in terms of runway surface, climate, and traffic; this leads to shifts in data distribution and model degradation. Domain adaptation, data augmentation, and synthetic-real hybrid datasets are emerging as solutions (Shan et al., 2025). Secondly, although rare, labelling costs, FODs, and critical defects are quite low, offering hope for combinations of weak/unsupervised learning and interactive/active learning (Yasuda et al., 2022). Thirdly, reliability and explainability: Supporting PdM/SHM decisions with PoD, confidence intervals, and explainable AI representations is a decisive factor in maintenance authority and regulatory processes (Galasso et al., 2024; Fu et al., 2023). Finally, for system-level integration, AI-based detection outputs must be linked online with CMMS/MRO planning tools and digital twins to maximise operational benefits (Fu et al., 2023).

In conclusion, post-2020 literature indicates that AI is a maturing technology in maintenance detection and FOD management, yet it still requires solutions in terms of data, reliability, and field integration. Infrared-visible fusion, lightweight, and attention-focused detectors are the closest approaches to achieving a balance between high safety and economic efficiency in maintenance decisions, while PoD-supported SHM and XAI-rich PdM approaches are the closest approaches to achieving a balance between high safety and economic efficiency in maintenance decisions (Mo et al., 2024; Noroozi et al., 2023; Galasso et al., 2024; Fu et al., 2023; Shan et al., 2025; Ali et al., 2025).

6. Decision Support and Maintenance Management Systems

Traditional maintenance planning is typically based on fixed schedules or post-failure intervention. This leads to unnecessary maintenance, wasted resources, or high cost periods due to unexpected failures. Machine learning algorithms and real-time data from IoT-enabled sensors are used to overcome these challenges through AI-supported planning and optimisation (Baryannis et al., 2019).

The most important application in this field is artificial intelligence-supported predictive maintenance (PdM) systems. PdM analyses operational data such as vibration, temperature, pressure and current to predict with high accuracy when equipment or machines will fail (Lee et al., 2020). These systems learn from past failure records and normal operating patterns to detect anomalies and predict maintenance needs before a potential failure point. This allows maintenance activities to be scheduled at the most appropriate time when the equipment truly needs it, thereby reducing unplanned downtime and minimising unnecessary maintenance costs (Ding et al., 2021). On the optimisation side, artificial intelligence algorithms such as Decision Trees, Support Vector Machines, and Deep Learning models are highly effective methods for creating the most efficient maintenance programmes by simultaneously evaluating multiple constraints, including personnel, vehicles, budget, and equipment criticality. For example, Mixed-Integer Programming approaches, combined with large language models (LLMs), can create integrated maintenance schedules that combine both numerical optimisation results and strategic qualitative analyses ( ) (Wandabwa, 2025). This enables maintenance teams to focus their time on the most critical tasks, increasing the effective use of human resources and operational reliability (Deloitte, 2024). Spare parts inventory management and logistics, an integral part of maintenance management, is another critical area where artificial intelligence applications provide significant benefits. The high variety of spare parts and challenges such as typically intermittent and irregular demand patterns (lumpy demand) render traditional statistical forecasting methods inadequate (Gopalakrishnan and Banerji, 2014; Boute and Udenio, 2021).

For spare parts demand forecasting, artificial neural networks and other machine learning models offer higher accuracy than traditional methods in predicting spare parts demand. These models enable more accurate predictions by analysing not only historical demand data but also a wide variety of predictors such as equipment age, usage intensity, maintenance history, and even environmental conditions (Młyńczak, 2008). This allows businesses to minimise inventory costs while also reducing the risk of stock-outs. Reinforcement learning, in particular, is a highly successful method for optimising the cost balance between excess and shortage of stock by dynamically adjusting stock levels (Malyk, 2023).

Logistics and Supply Chain Optimisation is utilised in maintenance logistics to ensure that parts and technicians arrive at the right place at the right time through the use of artificial intelligence. AI-supported route optimisation is used to calculate the most efficient transport and field service routes, taking into account multiple variables such as traffic conditions, vehicle capacity, delivery urgency, and prioritised maintenance plans (Talaat et al., 2025). This reduces transportation costs, shortens delivery times, and helps reduce the carbon footprint (Boute and Udenio, 2021). Furthermore, artificial intelligence supports risk management and sustainable supplier selection by increasing visibility throughout the supply chain (Baryannis et al., 2019).

The integration of AI into Decision Support and Maintenance Management Systems represents a highly beneficial transformation for industrial operations. AI-supported PdM systems significantly increase equipment reliability and operational efficiency by shifting planning and optimisation from traditional, reactive approaches to proactive, data-driven approaches. Furthermore, the use of artificial intelligence in spare parts and logistics management plays a critical role in reducing overall costs and environmental impacts for businesses by enabling more accurate demand forecasting, optimised inventory levels, and more efficient supply chain logistics. In the future, with the proliferation of AI-based CMMS, maintenance processes will become autonomous, and collaboration between humans and intelligent systems will become the new standard in the industry. However, issues such as data quality, ethics, and the transparency of AI models, as well as their successful implementation in systems, present important challenges that need to be addressed.

7. Safety, Regulations, and Human-Machine Collaboration

Like many technologies used in the aviation sector, artificial intelligence must also undergo international certification to become standardised. RTCA and EURA guidance documents incorporate artificial intelligence adaptations into the DO-178C software standardisation (RTCA, 2024). The Artificial Intelligence Safety Assurance Roadmap published by the FAA is considered a crucial framework in terms of AI risk management, AI testing, and adapting aircraft airworthiness processes. Recent AI-based systems have enabled maintenance to be managed in a safer, more efficient manner, with more accurate predictions of outcomes (FAA, 2024). Furthermore, the integration of artificial intelligence into aviation necessitates broad consideration not only of technical aspects but also of regulations, ethical standards, and the human factor (EASA, 2024). EASA has developed long-term strategies to ensure the safe use of artificial intelligence in aviation (EASA, 2023). The AI Roadmap 2.0 document adopts a human-centred approach and emphasises that artificial intelligence must be evaluated not only technically but also ethically and in terms of safety (EASA, 2023). Concept Paper Issue 01 and Issue 2 documents explain the applications of machine learning and how it will be implemented through regulations (EASA, 2021). On the US side, the FAA provides corporate guidance called STEP resources to support artificial intelligence. This resource shows how to ensure the compliance of artificial intelligence in the design, verification, testing, and operational phases of safety compliance (FAA, 2024). The human factor is always central to aircraft maintenance. Research shows that maintenance technicians working with artificial intelligence systems have a very low probability of making mistakes (Kirwan et al., 2025). Reports published by NASA recommend the development of evidence-based safety reasoning in human-machine teamwork. In situations where humans and machines work together, the importance of responsibility distribution and who the decision-maker is is emphasised. Furthermore, it is thought that AI systems will reduce the workload of technicians but cannot assume responsibility alone (Graydon et al., 2025). It should never be forgotten that integrating AI into aircraft maintenance carries not only technical but also ethical responsibilities. The Ethics Guidelines for Trustworthy AI defined by the European Commission outline fundamental requirements such as fairness, accountability, and transparency (European Commission High-Level Expert Group on AI, 2019). The greatest contribution of artificial intelligence lies in its positive potential within aircraft maintenance processes (EASA, 2024). When considering its efficiency in terms of safety, regulation, and human-machine collaboration, its greatest contribution is to increase flight and ground safety as well as maintenance efficiency (Demir et al., 2024). However, the successful use of artificial intelligence technology is only possible with transparency, ethics, compliance, risk assessment, and a detailed examination of the human factor (ISO, 2023). It is predicted that in future processes, safer, more transparent, and human-centred approaches will lead the way in artificial intelligence (INCOSE, 2025).

8. Current Applications and Future Perspectives

Artificial intelligence has ushered in an innovative new era in aircraft maintenance in recent years (Bisanti et al., 2023). Extensive and widespread applications have begun in the aviation sector in key technological areas such as digital twins, explainable artificial intelligence, predictive maintenance, and data analysis (Chia et al., 2024).

Digital twin technology enables the maintenance process to be monitored in real time and simultaneously by creating a virtual copy of the aircraft (Bisanti et al., 2023). Using this method, maintenance personnel, engineers, and technicians can detect and diagnose signs of wear or failure before they occur and plan maintenance in advance. Digital twins are predicted to play a critical role in aircraft fuselage and structural integrity analyses in the coming years (Chia et al., 2024). Looking ahead to future perspectives, digital twin-based ecosystems are expected to be integrated into maintenance and also used in education (Kabashkin et al., 2025). Explainable artificial intelligence, on the other hand, is anticipated to be a critical requirement for regulations, as artificial intelligence covering maintenance processes must be explainable (Dereci et al., 2024). Many artificial intelligence models are being developed to increase the transparency of these artificial intelligence models. In data-driven transformation, the PAM 2023 conference suggests that the future of maintenance in aviation will be entirely data-driven (Aviation Business News, 2023). Another area of application for artificial intelligence is predictive and proactive maintenance. This type of maintenance has the ability to predict the likelihood of failures in advance using information from real-time analysis of aircraft components, replacing traditional maintenance (Stanton et al., 2023). Predictive and proactive maintenance significantly reduces costs while increasing operational maintenance and safety. According to research conducted by NASA, regulatory approvals and cultural adaptation are considered to be the limiting factors for predictive maintenance (Teubert et al., 2023). It is stated that Airbus has made considerable efforts to promote the widespread adoption of Skywise Predictive Maintenance applications within some of its aircraft type programmes, and that the world is likely to move in this direction, with standardisation across all aircraft models considered highly probable (Airbus, 2024). When considering regulations and standards, the Artificial Intelligence Roadmap 2.0 document published by EASA emphasises the adoption of a human-centred approach to AI integration in aviation (EASA, 2023). In addition, EASA has initiated certification processes with some guidance programmes (EASA, 2024). Similarly, the FAA outlines the framework for safety verification in its Assurance Roadmap report (FAA, 2024). RTCA and SAE International provide standards programmes supporting integration through AI/ML integration (RTCA, 2023).

9. Conclusion

This highlights the contributions that the transition from traditional methods to AI-supported approaches in aircraft maintenance processes brings to the aviation sector and its future potential. Artificial intelligence-based systems have transformed maintenance activities from a mere technical necessity into a strategic decision-support element. Predictive maintenance systems can detect faults before they occur by analysing sensor data, thereby significantly reducing unplanned downtime and operational disruptions. This approach both enhances flight safety and contributes to lower maintenance costs. Digital twin technology enables engineers and technicians to make more effective decisions by providing the ability to monitor maintenance processes in real time and simultaneously. AI-supported applications, such as the automation of visual inspections and runway foreign object detection, reduce human error while accelerating maintenance cycles and raising quality standards. Decision support and inventory management systems ensure more efficient use of resources and more sustainable operations. However, the integration of artificial intelligence technologies into maintenance processes still has areas that need to be developed, such as data reliability, ethical principles, regulatory compliance, and human-machine collaboration. At this point, it is crucial that technological advances are addressed in a manner consistent with regulatory frameworks and the human factor.

In conclusion, the contributions of artificial intelligence to aircraft maintenance offer significant opportunities to the aviation sector in terms of safety, cost-effectiveness, sustainability, and environmental responsibility. With the more widespread use of these technologies in the future, it is anticipated that maintenance processes will become safer, more efficient, and more human-centred.

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