Systematic Review Article

A Systematic Review of The Impacts of Predictive Maintenance Using AI in the Aerospace Industry

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ABSTRACT

Airlines and aerospace companies continuously seek to reduce operational costs while maintaining the highest safety standards. Since aircraft maintenance constitutes a significant portion of these costs, manufacturers and operators are exploring new methods to improve efficiency. One promising approach is predictive maintenance, which leverages sensor data and machine learning algorithms to predict component or system failures before they occur. Maintenance can then be scheduled at optimal times to maximize component lifespan and minimize downtime. This paper employs a systematic literature review method analyzing 60 sources to evaluate the impacts of predictive maintenance in the aerospace industry. The findings indicate that predictive maintenance offers several benefits, including reduced operational costs, enhanced safety, lower environmental impact, and improved passenger experience. However, implementation challenges remain, particularly regarding data availability, lack of regulatory standardization, limited technical expertise, and integration into legacy aircraft systems. This topic was selected due to its significant potential as an emerging technology with transformative implications for aviation. The primary limitation of this study is the limited number of available case studies; however, all relevant cases identified were included in the analysis.

Keywords: Predictive Maintenance; Aerospace Industry; Machine Learning; Artificial Intelligence; Maintenance

INTRODUCTION

Aircraft maintenance is a very complex and meticulous process with many rules and regulations in place to maintain safety and quality. In the past, aircraft maintenance consisted of only preventive and reactive maintenance. This is called traditional maintenance. Preventive maintenance is maintenance that is intended to catch system and component failures before they happen (1). An example of this is scheduled maintenance that occurs at specific intervals based on estimates of when certain systems and components will begin to degrade (1). Reactive maintenance occurs after a component or system fails and is intended to restore the aircraft to its previous safety and reliability levels (1). However, traditional maintenance strategies often incur additional and unnecessary costs. These costs can come from unneeded maintenance, component failure, more aircraft on ground time, and many other costs (2).

However, in recent years, predictive maintenance using artificial intelligence and machine learning has shown promise in reducing maintenance costs. A predictive maintenance model utilizes AI and machine learning to create predictions of the remaining useful

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life (RUL) of a component, and it is trained using sensor data from aircraft (3). Once the model is trained and deployed, it uses the data it receives from sensors on the aircraft to predict when a certain component or system will fail (3). Based on this prediction, maintenance can be scheduled at the most optimal times that maximize the component's useful life but still take place before the component's failure (4). This minimizes costs by ensuring components are not replaced or maintained prematurely and by ensuring that the components do not fail before maintenance can occur (4).

Predictive maintenance has a variety of advantages that come in the form of decreased maintenance costs, but there are also other impacts, such as challenges and additional benefits that accompany predictive maintenance. Challenges such as data quality and quantity, difficulty obtaining certifications, initial costs, and many more can discourage airlines from adopting predictive maintenance strategies. (2) Additionally, because predictive maintenance is a relatively new idea, there are still areas in which research must be done to fully understand its impact.

This literature review aims to address and explain the impacts that the benefits and challenges of predictive maintenance have on aircraft maintenance and operations, as well as to present areas in which further research should be done. Because little research has been done on the impacts predictive maintenance has on the supply chain, the environment, and passengers, this paper aims to address these gaps and explain the potential implications predictive maintenance has in these areas. Knowing these implications can help airlines and aircraft manufacturers fully understand the benefits and drawbacks that predictive maintenance has. This knowledge can be used to determine whether predictive maintenance has benefits that are significant enough for further resources to be allocated to its development and implementation.

METHODS AND MATERIALS

This paper utilizes a systematic literature review method where 70 articles and papers were read and thoroughly analyzed. During a search period of five months, 17435 sources were screened through Google Scholar, IEEE, and Scopus. Key terms such as "Predictive Maintenance," "Aircraft Maintenance," "Prognostics and Health Management," "Machine Learning," and "Artificial Intelligence" were used to screen sources. Then 17401 records were excluded or not retrieved, resulting in 34 sources being included (Figure 1). The list of the included studies is summarized in Table 1. The methodology for this literature review was adapted from PRISMA guidelines. First, the research question was established to be "What are the impacts of predictive maintenance using AI on the aerospace industry?". Next, the inclusion criteria were determined. The selected papers were required to discuss predictive maintenance that used artificial intelligence (AI), discuss predictive maintenance using AI in an aerospace setting, be published after 2020, and contribute new information that was not already discussed in a previously selected source. The inclusion and quality criteria were applied, and the selected sources and their findings were then used in conversation with each other to provide a complete

Table 1. Table of included studies and their key focuses and findings

Reference	Title	Key Focus	Findings
2	An Analysis of Barriers Preventing the Widespread Adoption of Predictive and Prescriptive Maintenance in Aviation	Analyzing the barriers preventing predictive maintenance from being adopted.	Main barriers to adopting Predictive maintenance are the complexity of prediction, validation, the cost of adoption, impact estimation, and data availability.
3	Predictive Maintenance Analytics and Implementation for Aircraft: Challenges and Opportunities	To review different data types, applications, projects, and opportunities for predictive maintenance in this industry	Research is biased towards aircraft engines due to the lack of available data sets.
5	Unified Ecosystem for Data Sharing and AI-driven Predictive Maintenance in Aviation. Computers	Introducing a unified data sharing ecosystem model	This ecosystem results in safer, more efficient, and more sustainable aviation operations.

Continued Table 1. Table of included studies and their key focuses and findings

Reference	Title	Key Focus	Findings
6	SKYWISE - Big Data Platform as a Foundation of Airlines' Predictive and Health Monitoring	Explaining Airbus's Skywise predictive maintenance technology.	Skywise successfully addresses operational and maintenance needs.
8	Alarm-based Predictive Maintenance Scheduling for Aircraft Engines with Imperfect Remaining Useful Life Prognostics	Creating an accurate alarm-based predictive maintenance model for remaining useful life predictions.	After implementing the model with imperfect RUL predictions for engines, only 7.4% of maintenance costs were from engine failures.
11	Predictive Analytics of Fuel Consumption for the Boeing 787-9 Trent 1000 Dreamliner Engine Propulsion System Using Data-driven Regression Learner Algorithms	Creating a predictive maintenance model for Trent 1000 engines on the Boeing 787-9 Dreamliner using regression learner algorithms.	The step-wise linear regression algorithm was most accurate. Additionally, these models can be used to maximize engine performance and fuel efficiency.
15	Implementation of Predictive Maintenance in the Army	Analyzing the impacts of predictive maintenance on army operations.	Predictive maintenance can increase the army's lethality and readiness.
18	Roadmap for Artificial Intelligence Safety Assurance Version I	Outlining the FAA's regulations regarding AI.	AI may complement and alter human behavior but it may not behave like a human.
19	EASA Artificial Intelligence Roadmap 2.0 - a Human-centric Approach to AI in Aviation	Outlining EASA's regulations regarding AI.	AI may not manipulate human behavior.
20	Model based and Big Data Enabled Predictive Maintenance Capability Development experience	To discuss strategies, lessons for how to build, a team of engineers, data scientists, software developers and others.	People of many professions must work together in order to create and maintain a successful predictive maintenance model.
21	A Holistic View of Predictive Maintenance in Aviation Maintenance Practices	A literature review aimed at finding the potential benefits of predictive maintenance.	There is a need for deeper cost-benefit analysis, strategies for managing resistance to change, and developing methodologies for economic performance evaluation.
23	Evaluation of Big Data Initiatives in the Aviation Industry and Boeing's Readiness for the Digital Age	Evaluating Boeing s readiness for the digital age.	Boeing has lower levels of automation in its planes compared to Airbus.
32	Global Supply Chain Quality Integration Strategies and the case of the Boeing 787 Dreamliner development	Analyzing the development of the 787 Dreamliner and its supply chain integration.	Boeing experiences supply chain issues and delays.
33	Validation for Predictive Maintenance of Aircraft Systems Using AI Models Developed with Rotor Blade Vibration Data	Creating a predictive maintenance model using rotor blade vibration data.	achieve an accuracy of 97% and a precision of 98% when predicting faults using a convolutional neural network.
34	Predictive Maintenance in Aerospace Industry Using Convolutional Neural Network	Creating a predictive maintenance model using engine data and a convolutional neural network.	The model achieved an accuracy of 98% and a precision of 96%

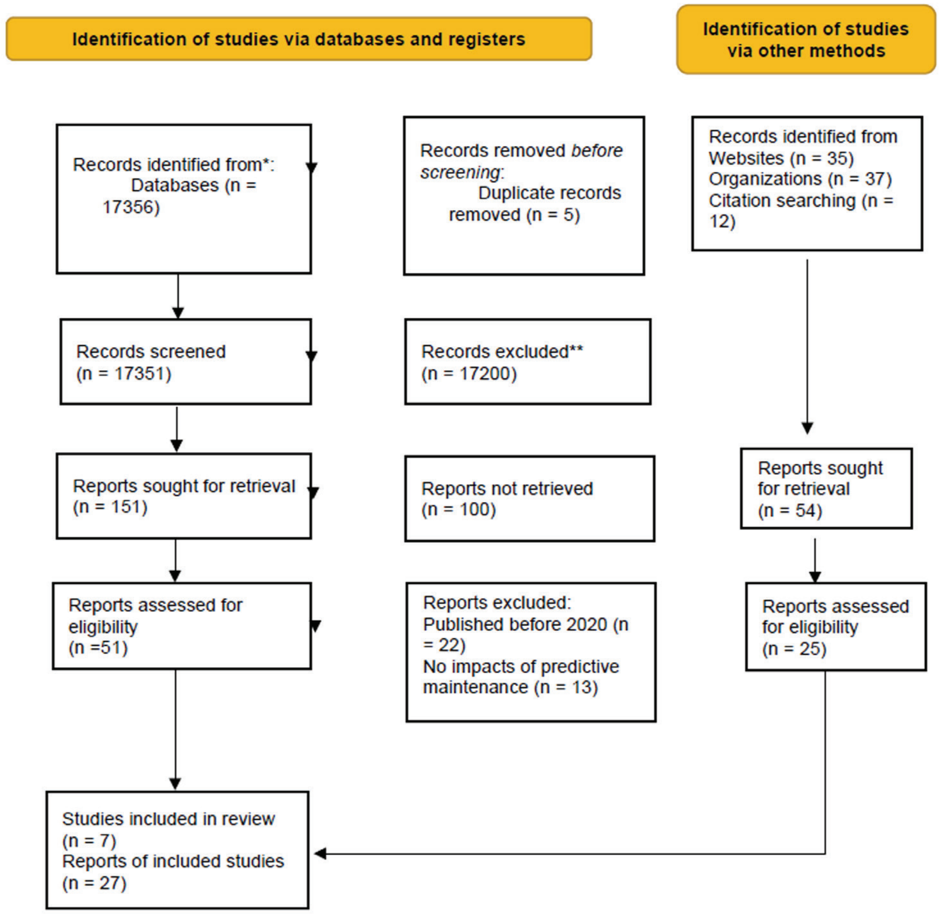

Figure 1. Prisma Flow Chart showing the process of article identification and screening.
*Consider, if feasible to do so, reporting the number of records identified from each database or register searched (rather than the total number across all databases/registers). **If automation tools were used, indicate how many records were excluded by a human and how many were excluded by automation tools.

explanation of the impacts of predictive maintenance on aerospace operations and maintenance. Potential biases in source selection may have occurred because the research question for this paper revolved around the benefits and challenges of implementing predictive maintenance in aviation. So, many sources discussing the development of these predictive maintenance models and the coding behind them were not used.

RESULTS

Benefits of Predictive Maintenance

The first and most immediate benefit of predictive maintenance is decreased costs. Predictive maintenance decreases costs in many ways. First, predictive maintenance can decrease aircraft downtime by eliminating unexpected maintenance needs and failures that may require the aircraft to be grounded for long periods of time.(5) An example of this is with Scandinavian Airlines. After Scandinavian Airlines implemented Airbus's Skywise, a predictive maintenance technology that uses aircraft data to improve maintenance, fuel efficiency, and flight operations (6), in their fleet, the aircraft equipped with Skywise experienced a 37% decrease in unscheduled downtime (7). Unscheduled downtime is a major cost for airlines, and reducing this can save a significant amount of money. Additionally, predictive maintenance can reduce the chances of components failing, resulting in the costs associated with repairing and replacing these components being eliminated (8). In addition after Skywise was implemented in easyJet airlines, it was able to prevent 79 flight cancellations in two months (9). Given that a flight cancellation can cost airlines up to $130,600 per cancellation (10), significant amounts of money are saved when these cancellations are prevented. Something worth mentioning is that even when imperfect RUL predictions were used to estimate the RUL of engines, only 7.4% of maintenance costs were from engine failures (8), showing that a predictive maintenance model does not have to be perfect to cut costs and failures. Furthermore, predictive maintenance models can be used to optimize flight paths and fuel efficiency (11). Javadi et al. (11) conducted an analysis of Rolls Royce Trent 1000 engines and created an accurate model that predicted the behavior of these engines in flight (11). The step-wise linear regression algorithm was used to identify the most significant predictors of fuel consumption, which can in turn be used to optimize engine performance and fuel efficiency (11). Fuel costs account for about 30% of airline operational costs (12), so decreasing this would save airlines significant amounts of money.

Another benefit is increased safety. Predictive maintenance can assist in keeping aircraft in the best condition and make unseen issues known (13). For example, AFI KLM E&M has also developed a predictive maintenance technology called Prognos. Prognos achieved accurate results, where every part that Prognos indicated must be removed was proven to be faulty. Because of this, the aircraft will be much less likely to have any component failures that could be detrimental to the aircraft and cause potentially fatal crashes (14). Another way predictive maintenance can increase safety is through the Army and the Air Force. Predictive maintenance can decrease the downtime of mechanized units, including aircraft in the Air Force, and can also keep these units in the best condition possible by helping operators to address failures and degradation before they can take effect (15). For example, the United States Air Force utilizes a predictive maintenance technology called Predictive Analysis and Decision Assistant (PANDA) (16). PANDA actively monitors over 1000 components and, although the exact number is not stated, has successfully detected hundreds of faults before they occurred. (16). This increases the Army and Air Force's readiness and lethality (15). When the military is more lethal and ready, the citizens are safer and more protected.

Challenges of Predictive Maintenance

The first challenge is data availability and quality. Predictive maintenance relies heavily on data from sensors on aircraft and the information they provide (2). However, sometimes the information that is required cannot be obtained because the technology required to get this information does not exist yet (2). Additionally, because modern planes produce up to 20 terabytes of just engine data per hour (17), getting the data off the plane can be an issue due to bandwidth limitations (2). Furthermore, many airlines and airplane manufacturers are hesitant to share their data due to concerns about privacy and safety (2). In addition to this, these companies refrain from sharing data because they do not see any direct benefit from doing so (5). All these issues lead to a lack of quality data.

Another challenge is the lack of standardization among aviation agencies. The FAA and other organizations, such as EASA and ICAO, have not unified in creating international standards for the use of AI (2). This makes certifying predictive maintenance technologies difficult and elongates this process (2). While there are common themes among these authorities' regulations, they have not officially created an international standard. For example, the FAA's rules for AI state that it may alter the behavior of a human, but it cannot behave like a human (18). Similarly, EASA's AI rules state that a form of unacceptable AI is AI that manipulates human behavior (19).

The next challenge is the lack of skills necessary for predictive maintenance. Due to predictive maintenance's new nature, the skills and knowledge required may not be available yet (20). This means that there is a need for training that teaches participants the skills required to work with predictive maintenance technologies and interdisciplinary collaboration (2). Interdisciplinary collaboration is necessary because predictive maintenance utilizes a variety of skill sets and knowledge (20). Data science, hardware and software engineering, software development, and reliability engineering are among the main skill sets needed (20). Additionally, maintenance professionals and collaboration with airlines are needed to ensure the models created are practical and applicable to the situations they are applied to (21).

Another challenge is integrating predictive maintenance techniques in older legacy aircraft. Because of more advanced technology and sensor capabilities, newer aircraft create much more data than older aircraft (22). Because predictive maintenance relies on large amounts of data to create the model and make predictions, there are concerns as to how and if these technologies can be used in older aircraft (23). An example of this is comparing Airbus and Boeing. Airbus designs its planes to be more automated than Boeing does, even the older planes (24). As a result, Skywise can be applied to all aircraft in Airbus's fleet, no matter the age (25). However, Boeing Airplane Health Management, Boeing's predictive maintenance technology, can only be used on the Next Generation 737, 737 MAX, 747-400, 747-8, 777, and 787 because these aircraft produce more data and are more automated (26). This leaves out older planes, such as a majority of 757s and 767s, that do not have the fitting configurations.

DISCUSSION

Predictive maintenance not only improves operational efficiency but also triggers far-reaching economic, environmental, and social effects across the aerospace ecosystem. While its primary objective is cost and safety optimization, the cascading benefits extend to passengers, manufacturers, and the global environment.

Economic and Operational Implications

Reductions in operational costs directly enhance airline profitability. According to Baldanza (27), airline profit equals revenue minus operational costs; therefore, lowering maintenance expenses increases financial flexibility. Airlines can reinvest these savings into lowering ticket prices, expanding fleets, or funding research and development (R&D). Reduced ticket prices can democratize air travel, particularly in developing regions, while stimulating competition among carriers and producing an industry-wide economic ripple effect.

Furthermore, improved aircraft reliability through predictive maintenance minimizes cancellations, delays, and unscheduled downtime, thereby improving customer satisfaction and brand loyalty. Predictive systems also streamline supply-chain operations by forecasting part demand months in advance (21), reducing emergency procurement and expediting costs, and alleviating shortages that currently strain the aerospace logistics network (32). Collectively, these operational efficiencies strengthen both economic stability and service quality across the aviation sector.

Environmental and Technological Progress

Predictive maintenance contributes to the aviation industry's environmental and technological sustainability goals. Higher airline profit margins enable fleet modernization, allowing replacement of older, fuel-inefficient aircraft with newer models that emit fewer greenhouse gases (31). Simultaneously, predictive analytics supports real-time optimization of engine performance, maintaining peak efficiency and reducing fuel waste (11). These advancements directly support the global "Net Zero 2050" initiative by lowering emissions per flight hour. Further research should examine how predictive maintenance synergizes with the adoption of Sustainable Aviation Fuels (SAF). Predictive models can monitor how SAF influences engine wear, efficiency, and performance over time, ensuring safety while maximizing environmental benefits. Together, these developments demonstrate how predictive maintenance integrates economic viability with sustainable aviation practices.

Collaborative, Workforce, and Implementation Challenges

Despite its benefits, predictive maintenance adoption faces several structural and human-capital challenges. A major limitation is the fragmented nature of aviation data and the lack of regulatory harmonization. Kabashkin and Susanin (5) proposed a unified data-sharing ecosystem that integrates stakeholders—airlines, MROs, regulators, and manufacturers—into a common predictive maintenance framework. Establishing global AI certification standards across agencies such as the FAA, EASA, and ICAO would ensure uniform validation and ethical oversight (18,19). Policymakers can further promote adoption by offering incentives for participation in such standardized ecosystems.

Workforce development is another critical factor. The implementation of predictive maintenance requires expertise in data analytics, machine learning, and aerospace engineering. However, the current workforce lacks sufficient interdisciplinary training (20). Establishing educational programs that combine these skill sets could close this gap and create a new generation of predictive maintenance professionals (2,20). Finally, integrating predictive maintenance into legacy aircraft remains a practical challenge. Many older Boeing models lack the automation and data collection capabilities required for AI-based analysis (23). Targeted retrofitting—installing selective sensors on high-priority components—offers a cost-effective way to extend predictive maintenance benefits to older fleets. Addressing these challenges through collaboration, education, and targeted investment will be crucial for maximizing the global impact of predictive maintenance.

Future Directions

Predictive maintenance remains an emerging field of study, and extensive research is required to fully understand its long-term implications and applications across the aviation industry. Future investigations should address not only technical performance but also environmental, economic, and passenger-related outcomes.

Predictive maintenance has substantial potential to transform the aerospace supply chain. By alerting operators when specific components are likely to fail or degrade, predictive models enable proactive planning for part replacements and inventory management (5). This approach minimizes last-minute orders and emergency part deliveries, which are often expensive and inefficient. As predictive models continue to learn the operational patterns of individual aircraft, they can forecast part replacement needs months or even years in advance, further improving maintenance scheduling and supply-chain reliability (23). Consequently, the reduced frequency of urgent procurement and expedited shipping can lead to significant cost savings for airlines and manufacturers.

Predictive maintenance also offers promising environmental benefits. By optimizing engine performance and fuel efficiency, it can help mitigate the carbon footprint of aviation operations (11). However, comprehensive empirical studies are still needed to quantify these benefits under real-world conditions. Additionally, future research should explore how predictive maintenance can be integrated with the use of Sustainable Aviation Fuels (SAFs) to further reduce emissions. As SAF adoption becomes more widespread, predictive systems may play a crucial role in monitoring how these fuels affect engine behavior, component longevity, and overall aircraft performance, ensuring both environmental and operational safety.

Finally, predictive maintenance may indirectly enhance the passenger experience. While improved safety is an obvious benefit, reduced operational costs can translate into lower ticket prices, fewer flight cancellations, and increased service reliability. Despite these potential advantages, there is a notable lack of research examining the passenger-level impacts of predictive maintenance. Future studies should therefore assess how these technologies influence customer satisfaction, trust in airline safety, and overall accessibility of air travel.

CONCLUSION

Predictive maintenance benefits the aerospace industry through reduced costs, increased safety, decreased environmental harm, and supply chain benefits. In addition to this, predictive maintenance can also benefit citizens around the world through cheaper travel and increased safety. It is important to consider the implications of new technologies for passengers and citizens, as well as the implications for the aerospace industry. Only then will the full effects of new technology be known.

However, several barriers must be addressed before predictive maintenance can achieve widespread adoption. The foremost challenge is the limited availability and sharing of high-quality data. Although various solutions have been proposed, most require further validation and standardization. In addition, international aviation agencies should collaborate to establish unified global standards for AI and predictive maintenance certification. Equally important is workforce development—educational programs, training courses, and workshops should be implemented to equip professionals with the interdisciplinary skills necessary for predictive maintenance. Finally, targeted research is needed to explore how legacy aircraft systems can be integrated into predictive maintenance frameworks.

Predictive maintenance holds remarkable promise for transforming the aerospace sector and benefiting passengers worldwide. To fully realize its potential, continued investment in research, collaboration, and education will be essential.

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CONFLICT OF INTEREST

The author declares that there are no conflicts of interest related to this work

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