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Subject review
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Advancing Aircraft Maintenance through Predictive Technologies and Artificial Intelligence

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Abstract: This paper explores the transition in aircraft maintenance from conventional preventative methods to predictive maintenance driven by artificial intelligence (AI). Predictive maintenance utilizes data-driven methodologies to predict failures, reduce downtime and enhance safety. Artificial intelligence plays a pivotal role by processing substantial data to identify patterns and predict maintenance requirements with a high degree of accuracy. The present study addresses the fundamental challenges associated with integrating AI into aircraft maintenance, including robust data collection, algorithm transparency and cybersecurity risks. By addressing these issues, the paper provides actionable insights and solutions to effectively utilize AI while minimizing the associated risks. This study offers a novel perspective on the use of AI to revolutionize aircraft maintenance and improve efficiency and reliability, building on existing research and identifying opportunities to advance AI-driven maintenance strategies in aviation.

Keywords: artificial intelligence; Industry 4.0; passenger aircraft; predictive maintenance; quality process

1 INTRODUCTION

The increasing complexity of modern aircrafts, particularly in the area of electronic systems, has sparked a research interest in exploring innovative solutions for aircraft maintenance [1]. This area encompasses not only technical requirements but also critical factors to ensure passenger safety, operational efficiency, and cost effectiveness in the aviation industry [2]. The impetus for this research stems from the realization that traditional preventive maintenance approaches, while effective to a certain extent, are no longer sufficient to meet the demands of today's highly interconnected and technology-driven systems [3].

The emergence of predictive maintenance supported by artificial intelligence (AI) has proven to be a transformative opportunity in this area [4]. The potential of this approach lies in its ability to anticipate failures before they occur, leading to a significant reduction in unplanned downtime, optimized resource allocation and improved safety standards [5-7]. Despite the promising possibilities of this approach, it is important to recognize the challenges associated with it, such as the need for reliable data, transparent algorithms, and robust cybersecurity measures [8-10]. These challenges underscore the necessity for concerted research and innovation in this field. With this in mind, a systematic literature review providing a basic understanding of the challenges in aircraft maintenance associated with the shift from preventative to AI-powered predictive maintenance is provided in this paper.

Prior to presenting the main literature review findings, it is first necessary to give sufficient background information about the key concepts that undergird this study. Some of these concepts also form the basis for the keywords for the literature search. This is therefore done throughout the course of the subsequent chapter.

2 OVERVIEW OF KEY THEORETICAL CONCEPTS

2.1 Predictive Maintenance

The term "predictive maintenance" refers to condition-based maintenance that is conducted based on forecasts from analytics and known qualities of the characteristics of the state of an asset's degradation. It is considered to be an advancement from traditional maintenance practices, which typically only take place based upon information concerning the current condition of assets. It frequently draws upon data provided via artificial intelligence and the Internet of Things, which facilitate real-time access to insights into the asset's availability, condition, and location. This enables the augmentation of human decision-making via the prediction of asset health and allows responses to be made pre-emptively as opposed to reactively [11].

2.2 Artificial Intelligence

Although there is no ubiquitously defined definition of AI, it can be broadly conceptualized as digital technology that seeks to make machines operate in an intelligent manner dependent on workings that resembles those of the human mind [12, 13]. Within this context, the term "intelligent" refers to possessing the ability to find a solution to complex problems. It typically evolves data analysis, with the deployment of computer-generated rules based upon this data for the purpose of problem-solving being known as "machine learning" [12, 13].

AI has undergone numerous different advancements since the 1950s and recently experienced a period of dramatic progression. This has been heralded by various different developments including more sophisticated algorithms coming into being, improvements in the leveraging of big data, and an increase in computation speed [12]. Artificial intelligence is regarded as being especially important in the field of maintenance, where it can be regarded as a particularly disruptive innovation [14].

2.3 Industry 4.0

The term "Industry 4.0" refers to an industrial paradigm characterized by the integration of communication technologies, intelligence and digitalization into manufacturing practices [4]. This concept has been included in this section on account of the fact that both AI and

preventative management are considered to be closely tied to it [4, 15, 16] Although there are various different perspectives on what Industry 4.0 entails, it is generally held to be characterized by the following 9 pillars:

- Big data – high volumes of data are collected, prepared and analysed in order to facilitate advanced decision-making.
- Autonomous robots – intelligent machines that are able to carry out tasks with minimum human involvement.
- Simulation – digital imitations of systems and their characteristics are used for testing purposes.
- Additive manufacturing – the production of physical objects based upon 3D models by joining together successive material-layers.
- Vertical and horizontal integration – the former entails an interaction at various different levels within the hierarchical management-structure of an organization. The latter assumes that all internal and external entities and department are involved in creating value chains.
- The Internet of Things – physical objects are equipped with sensors that store, interchange and analyze data in order to enable adaptive decision-making and improve efficiency.
- Cloud computing – the storage of data and usage of resources via remote online platforms.
- Cybersecurity – practices, processes and technologies aimed at defending interconnected systems from cyber-attacks and data leaks.
- Augmented reality – the use of enhanced replicas of the physical domain using sound, computer graphics and other sensory data [17].

The impact of Industry 4.0 on maintenance has been identified as one of the main ways in which it can drive value for an organization [18]. The use of Industry 4.0 technologies for industrial-maintenance purposes is known as Maintenance 4.0 [19]. Now that the key concepts that underpin this study have been defined and described, the methodology can be presented.

3 METHODOLOGY

Before carrying out a systematic literature review, it is necessary to create a search protocol. The Systematic Review Model, as detailed by Vasquez and Castrillon, formed the basis for this protocol [20]. This model holds that the protocol consists of three different elements: the search question, keywords, and exclusion and inclusion criteria. The search question is the question that the review is geared towards answering [20]. It is "What are the main challenges associated with these advancements?"

The keywords that were used in this review are "artificial intelligence", "predictive maintenance", "quality process", "passenger aircraft" and "Industry 4.0". Predictive maintenance and artificial intelligence are both considered to be products of Industry 4.0, hence the selection of this concept as a search term [15, 16].

The inclusion criteria for the papers included in this study are that they need to have been published in the last 5 years and appear in a peer-reviewed academic journal, book published by an academic publisher, or proceedings of a reputable academic conference. They also need to be directly relevant to the topic of study. The exclusion criteria are publication over 5 years ago, appearance in texts other than those listed in the inclusion criteria, and obvious sources of bias or error. It was determined that the Scopus database would be used for the literature search, as it is considered to be amongst the most substantial curated databases, containing over 1.7 billion sources [21]. This means that it is likely to provide a suitably broad view of the current base of theory and research about the subject of study.

Furthermore, it is notable that Zaaba et al. have previously described Scopus as a "valuable resource for obtaining a global overview of scientific research output" [21, p. 533]. They express the view that it can facilitate significant insights into specific topics and trends [22]. This highlights the utility of searching within this database and its suitability for the present review. The Web of Science database was also used to further expand the volume of results.

The data included in the review was extracted by first screening the abstracts of articles for relevance and to see if they pass the inclusion criteria then thoroughly reading to full text articles to further check eligibility. The relevant portions of each text were then compiled in a document along with the accompanying bibliographical data ready for review. The data was analysed by identifying key themes relevant to the subject of study.

In addition to synthesizing, analysing and discussing the literature that is revealed by this search within the context of the research topic, the visualization tool VOSviewer was also deployed to provide a visualization of the connections and key concept clusters in the research area. It was selected for this purpose on account of it being easy and efficient to use and the fact that Ma has emphasized It is also useful for providing a rich, insightful display of bibliometric data and linkages [22]. The findings of the literature review are now outlined.

4 LITERATURE REVIEW

Fig. 1 shows the visualization of the connections and key concept clusters. As can be seen, digital twins, artificial neural networks, prediction accuracy, prediction models, maintenance costs, and maintenance accuracy emerged as prominent concepts within the literature in addition to topics such as predictive maintenance and artificial intelligence that featured as keywords. Various other related paradigms were also touched upon in the literature including AI techniques, data quality, defect detection and process monitoring. A total of 19 articles are included in the review.

It is now necessary to examine the main insights from the review. Kabashkin, Federov and Perekrestov note that it needs to be possible to integrate the requisite programs for AI-drive predictive-maintenance with the organization’s existing maintenance systems [23]. Furthermore, Kabashin et al. and Kabashkin and Susanin put forward the perspective that organizational resistance can act as an impediment to the

effective utilization of AI-based predictive maintenance in aircrafts [2, 23]. The latter point out that concerns about jobs being replaced could potentially act as a catalyst for discontent about the deployment of AI for this purpose [2]. Kabashin et al. and Kabashkin and Susanin posit that change management can go some way towards rectifying this issue [2, 23].

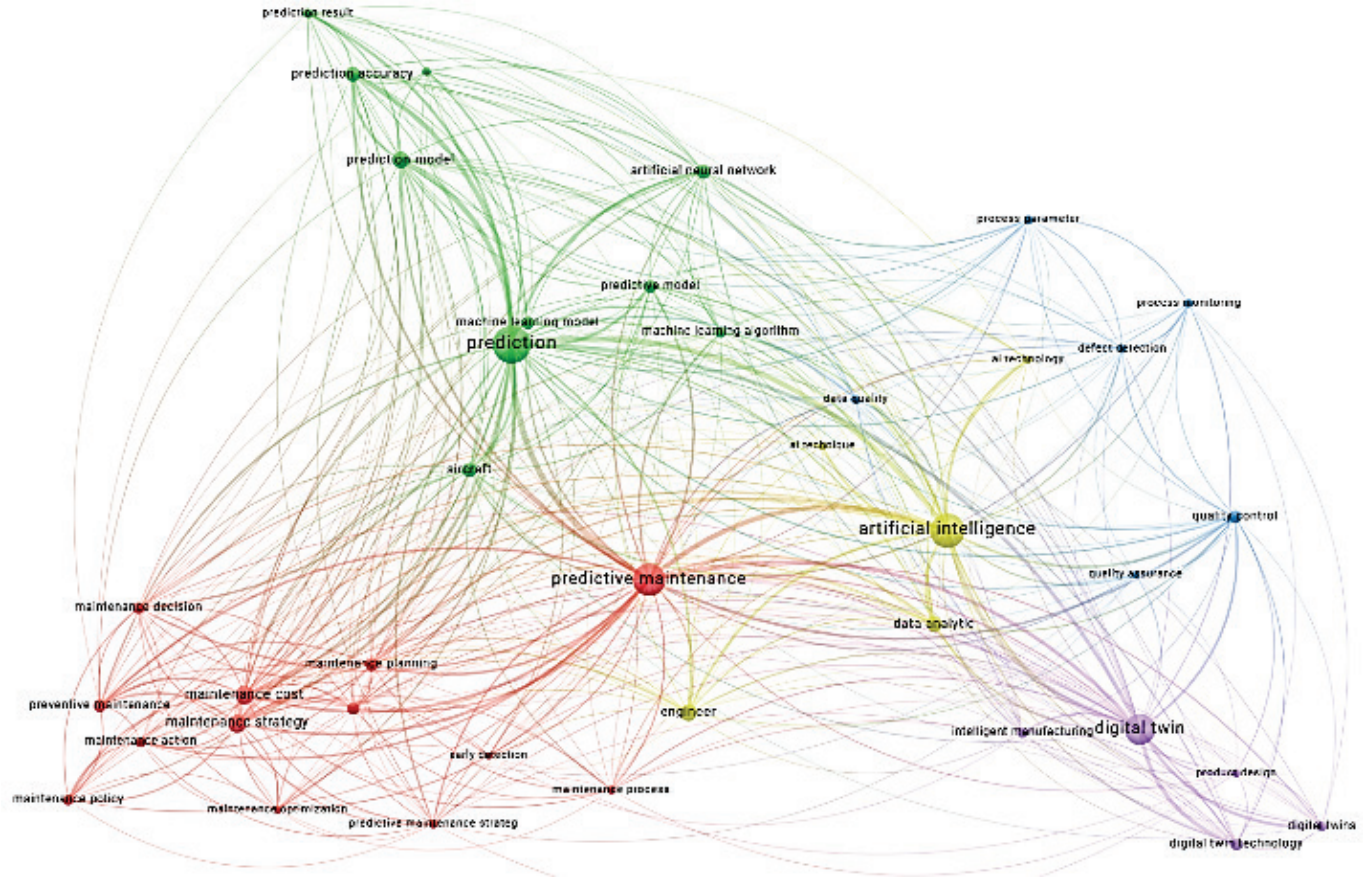


Figure 1 Visualization of Connections and Key Concept Clusters

Furthermore, Kabashkin and Susanin point out that there are challenges associated with the new skill sets required for employees to deal with AI-driven predictive-maintenance systems. They indicate that additional training is required in order to accommodate the new requirements. The workforce essentially needs to be upskilled in order to enable it to interact effectively with the new approaches [2].

Kabashkin et al. claim that compliance and regulatory requirements create additional complications, as they mean that predictive-maintenance strategies need to gain approval before being implemented [23]. Kabashkin points out that it can be time consuming for aviation authorities to approve comprehensive changes to maintenance of the types required to implement predictive-maintenance systems involving AI. He pinpoints this as a potential barrier to adoption. The literature also indicates that a considerable number of resources frequently typically need to be put towards attaining approval and thorough documentation and validation are needed to demonstrate compliance [24]. This could potentially reduce the usefulness of machine-learning-oriented predictive-maintenance systems, given that it means that they are relatively resource-intensive.

Furthermore, the aviation industry's global nature adds extra complexity to the situation, as different nations have different regulations that need to be adhered to. They also have different data-protection requirements and available technologies. These factors make it more complicated to meet the compliance-based and technical requirements of AI-based predictive-maintenance systems [2].

Kabashkin points out that transparency is needed in order to meet regulatory requirements [25]. AI decisions need to be adequately explained to ensure that regulations are met. This is especially the case with regards to safety-critical scenarios [2, 25]. Transparency is also necessary for building trust amongst stakeholders [2].

According to Kabashkin and Susanin, the key to additional transparency lies in conducting further research into interpretable models for machine learning and explanation frameworks intended for blackbox models. Furthermore, Pelt and Stamoulis highlight the additional legal and compliance-based issues that are brought up by the utilisation of AI in predictive maintenance [26]. Kabashkin and Susanin point out that it raises questions regarding certification and liability. This could potentially make it more complicated to navigate the regulatory environment. It can

also make it more expensive and resource-intensive to do so [2].

Kabashkin and Susanin also highlight the ethical challenges posed by the use of AI-based predictive-maintenance systems in aircrafts [2]. They state that "Questions arise about the level of autonomy these systems should have and where human oversight is necessary" [2]. Difficult human decisions clearly need to be made in order to accommodate the changes to new approaches to maintenance.

According to Kabashkin, there are also questions regarding who should be accountable for safety issues stemming from inaccurate predictions made by AI-based predictive-maintenance systems. This is likely to be more of an issue throughout the years to come as AI develops the possibility of acting more and more autonomously [25].

Further to this, Korba et al. have identified privacy-related challenges associated with the use of AI-based predictive-maintenance systems [27]. Korba et al. point out that sensitive operational data should be kept safe and Kabashkin and Susanin note that difficulties may arise regarding the responsible collection of data and the avoidance of impinging upon privacy rights of crew members and passengers [2, 37]. This could potentially necessitate additional effort and the deployment of extra resources.

This is especially the case when it comes to sharing training data for machine learning between airlines. When sharing data for this purpose, the issue of information being shared that about an aviation company that could potentially provide a rival with a competitive advantage also arises [2; 25]. Kabashkin and Susanin note that federated learning can be deployed in order to mitigate this issue. This entails multiple different airlines collaboratively training models without sharing any raw data [2]. Aircrafts learn from their own data and only share model updates with the central server. The server then aggregates the updates [25].

However, it is notable that federated learning is not without its limitations, as it creates additional computational complexity. Furthermore, it can be hampered by differences in the models used by airlines. It also requires careful coordination, meaning that it could potentially be demanding in terms of the staff competencies that are required in order to effectively facilitate it [2].

In addition to these points, federated learning involves the additional challenge of ensuring that the model generalises effectively across different operating conditions and aircrafts. Furthermore, cybersecurity is paramount and it is important to protect against vulnerabilities throughout the learning process. It is also notable that the airplanes generate substantial highly heterogenous datasets that necessitate efficient processing in order to facilitate real-time decision-making. However, the extensive data aggregation involved in federated learning can cause delays that can compromise safety in some cases [25]. This suggests that this is not always an ideal solution for privacy concerns.

Kabashkin and Susanin indicate that data privacy issues can also be mitigated by encrypting and anonymising sensitive information. They indicate that privacy constraints should be identified from the outset, as should data-sharing requirements. Comprehensive data-governance policies can further safeguard against the improper sharing or usage of data [2].

Stanton et al. highlight the expenses involved in AI-based predictive maintenance. They point out that it can be costly to attain the necessary resources and train staff to effectively utilise the requisite new technologies. Furthermore, they point out that the fact that aircrafts are complex, engineered objects contributes substantially to the costs that are involved. They highlight the fact that installing advanced predictive-maintenance systems in these vehicles requires specialist knowledge and especially intensive sensor-networks. According to them, the required expenses can create psychological barriers to aviation companies implementing AI-based preventative maintenance [28].

Kang et al. note that HetGPO, the current best-performing machine-learning-based method for resource scheduling in aircrafts based on ongoing feedback, lacks sufficient competency at modelling more complex multi-level and multi-dimensional relationships. This limits the usefulness of predictive maintenance based upon it, as the relevant models are unable to comprehensively capture the required depth of information from the available data [29].

Lee, Hussain and Oh also highlight the unsuitability of some AI-based approaches to predictive learning that are deployed in aircrafts for dealing with situations involving high complexity-levels. They point out that logistic regression is ineffective at dealing with complex, non-linear patterns [2]. This suggests that some of the current techniques for predictive maintenance are sometimes unable to cope with the complicated requirements of passenger aircrafts. However, Kang et al. proposed and tested a solution involving algorithms that leverage heterogeneous hypergraphs and found that they are more capable of handling the necessary levels of complexity [29]. This indicates that as the underlying models to continue to become more and more advanced, issues of this nature are likely to become less and less prominent throughout the years to come.

Klekowicki et al. indicate that insufficient access to real-world data can act as an impediment to the use of predictive-maintenance systems based on large language models. A large language model is a machine-learning model that is capable of designing and processing human-like text based upon a vast quantity of training data. Whilst synthetic, non-real-world data can be leveraged in order to mitigate issues relating to data access, it does not typically accurately replicate the anomalies and noise that naturally take place during the actual functioning of aircraft equipment. According to Klekowicki et al., these real-world irregularities often come about as the result of environmental factors, wear and tear and unpredictable environmental conditions and are essential for comprehensive diagnostics. This can limit the potential for accurate predictions and decrease the robustness of models for diagnosis when they are applied to live circumstances [31].

Berghout et al. claim that predictive-maintenance systems for aircrafts based on deep-learning models can often struggle in situations in which there is high levels of noise,

outliers, large numbers of required measurements, and high levels of distortion. They indicate that this makes it hard for the models to accurately capture data points and the relationships that exist between them. However, they indicate that this challenge can be overcome by implementing sufficient data-processing to mitigate the impact [32].

It is also notable that Berghout et al. highlight the need for additional research into outlier removal algorithms, denoising and data-complexity reduction methods. They indicate that this could potentially reveal insights that go some way towards remedying the aforementioned challenges [32]. This therefore appears to constitute a means of uncovering information that can help to circumnavigate this limitation.

The literature suggests that support-vector-machine-based and K-nearest-neighbour-based predictive-maintenance systems for aircrafts in particular tend to be sensitive to noisy datasets, outliers and missing data points. Support-vector-machine-based also tend to underperform in situations in which the number of features is greater than the number of dimensions. K-nearest-neighbour-based systems are unable to effectively deal with large numbers of dimensions and necessitate feature-scaling [28, 33]. Research conducted by Farina et al. involving the use of AI-driven predictive maintenance in aviation suggests that k-means clustering algorithms can sometimes produce false positives as a result of overlapping clusters [34]. This suggests that this is a challenge associated with this type of model.

According to Berghout et al., drift is another significant issue associated with predictive-maintenance systems based on deep learning [32]. They define this as "continuous change in statistical properties over time" [32]. It can occur as a result of variations in conditions and changes to the system's undergirding dynamics.

Berghout et al. [32] also draw attention to the need for data quality. They express the view that there is a pressing need for additional techniques to be developed that centre upon assessing it [32]. Research in this area could therefore potentially help to overcome this challenge.

Apostolidis, Bouriquet and Stamoulis highlight the fact that required data-quality cannot be considered to be fixed within the context of AI-based predictive-maintenance systems for aircrafts. They point out that it depends upon the desired outcome and application [35]. This indicates that there are also challenges involved in defining what actually constitutes a high standard of data in different situations.

Furthermore, it is notable that Korba et al. also highlight the fact that a high quality of data is necessary for implementing artificial-intelligence-driven predictive-maintenance systems in aircrafts while also acknowledging that effective data-management systems need to be in place [27]. This suggests that it is insufficient to merely have the necessary data; procedures also need to be in place for ensuring that it is adequately stored and managed. It highlights the role of systemic, organisational factors in the effective usage of this technology.

Kabashkin expresses concern that there is a danger that overconfidence in machine-learning-driven predictions could potentially result in human oversight [24]. He points out that for predictive maintenance driven by AI to be successful within the context of the aviation industry, it is essential to maintain "a balance between technological assistance and human expertise in decision-making" [24]. This indicates that there are challenges associated with obtaining this balance and that failure to do so could have life-threatening consequences.

The findings of research carried out by Lee at al. suggest that recurrent neural networks, which are an AI-based approach that is sometimes used in aircrafts, have high computational costs associated with them [29]. Kabashkin and Susanin also note that AI-based predictive-maintenance systems can be computationally demanding. Furthermore, they can necessitate extensive infrastructures, which could be challenging to smaller airlines. Optimisation techniques and lightweight AI models can help to mitigate this issue [2].

The literature also indicates that random-forest-based and particle-filler-based predictive-maintenance systems used in aviation are computationally intensive. The former also suffers from long training times and struggles to work out the significance of parameters. Convolutional neural networks also struggle with slow training-times and are unable to model long-term dependencies [28].

Lee et al.'s research indicates that recurrent neural networks suffer from a vanishing gradient problem, as do approaches involving Long Short-Term Memory. This reduces the effectiveness of these methods [30]. The former of these techniques also requires a considerable number of resources. Furthermore it, is incapable of modelling long-term dependencies. The latter suffers from high computational requirements and slow training times [28]. Zhou et al. note that Long Short-Term Memory models also have poor generalisation ability when under multiple different operating conditions or when multiple different faults are present [36]. Given the possibility of a diverse range of faults taking place in aviation, this arguably substantially reduces their suitability for usage within the context of aircrafts.

It is also notable that Lee et al. found that approaches involving Support Vector Machines can suffer from high processing-times when attempting to deal with high-dimensional data. The researchers point out that whilst convolutional neural networks appear to constitute the most effective approach for usage in predictive maintenance, they have not yet been validated for all aircraft components [30]. This arguably limits their utility.

Kabashin and Perekrestov note that it is both costly and technically challenging to integrate the new security measures that are required for AI-driven preventative maintenance with the existing aviation infrastructures. This could also be problematic in many cases and might necessitate expensive upgrades or even tailor-made solutions that fail to provide the same degree of protection as before. Furthermore, security threats need to be constantly evaluated in order to identify and address emerging threats to the systems [14].

According to Kabashin and Perekrestov, the solution to this lies in collaboration throughout the industry to create

standardised security-protocols. They claim that this can help to mitigate the additional security risks that AI brings with it. However, these protocols nevertheless still need to be regularly revised [14].

The findings of research carried out by Kumar et al. and Khalifeh and AlMeqdadi indicate that there is a trade-off between the time taken to complete the necessary computations and the accuracy of the results when it comes to the underlying mechanisms behind machine-learning-powered predictive-maintenance systems that are suitable for the aviation industry [35; 36]. Finding the optimum balance for each use case consequently constitutes an additional challenge [37]. Kumar et al. also highlight the fact that models can be complex to train [36]. This could potentially necessitate a high level of human expertise.

Yildirim and Yana express the view that some of the machine-learning models used for predictive maintenance in aircrafts lack the ability to effectively harness temporal correlation characteristics that are present within time series data. This can hamper their competence at making accurate and precise predictions in some circumstances [39]. This appears to constitute a challenge associated with the usage of such models that needs to be overcome.

Further to this, Stanton et al. indicate that the datasets that are utilised for training the machine-learning models for predictive-maintenance systems used in aviation are frequently imbalanced. This is due to the fact that faults are not common in aircrafts. This results in the available data being skewed towards normal operation, leading models to struggle to adequately learn about system failures. According to Stanton et al., in some cases there is a complete lack of failure data as faulty components are replaced prior to reaching the failure stage [28].

Stanton et al. also note that the substantial numbers of sensors in aircrafts can result in high dimensionality within the data that is collected [28]. This can result in what they refer to as the "curse of dimensionality", which is when "the higher the dimension space, the denser the data samples are required" [28, p. 230]. This constitutes yet another potential challenge.

Korba et al. highlight the need for incorporating AI-driven predictive maintenance into existing workflows. This suggests that there are challenges associated with factoring it into preexisting routines and processes. They point out that the algorithms that are utilised need to be able to be used in conjunction with existing operational procedures, databases and databases and sources of data. Failure to do this can result in disruptions to existing workflows [27].

Cheng et al. highlight the fact that there is a plethora of different machine-learning-based predictive-maintenance methods available that are suitable for use in aviation and indicate that this in and of itself poses challenges. They point out that each technique has its own unique limitations and applicable conditions associated with it. According to Cheng et al., this means that it is often hard to determine which method is likely to perform best in which situation. They claim that this issue is compounded by the fact that prediction performance can be compromised by applying deep-learning-based methods to diverse scenarios, meaning that the results suffer as a consequence. This can make it harder to pinpoint which method is best for which purpose [40].

The literature also highlights some challenges that specifically relate to deep-belief-network-based predictive-maintenance systems. They underlying models struggle to model temporal relaxations. Furthermore, they suffer from a tendency to overfit [28].

Furthermore, ongoing innovation and the need for continuous adaptation constitutes another challenge, as rapid technological development means that predictive-maintenance technologies need to be sufficiently flexible to incorporate new analytical methods, sensors and other technologies as they emerge. This necessitates a commitment to ongoing investment and improvement. As predictive maintenance systems incorporate more and more data from different sources throughout the years to come, the need for complex algorithms that are able to efficaciously combine and analyse disparate data types will grow. Changes will also be required in order to accommodate this [38].

Kabashkin and Perekrestov also note that AI models for predictive maintenance need to be capable of evolving with changing operational practices and aircraft technologies. They need to be easily updated in order to maintain their relevance and accuracy as time goes on [14]. This could also potentially prove challenging.

Now that the insights provided within the literature have been synthesised and detailed, it is necessary to present a detailed discussion of them. This allows for them to be understood within the context of the subject of the review. It is consequently done throughout the course of the subsequent chapter.

5 DISCUSSION

As can be seen in Fig. 2, the challenges in aircraft maintenance associated with the shift from preventative to AI-powered predictive maintenance fit broadly into five main categories. The first of these categories is finance- and resource-based challenges. These challenges include the fact that additional resources need to be put towards implementing predictive-maintenance systems and ensuring compliance [23, 28]. This category is connected to the next category; legal, accountability-oriented and ethical challenges; as the additional legal and ethical complications brought about by the move to machine-learning-oriented predictive maintenance necessitates the additional costs and resources [2]. Challenges within this category include questions regarding accountability, more complex considerations concerning compliance and difficulties in gaining approval for new systems [2, 23]. Ways of mitigating challenges in this area include a number of different measures geared towards bolstering transparency [2, 25].

The two aforementioned categories are also linked to the next category, human factors, as staff can be classed as a resource and human beings are inherently bound up in the ethical and legal decision-making within a firm. Human factors that pose challenges include attitudinal issues such as concerns about AI replacing jobs and scepticism about it and also those related to staff being adequately skilled to deal

with the new predictive-maintenance systems. Solutions involve change management and the provision of training [2].

All three of these categories are connected to the category of privacy and cybersecurity, as this requires resources and human input and breaches have potential legal consequences. Means of mitigating these challenges include encrypting and anonymising sensitive information and putting comprehensive data-governance policies in place [2].

The final category is performance- and efficiency-based issues, which is linked to human factors, as the models themselves are implemented by human actors, and finance- and resource-based challenges, as some are related to resources such as computing power [2]. A wide variety of challenges arose in this area, some specific to certain types of AI and some having implications across the spectrum. They include but are not limited to issues related to computational intensity, handling complexity, dealing with noise and anomalies and coping with outliers [2, 29, 31, 32]. Solutions include the careful choice of AI models to ensure the most suitable is selected for each purpose and a variety of strategies tailored to various individual problems [2, 32, 39].

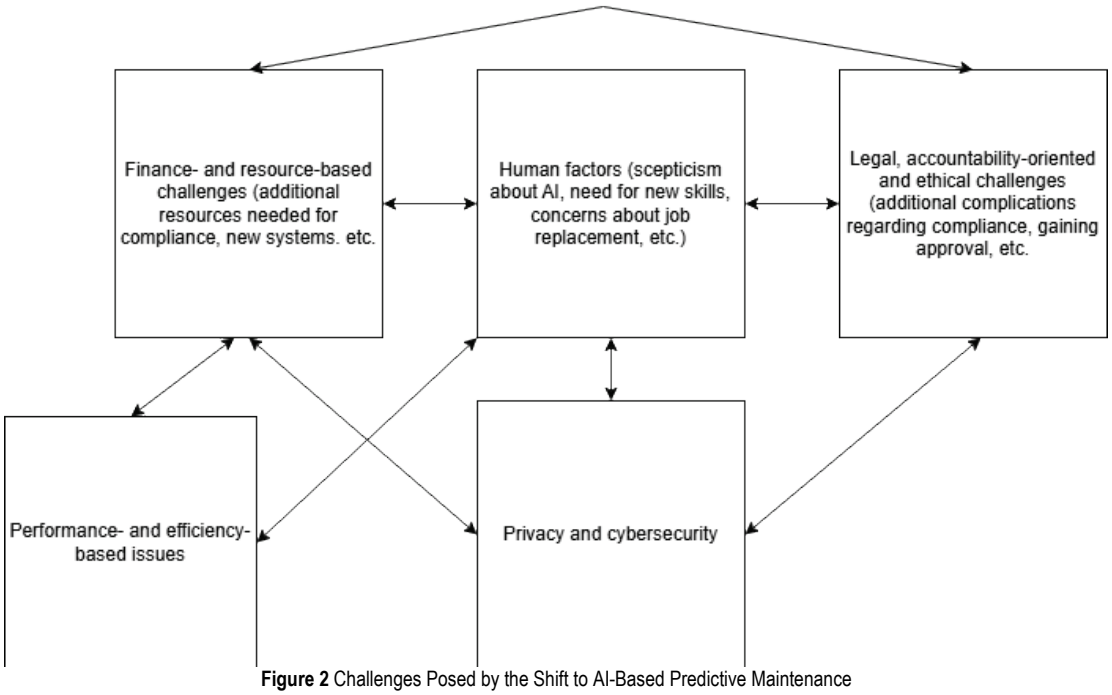


Figure 2 Challenges Posed by the Shift to AI-Based Predictive Maintenance

The findings also suggest are differences in the challenges posed by different AI models. They suggest that HetGPO lacks sufficient competency at modelling more complex multi-level and multi-dimensional relationships [29], whereas logistic regression is ineffective at dealing with complex, non-linear patterns [2]. They indicate that K-nearest-neighbour-based predictive-maintenance systems for aircrafts tend to be especially sensitive to noisy datasets, outliers and missing data points and that they are unable to effectively deal with large numbers of dimensions [28], whereas neural networks and random-forest-based and particle-filler-based predictive-maintenance systems have high computational costs associated with them [28, 29]. This suggests that rather than adhering to the perspective that there is a single optimum model, they should be chosen according to the degree to which their weaknesses compromise the specific purposes for which they are utilised.

Overall, the results highlight a multitude of different obstacles that need to be effectively navigated in a number of different areas. While some remedies emerged from the literature, other challenges do not appear to have a clear solution. This suggests a pressing need for additional research in this area.

6 CONCLUSION

This literature set out to identify the challenges associated with the challenges in aircraft maintenance associated with the shift from preventative to AI-powered predictive maintenance. It revealed that five main types of challenges exist: those related to the requisite financial and non-financial resources and the strain that implementing a new system entails with regards to them; human factors; legal, accountability-related and ethical challenges; novel privacy- and cybersecurity-related issues stemming from the new systems; and issues related to the performance and efficiency of the AI models. Pressing challenges that arose throughout the course of the review include the need for transparency to more easily demonstrate compliance; the limitations associated with the functionality of various different AI models; staff resistance to a new system and scepticism of AI; and economic constraints.

A number of different solutions arose from within the literature. Change management could be implemented to reduce scepticism and ill feeling towards AI. Training could be provided to staff in order to endow them with the relevant competencies. A concerted effort could be made to keep

sensitive operational data secure and federated learning could be deployed. Sensitive information could also be encrypted and anonymised. Privacy constraints should be identified from the outset, as should data-sharing requirements, and comprehensive data-governance policies can help to overcome challenges regarding upholding data privacy. Sufficient data processing can go some way towards remedying issues with noise and outliers, as can the careful selection of AI models that are appropriate for the specific purpose within aviation that they are being used for.

Further to this, efforts could also be made to strike a balance between human diligence and the use of AI in order to avoid errors stemming from overconfidence in the latter. Lightweight AI models can be deployed to mitigate issues with computational requirements. A commitment to ongoing investment in AI-based predictive maintenance and the improvement of systems can also help to safeguard against future issues.

It is notable that the rapid rate at which technology changes means that the findings of this review might not necessarily hold true within the immediate future. It is therefore recommended that future literature reviews on this topic are carried out at regular interviews. Furthermore, given the heterogenous nature of machine learning models, primary research focussing upon specific models should also be conducted at frequent intervals.

Another limitation of this study is the fact that it merely reviewed published sources, meaning that grey literature and sources yet to be published were excluded. It can therefore be considered to be a review of a large number of relevant sources as opposed to being exhaustive. Its findings could also potentially have been impacted upon by publication bias.

Furthermore, given that the search strategy was devised by the researchers, the possibility exists that this might have influenced the sources that were included in the review. However, the use of a rigorous search strategy means that efforts were made to reduce the extent to which this affected the results. Efforts were also made to ensure that the keywords were as tightly related to the subject of the review as possible.

In order to enhance aviation companies' ability to further mitigate the challenges that have been identified, it is recommended that additional research is carried out on predictive maintenance that takes the industry's strict safety requirements into consideration given that a dearth of empirical research in this area was mentioned within the literature. Furthermore, given that the literature identified a lack of studies that evaluate the feasibility of machine-learning-driven predictive-maintenance systems across critical operational and economic dimensions, it is also advised that this is an area in which additional research is required.

It is also recommended that future studies should focus upon who is accountable for faults on the part of the AI involved in predictive-maintenance systems, given that the literature also indicates a gap in this area. It is also advised that additional research into outlier removal algorithms, denoising and data-complexity reduction methods should take place. Future studies into interpretable models for machine learning and explanation frameworks intended for blackbox models could also help to mitigate issues with the transparency of the AI used in predictive maintenance in aviation.

This literature review has helped to provide a clear insight into the various different obstacles, problems and pitfalls associated with the ongoing shift towards the usage of AI and predictive maintenance in aviation. It has shed light on not only what challenges have manifested but also those that are likely to become prominent throughout the years to come. Furthermore, it has illuminated the precise form that some of these issues take.

Furthermore, the study has shown what the current base of literature says about how to overcome some of the challenges that were identified. Although solutions were not identified for some problems, it is nevertheless useful to gain an insight into their characteristics so that future remedies can be established. This paper has therefore contributed a thorough overview of the issues associated with this facet of Industry 4.0 within the context of aviation. Given the importance of safety within this field, its findings have clear utility and can act as a firm basis for future research in this domain.

7 REFERENCES

[1] Karim, R., Galgar, D., & Kumar, U. (2023). *AI factory: Theories, applications and case studies*. Boca Raton, FL: CRC Press, 2023. https://doi.org/10.1201/9781003208686

[2] Kabashin, I., & Susanin, V. (2024). Unified ecosystem for data sharing and AI-driven predictive maintenance in aviation. *Computer*s, *13*(12). https://doi.org/10.3390/computers13120318

[3] Doogakant, B., Fowdur, T., Milovanovic, D., & Bojkovic, Z. (2025). 5G/6G-based sustainable systems for Industry 4.0, in T. Fowdur, D. Milovanovic & Z. Bojkovic (eds.), *Intelligent and Sustainable Engineering Systems for Industry 4.0 and Beyond* (pp. 29-58). CRC Press. https://doi.org/10.1201/9781003511298-2

[4] Bhatia, V., Sidhartha, S., Khare, S., Ghorpade, S., Kumar, P., Kumar, A., & Agarwal, A. (2024). Intelligent manufacturing in aerospace: Integrating Industry 4.0 technologies for operational excellence and digital transformation, in A. Kumar, P. Kumar & Y. Liu (eds.), *Industry 4.0 Driven Manufacturing Technologies*. Springer Natuire Switzerland. https://doi.org/10.1007/978-3-031-68271-1_18

[5] Mazumdar, B., Mishra, M., Ghatak, A., & Verma, V. (2025). AI for industry 4.0 with real-world problems, in A. Tyagi, S. Tiwari and G. Soni (eds.), *Data Analytics and Artificial Intelligence for Predictive Maintenance in Smart Manufacturing* (pp. 326-352). CRC Press. https://doi.org/10.1201/9781003480860-15

[6] Sivakumar, M., Maranco, M., & Krishnaraj, N. (2025). Data analytics and artificial intelligence for predictive maintenance and manufacturing, in A. Tyagi, S. Tiwari and G. Soni (eds.), *Data Analytics and Artificial Intelligence for Predictive Maintenance in Smart Manufacturing* (pp. 29-55). CRC Press. https://doi.org/10.1201/9781003480860-3

[7] Kumar, D. & Batra, J. (2024). The pioneering convergence of data analysis and predictive maintenance. In Gatti R., & Singh, C. (eds.), *Shaping the Future of Automation with Cloud-enhanced Robotics* (pp. 38-64). IGI Global.

https://doi.org/10.4018/979-8-3693-1914-7.ch003
[8] Shukla, A., & Dubey, K. (2024). Deployment issues in industrial resolution. In Dubey, A., Yadav, V., & Trivedi, M. (eds.), *Computational Intelligence in the Industry 4.0* (pp. 161-188.). CRC Press. https://doi.org/10.1201/9781003479031-10
[9] Ucar, A., Karakose, M., & Kirimca, N. (2024). Artificial intelligence for pedictive maintenance applications: Key components, trustworthiness, and future trends. *Applied Sciences*, *4*(2). https://doi.org/10.3390/app14020898
[10] Padmavathi, S., Nevetha, B., Sakthi, R. & Varshini, K. (2025). Machine learning for reliable industrial operations: Predictive maintenance. In Murugan, T., & Singh, W. (eds.), *Cybersecurity and Data Science Innovations for Sustainable Development of HEICC* (pp. 316-330). CRC Press. https://doi.org/10.1201/9781032711300-22
[11] Kristoffersen, E., Aremu, O. O., Blomsma, F., Mikalef, P., & Li, J. (2019). Exploring the Relationship Between Data Science and Circular Economy: An Enhanced CRISP-DM Process Model. In Pappas, I. O., Mikalef, P., Dwivedi, Y. K., Jaccheri, L., Krogstie, J., & Mäntymäki, M. (eds) *Digital Transformation for a Sustainable Society in the 21st Century. I3E 2019*. Lecture Notes in Computer Science, vol 11701. Springer, Cham. https://doi.org/10.1007/978-3-030-29374-1_15
[12] Collins, C., Dennehy, D., Conboy, K., & Mikalef, P. (2021). Artificial intelligence in information systems research: A systematic literature review and research agenda. *International Journal of Information Management*, *60*. https://doi.org/10.1016/j.ijinfomgt.2021.102383
[13] Kavanagh, K. (2024). *Google machine learning and generative AI for solutions architects*. Packt Publishing.
[14] Kabashkin, I., & Perekrestov, I. (2024). Ecosystem of aviation maintenance: Transition from aircraft health monitoring to health management based on IoT and AI synergy. *Applied Sciences*, *14*(11). https:// doi.org/10.3390/app14114394
[15] Hicham, T., Khalifa, M., Kamal, E., & Fatiha, A. (2023). Machine and deep learning applications in Industry 4.0, in Institute of Electrical and Electronics Engineers (ed.), *Proceedings of the 2023 International Conference on Technology, Engineering, and Computing Applications (ICTECA).* Institute of Electrical and Electronics Engineers. Retrieved from https://ieeexplore.ieee.org/document/10490844
[16] Gera, I., & Singh, S. (2024). Integration revolution: Building trust with technology. In Leong, W., Chuah, J., & Tee, B. (eds.), *The Nine Pillars of Technologies for Industry 4.0*. Institution of Engineering & Technology. https://doi.org/10.1049/PBTE088E_ch10
[17] Suleiman, Z., Shaikholla, S., Dikhanbayeva, D., Shehab, E., & Turkyilmaz, A. (2022)., Industry 4.0: clustering of concepts and characteristics. *Cogent Engingeering*, *9*(1). https://doi.org/10.1080/23311916.2022.2034264
[18] Silvestri, L., Forcina, A., Introna, V., Santolamazza, A., & Cesarotti, V. (2020). Maintenance transformation through Industry 4.0 technologies: A systematic literature review. *Computers in Industry*, *123*. https://doi.org/10.1016/j.compind.2020.103335
[19] Jasiulewicz-Kaczmarek, M. (2024). Maintenance 4.0 technologies for sustainable manufacturing. *Applies Sciences*, 14(6). https://doi.org/10.3390/app14167360
[20] Vasquez, G., & Castrillon, H. (2022). Scientific literature review for the search of vulnerabilities and pentesting tools for SCADA system. In Mata-Rivera, M., & Zagal-Flores, R. (eds.), *Telematics and Computing* (pp. 90-103). Springer Nature Switzerland. https://doi.org/10.1007/978-3-030-89586-0_7
[21] Zaaba, M., Zainuddin, S., Abdullah, T., Zaib, S., Mohamed, A., Kadir, H., & Hashim, N. (2024). Blockchain technology and food supply chain: A bibliometric analysis. In El Khoury, R. (ed.), *Technology-Driven Business Innovation: Unleashing the Digital Advantage* (vol. 2) (pp. 531-540). Springer Nature Switzerland. https://doi.org/10.1007/978-3-031-62656-2_47
[22] Ma, D. (2023). A bibliometric viualisation of CNKI-based visual metaphor studies. In Chen, C., Singh, S., Saxena, S., & Wheeb, A. (eds.), *Proceedings of the 3rd International Conference on Digital Economy and Computer Application (DECA 2023)* (vol. 17) (pp. 644-659). Atlantis Press. https://doi.org/10.2991/978-94-6463-304-7_68
[23] Kabashkin, I., Federov, R. & Perekrestov, V. (2025). Decision-making framework for aviation safety in predictive maintenance strategies. *Applied Sciences*, *15*(3). https://doi.org/10.3390/app15031626
[24] Kabashin, I. (2024). The iceberg model for integrated aircraft health monitoring based on AI, blockchain, and data analytics. *Electronics*, *13*(19). https://doi.org/10.3390/electronics13193822
[25] Kabashkin, I. (2024). Integration of foundation models and federated learning in AIoT-based aircraft health monitoring systems. *Mathematics*, *12*(21). https://doi.org/10.3390/math12213428
[26] Apostolidis, A., Pelt, M., & Stamoulis, K. (2020). Aviation data analytics in MRO operations: Prospects and pitfalls, in Institute of Environmental Sciences and Technology (ed.), *Proceedings of the 2020 Annual Reliability and Maintainability Symposium (RAMS 2020)*. Institute of Environmental Sciences and Technology. https://doi.org/10.1109/rams48030.2020.9153694
[27] Korba, P., Svab, P., Veres, M., & Lukac, J. (2023). Optimizing aviation maintenance through algorithmic approach of real-life data. *Applied Sciences*, *13*(6). https://doi.org/10.3390/app13063824
[28] Stanton, I., Munir, K., Ikram, A., & El-Bakry, M. (2022). Predictive maintenance analytics and implementation for aircraft: Challenges and opportunities. *Systems Engineering*, 26(2), 216-237. https://doi.org/10.1002/sys.21651
[29] Kang, L., He, M., Zhou, J., Hou, Y., Xu, B., & Liu, H. (2025). A method for the predictive maintenance resource scheduling of aircraft based on heterogeneous hypergraphs. *Electronics*, 14(4). https://doi.org/10.3390/electronics14040782
[30] Lee, K., Hussain, K., & Oh, I., (2025). Validation for predictive maintenance of aircraft systems using AI models developed with rotor blade vibration data. *IEEE Access*, 13, 48173-48178. https://doi.org/10.1109/ACCESS.2025.3550822
[31] Zhou, M., Miu, K., Sun, J., Shen, Y., & Han, B. (2024). Data-driven modeling of aero-engine performance degradation models. *IEEE Access*, *12*, 150020-150031. https://doi.org/10.1109/ACCESS.2024.3460872
[32] Berghout, T., Bentrcia, T., Lim, W., & Benbouzid, M. (2023). A neural network weights initialization approach for diagnosing real aircraft engine inter-shaft bearing faults. *Machines*, *11*(19). https://doi.org/10.3390/machines11121089
[33] Basora, L., Olive, X., & Dubot, T. (2019). Recent advances in anomaly detection methods applied to aviation. *Aerospace*, *6*(11). https://doi.org/10.3390/aerospace6110117
[34] Farina, D., Machrafi, H., Queeckers, P., Dong, P., & Iorio, C. (2024). Innovative AI-enhanced ice detection system using graphene-based sensors for enhanced aviation safety and efficiency. *Nanomaterials*, *14*(13). https://doi.org/10.3390/nano14131135

[35] Apostolidis, A., Bouriquet, N., & Stamoulis, K. (2022). AI-based exhaust gas temperature prediction for trustworthy safety-critical applications. *Aerospace*, *9*(11), 1-16. https://doi.org/10.3390/aerospace9110722
[36] Klekowicki, M., Szymanski, G., Waligorski, M., & Misztal, W. (2025). Application of large language models in diagnostics and maintenance of aircraft propulsion systems. *Advances in Science and Technology Research Journal*, *19*(2), 304-320. https://doi.org/10.12913/22998624/196264
[37] Kumar, D., Sowmya, B., Kanavalli, A., Supreeth, S., Shruthi, G., & Rohith, S. (2024). Deep learning methodologies based on metaheuristics for predictive engine maintenance. Acta *IMEKO*, *13*(2), 1-15. https://doi.org/10.21014/actaimeko.v13i2.1667
[38] Khalife, A., & AlMeqdadi, S. (2024). Machine learning-based remaining useful life predictions and its application on predictive maintenance, in Institute of Electrical and Electronics Engineers (eds.), *Proceedings of the 22nd International Conference on Research and Education in Mechatronics (REM)*. Institute of Electrical and Electronics Engineers. https://doi.org/10.1109/REM63063.2024.10735638
[39] Yildrim, S., & Rana, Z. (2024). Enhancing aircraft safety through advanced engine health monitoring with Long Short-Term Memory. *Sensors*, 24(2). https://doi.org 10.3390/s24020518
[40] Cheng, Y., Zeng, J., Wang, Z., & Song, D. (2023). A health state-related ensemble deep learning method for aircraft engine remaining useful life prediction. *Applied Soft Computing*, *135*. https://doi.org/10.1016/j.asoc.2023.110041

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