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Industrial Applications of AI in Aircraft Manufacturing: A PRISMA Systematic Literature Review

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Abstract

Artificial Intelligence (AI) and Machine Learning (ML) are foundations in new manufacturing paradigms, yet their application in the aircraft industry remains limited, as this industry's expertise does not traditionally cover these technologies. Additionally, due to its specific features, the aircraft industry presents unique challenges, for instance, with data scarcity. To date, no systematic review has considered these features to enable stakeholders in this sector to undergo AI/ML transformation successfully. This study aims to analyze the state of the art by providing a PRISMA systematic literature review of 135 articles, focusing on the contexts, models, and methods employed in the development of AI/ML solutions. The authors propose a framework to summarize the findings on the development, applications, benefits, and challenges of AI/ML in the aircraft manufacturing industry. In addition, further research opportunities are identified through a comparison of current research applications, theoretical concepts of Industry 5.0, and cutting-edge technologies, such as Federated Learning, Transfer Learning, the use of Large Language Models (LLMs), the lack of supply chain investigation, and the integration of human factors, which are absent in major reviewed articles. This study contributes to the field by meticulously gathering methodologies and approaches that address and integrate the specificities of AI/ML use and integration in this high-value-added industry. It bridges the gap between cutting-edge research and practical industry needs, delivering actionable insights to drive innovation and guide strategic decision-making.

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1. Introduction

The aerospace industry is mainly composed of the commercial and military fields (Woo et al., 2021), where governments/countries can exert influence (Golich, 1992; Karwowski et al., 2023; Smith, 2001), for example, through financial support (Strube et al., 2017). This industry is characterized by several specific features, including a complex supply chain, low production volumes, high customization (Van Nguyen et al., 2023), and the risk to human life (Welch, 2021). From a manufacturing operational perspective, a commercial aircraft represents complex processes and materials to build the components, often supplied by subcontractors, as well as complex assembly procedures with low tolerance for defects which account for more than 50% of the workload (Moenck et al., 2025; Sarh et al., 2009), involving mainly manual tasks (Lockett et al., 2014) and skilled workers (Morsi et al., 2018). This industry, estimated at around $300 billion and highly competitive, is expected to experience significant demand growth in the future, especially in the Asia-Pacific region (Strube et al., 2017). However, some limitations can hinder production in the future, for instance, with resource availability, which can disrupt production (Dolganova et al., 2022), the rigorous certification requirements when a modification is made to the process (Zhang et al., 2019), or maintaining a high level of quality and performance when introducing new technologies into the process or product (Gohardani et al., 2011; Marudhappan et al., 2022).

Over the last two decades, Artificial Intelligence (AI) has made significant progress and is considered at the core of a new technological revolution (Jiang et al., 2022), which can tackle manufacturing challenges and improve companies' competitiveness (Oliveira et al., 2024). More specifically, in manufacturing, AI plays a key role in Industry 4.0 (Bertolini et al., 2021; Jan et al., 2023; Zonta et al., 2020) and Industry 5.0 (Moenck et al., 2025; Nahavandi, 2019; Narkhede et al., 2024). Industry 4.0 can be defined as the digitalization of production, whereas Industry 5.0 is more focused on elaborating an environment that is human-centric, flexible, and sustainable (Moenck et al., 2025). Several definitions of AI can be given, for instance, based on the level of intelligence achieved by the system (Saghiri et al., 2022). De Simone et al. (2023) define it as, "*AI represents a broad field of computer science concerned with building smart machines capable of performing tasks that typically require human intelligence*", which emphasizes two AI features in manufacturing: (1) the use of intelligent machines; (2) the potential capacity of these machines to achieve complex tasks, which marks a main difference with the previous industrial paradigms. Nevertheless, despite these new abilities, AI used in manufacturing faces limitations, as Plathottam et al. (2023) reported: "Almost all AI programs are meant for solving a single task for which it was specifically developed," highlighting its lack of versatility.

The term AI encompasses many concepts, but the most important concept in manufacturing is Machine Learning (ML) (Bertolini et al., 2021; De Simone et al., 2023). ML represents a set of methods that enable machines to learn and adapt to subsequent datasets, surpassing statistics (Hua, 2022). Its main advantages are improvements in manufacturing efficiency, productivity, sustainability, flexibility (De Simone et al., 2023; Plathottam et al., 2023), and leveraging the large amounts of data gathered from cyber-physical systems on the factory floor (Jan et al., 2023; Plathottam et al., 2023). Nevertheless, there are hindrances to implementing ML in manufacturing, which can be summarized as data-related, knowledge-related, cost-related, integration complexity, and management-related. Indeed, it was reported in the literature that: (1) the data may not reach a sufficient quality level for use (De Simone et al., 2023; Jan et al., 2023); (2) there is limited availability or unbalanced data (Bertolini et al., 2021; De Simone et al., 2023); (3) the time and financial costs required to collect data (Bertolini et al., 2021; Plathottam et al., 2023); (4) concerns about data confidentiality leaks and the reliability of cybersecurity systems (De Simone et al., 2023; Jan et al., 2023; Plathottam et al., 2023). Additionally, several gaps exist: first, the lack of knowledge comes from the lack of data understanding and ML capabilities (Bertolini et al., 2021); second, the lack of employee training (Bertolini et al., 2021; De Simone et al., 2023; Jan et al., 2023); and finally, the rapid evolution of the ML field, which makes it difficult to keep up (Plathottam et al., 2023). As for the cost, the main limitation is the difficulty of assessing the return on investment (De Simone et al., 2023), as companies must account for the costs of change and talent (De Simone et al., 2023; Jan et al., 2023). Following that, ML techniques can be perceived as too complex to integrate into companies (De Simone et al., 2023), for example, to maintain ML system performance in a dynamic industrial environment (Jan et al., 2023), which can be explained by a lack of reported use cases (Bertolini et al., 2021) and a lack of interpretability of ML models (Bertolini et al., 2021; Plathottam et al., 2023). Finally, management limitations stem from the lack of employee and manager involvement, which impacts the acceptance and potential benefits of ML (De Simone et al., 2023), or from the difficulty of changing customary practices on the factory floor (Plathottam et al., 2023). To address some of these challenges, a literature review can be conducted to provide a synthesis of current research knowledge (Page et al., 2021).

Manufacturing, defined as the transformation of raw materials into a final product through the interaction of products, processes, and resources (Cao et al., 2019), has increasingly attracted the attention of the ML research community. In the literature, several reviews have examined the use of ML in manufacturing. Bertolini et al. (2021) conducted a comprehensive review of the use of ML in industrial applications from an operations management perspective, identifying an increasing trend in this field in terms of promising topics, algorithms, and applications. Plathottam et al. (2023) published a review on the application of AI in manufacturing operations, providing a general idea of the current developments, challenges, and potential research areas. De Simone et al. (2023) focused on the use of AI in small and medium enterprises, highlighting different applications and challenges. Nti et al. (2022) conducted a systematic survey on applications of AI in engineering and manufacturing processes, detailing more technical aspects of ML development. Jan et al. (2023) conducted a systematic review of artificial intelligence within the Industry 4.0 scope across different industries, emphasizing on commonalities and differences between them. To narrow the scope to the aircraft industry, previous general reviews on the use of AI have been conducted in this field (Brunton et al., 2021; Hassan et al., 2024; Khan et al., 2024). Additionally, other reviews focus on one specific topic, for instance, aircraft maintenance (Agustian et al., 2024; Hasib et al., 2023; Karaoğlu et al., 2023), operational safety (Alreshidi et al., 2024), cyber-security (Garcia et al., 2021), materials (Das et al., 2020; Das et al., 2021; Ling et al., 2023), additive manufacturing (Chinchanikar et al., 2022), welding (Tsuzuki, 2022), battery (Chen et al., 2023b; Raoofi et al., 2023), environmental topics (Gao et al., 2022), blockchain (Abdulrahman et al., 2022), aircraft performance (Le Clainche et al., 2023), mixed-reality (Jiang et al., 2023), risk-management (Mendes et al., 2022), digital-twin (Aggarwal et al., 2023), fault diagnosis (Kumar et al., 2017; Li et al., 2023a), visual inspection (Yasuda et al., 2022), aircraft structures (Kosova et al., 2024; Raouf et al., 2025), human-AI teaming (De Oliveira Morais et al., 2024), systems-engineering (Raz et al., 2021) and biofuel energy (He et al., 2024). Nevertheless, existing studies lack an aircraft manufacturing approach, as well as a rigorous literature review methodology, and they do not consider the industry's actual features, as mentioned earlier. Additionally, previous reviews in the literature yield differing results and fail to address the unique challenges related to AI, particularly for aircraft manufacturers. Therefore, this paper aims to tackle this research gap by providing a comprehensive analysis that not only addresses these challenges but also offers a fresh perspective by integrating Industry 5.0 principles with current applications. Hence, the following research questions are:

- RQ1 – What are the current trends in the application of AI in aircraft manufacturing operations in terms of technologies used and areas of application?
- RQ2 – What are the best practices and challenges encountered when implementing AI solutions in aircraft manufacturing?
- RQ3 – Which countries are leaders in research on AI applications in aircraft manufacturing?
- RQ4 – What materials and aircraft components are primarily targeted by AI applications in this industry?
- RQ5 – What are the different methods to tackle the lack of data for AI training?
- RQ6 – What new models or approaches to artificial intelligence have recently emerged in the aircraft manufacturing industry?

The contribution of this study is to provide a comprehensive overview and analysis of AI/ML applications in the aircraft manufacturing industry, especially for stakeholders operating in this field. In contrast with previous reviews, it addresses significant research gaps by introducing a framework that synthesizes state-of-the-art research, complemented by fine-grained analyses of materials, components, data-related strategies, and other industry-relevant perspectives that have not been systematically explored before. These analyses are designed to help both decision-makers and researchers understand the current global research landscape, providing insights into the advantages, limitations, and solutions reported. Our robust methodology delivers innovative results and proposes research directions aligned with Industry 5.0 objectives, thereby advancing the field.

The outline of this paper is as follows. Section 2 introduces the ML techniques screened in this paper. Section 3 describes the method used to conduct this literature review. Section 4 presents the study's results, along with several perspectives, and Section 5 concludes and discusses the main findings.

2. Introduction of ML techniques

In the literature, four main branches of the ML paradigm stand out: unsupervised learning (UL), supervised learning (SL), and reinforcement learning (RL), and semi-supervised learning (SSL) (Azar et al., 2020; Bertolini et al., 2021; Plathottam et al., 2023; Ramírez-Sanz et al., 2023; Rolf et al., 2024; Yan et al., 2022). Therefore, these four main techniques will be introduced in the following part.

2.1 Supervised learning

SL is defined as the ML method of learning using input-output training samples to predict an output with unseen data input (Nkemdilim et al., 2024; Sudhaman et al., 2022). This paradigm primarily relies on learning from correlations between variables in a labeled dataset (Fabris et al., 2017), and the labeled output indicates the expected results (Nkemdilim et al., 2024). The main tasks are classification and regression (Lawal et al., 2020), which are addressed using various techniques such as decision trees, naïve Bayes, logistic regression, support vector machine (SVM), discriminant analysis, ensemble methods, and neural networks (Nkemdilim et al., 2024). The advantages of SL are its ability to model complex relationships (Bergen et al., 2023) and its modularity for learning, as guidance is used in the training process (Dubey et al., 2023). Nevertheless, some flaws exist in this paradigm. Indeed, SL needs to have; (1) a considerable amount of labelled data (Fabris et al., 2017); (2) some methods can suffer from overfitting, high computational demands, and redundancy issues (Bergen et al., 2023); (3) are sensitive to outlier data and could be impacted by non-linear data (Dubey et al., 2023).

2.2 Unsupervised learning

UL is a paradigm for discovering underlying patterns and relationships in unlabeled datasets (Almuqati et al., 2024; Naeem et al., 2023; Rolf et al., 2024). The common uses of the UL are for anomaly detection and clustering (Rolf et al., 2024). The main benefits of this paradigm are; (1) its capacity to handle and analyze important datasets (Chaudhry et al., 2023; Naeem et al., 2023); (2) its flexibility since the data is not labeled, saving time by avoiding manual data labeling and possibly directly using raw data (Naeem et al., 2023); (3) its autonomy to discover unknown and complex patterns without human supervision (Rolf et al., 2024). This paradigm is well-suited for discovering insights from data (Almuqati et al., 2024). However, some limitations exist. For example, although UL can perform complex tasks, its performance compared to SL is less accurate because no explanations are given to the system, potentially leading to unexpected results (Naeem et al., 2023). Additionally, the lack of interpretability makes it challenging to understand the discovered patterns (Almuqati et al., 2024; Chaudhry et al., 2023). Furthermore, noise and outliers are additional factors reported to disrupt results (Almuqati et al., 2024). Eventually, the evaluation of UL is ambiguous due to the lack of ground truth (Almuqati et al., 2024; Rolf et al., 2024), and the performance is highly dependent on expert domain knowledge to set up thresholds for the hyperparameters that do not follow a rule of thumb (Rolf et al., 2024).

2.3 Reinforcement learning

RL is a ML paradigm based on trial-and-error learning, in which an agent learns from the most rewarding states in an environment (Dinneweth et al., 2022; Rahaman, 2024). This agent learns through a series of steps: it takes the environment as input, decides an action, and receives a reward to find its optimal policy (Rocha et al., 2020; She et al., 2023). The purpose of the agent is to attain the most rewarding state of the environment (Dinneweth et al., 2022) and learn through the consequences of its own actions (Rahaman, 2024). Generally, RL provides an agent that learns independently by taking actions without a mathematical model or prior training (Yau et al., 2024). Several RL methods exist, such as Q-Learning, SARSA, and Deep Q-Network (DQN) (Rahaman, 2024), with three main algorithms: value-based (deterministic policy), policy-based (stochastic policy), and actor-critic (combination of the two) (Dinneweth et al., 2022). The main advantages of RL are its flexibility to continuously learn from an environment without labeled data (Rahaman, 2024) and its usefulness in contexts where there is only evaluative feedback, which is contrary to SL based on instructive feedback (Van Otterlo, 2002). However, RL faces constraints such as high computational complexity, time-consuming training (Rahaman, 2024), large volumes of simulated data, and limited transferability to new environments (Rocha et al., 2020). In addition, due to its reward-based behavior, this paradigm can suffer from learning value instability, a lack of confidence in reaching the optimal solution (Van Otterlo, 2002), and sensitivity to initial settings, which can affect algorithm convergence (Li et al., 2005).

2.4 Semi-supervised learning

SSL is a machine learning paradigm that leverages both labeled and unlabeled data (Duarte et al., 2023; Song et al., 2023). The uses of SSL are mainly for fault detection (Ramírez-Sanz et al., 2023), natural language processing (Duarte et al., 2023), and image analysis (Han et al., 2024), including methods such as generative models, SVM, and graph-based methods (Jiao et al., 2024). The idea behind this paradigm is to improve the performance of SL with abundant unlabeled data (Han et al., 2024). This approach is considered a hybrid of SL and UL, aiming to obtain a better model than if only a few labeled data points were used (Ramírez-Sanz et al., 2023). First, a few data points are labeled and then used to classify other similar unlabeled data (Duarte et al., 2023; Song et al., 2023). It aims to address the challenge of collecting labeled data in settings where the ratio of labeled to unlabeled data is imbalanced (Song et al., 2023). The main advantages are time and cost savings (Duarte et al., 2023), the avoidance of ethical issues when labeling a dataset, and the ability to leverage unlabeled data (Ahfock et al., 2023). However, due to the limited amount of labeled data, SSL is not expected to achieve better results than SL (Yan et al., 2022). Despite the use of unlabeled data, its use is not necessarily appropriate in practice and can even worsen the performance in comparison with a model trained with only labeled data (Jiao et al., 2024; Ramírez-Sanz et al., 2023). Indeed, there are some requirements to assure that performances remain acceptable, for example, the risk of overfitting with non-uniform distribution of data features (Yan et al., 2022), the quantity of unlabeled data added in the total set with labeled data (Duarte et al., 2023), or the satisfaction of assumption such as smooth, cluster and low-density separation, and manifold assumptions (Ahfock et al., 2023; Han et al., 2024). Additionally, expertise is still needed to mitigate these effects, leverage information from unlabeled data, tune hyperparameters, and properly label the data, since it can play a key role in SSL performance. While noise and outliers can affect the model's output, appropriately added noise during training can improve its robustness (Jiao et al., 2024).

3. Materials and Methods

To conduct this literature review, the PRISMA method (Moher et al., 2009) and, more specifically, the latest guidelines (Page et al., 2021) were utilized. The PRISMA method is a method to enhance systematic literature reviews and avoid biases (e.g., selective reporting, publication bias, and so on) (Moher et al., 2009). This method is often regarded as a standard by journals for conducting systematic literature reviews (Pussegoda et al., 2017).

3.1 Search Strategy

Two databases were systematically analyzed, namely Scopus and Google Scholar. Scopus is a database developed by Elsevier that gathers data from 4000 publishers and is considered a reliable database for research (Burnham, 2006). Google Scholar is a free database tool that allows users to access research articles. Despite its weaknesses, such as its lack of transparency and lack of quality assurance reported, Google Scholar can be used in combination with other controlled databases (Halevi et al., 2017). In addition, we believe that the rigorous protocol applied in this literature review can overcome and mitigate these limitations. The queries used, as shown in Table 1, differ from those in the Scopus database. This is due to the fact that the query used in Scopus produced too many results in Google Scholar, which were impossible to handle. Therefore, the strategy for Google Scholar was to restrain the search by using keywords in the title. The queries were conducted on Scopus and Google Scholar on 24/07/2025, encompassing article titles, abstracts, and keywords.

Table 1. Queries used in Scopus and Google Scholar databases

Database	Query
Scopus	(aircraft OR aeronautical OR aeronautic OR aviation OR aerospace) AND (Production OR manufacturing) AND (AI OR artificial intelligence OR Machine learning)
Google Scholar	allintitle: aircraft AI allintitle: aircraft artificial intelligence allintitle: aircraft Machine learning allintitle: aeronautical AI allintitle: aeronautical artificial intelligence allintitle: aeronautical Machine learning allintitle: aeronautic AI allintitle: aeronautic artificial intelligence allintitle: aeronautic Machine learning allintitle: aviation AI allintitle: aviation artificial intelligence allintitle: aviation Machine learning allintitle: aerospace AI allintitle: aerospace artificial intelligence allintitle: aerospace Machine learning

3.2 Eligibility Criteria

Specific inclusion and exclusion criteria were established to conduct this literature review as follows:

Inclusion criteria (IC)

- IC-1 (Relevance): The paper should be related to aircraft manufacturing operations.
- IC-2 (Source Integrity): The article considered should come from a peer-reviewed journal or conference.
- IC-3 (Language): The paper should be written in English.
- IC-4 (Publication Period): The article should be published between 2000 and 2025.

Exclusion criteria (EC)

- EX-1 (Review): The study is a literature review.
- EX-2 (Research Type): The study did not conduct concrete or experimental research.
- EX-3 (Industry Application): The study has no practical applications in the aircraft manufacturing industry.
- EX-4 (Subject): The study did not incorporate concepts of AI or ML.

3.3 Study Selection

During this phase, the title, abstract, and keywords of each paper were compared with the exclusion criteria to determine whether to exclude it. Moreover, articles without full-text access were excluded. The process involved one person. Therefore, this step was repeated twice to mitigate potential misclassifications of a single article.

3.4 Data Collection Process

Data retrieval from articles was conducted manually by a single person. Specific variables were collected in a spreadsheet to analyze industry trends in relation to the research questions. The following features were extracted from each article:

- Keywords used in the article.
- Type of article (e.g. journal paper or conference paper).
- Domain applications, which include Maintenance Management (MM), Quality Management (QM), Production Planning and Control (PPC), Supply Chain Management (SCM), and Engineering Design (ED), based on the literature review by Bertolini et al. (2021). Additionally, Cybersecurity (CS) has been added as a category to extend this classification.
- Year of publication.
- Learning paradigm and model employed.
- Country of the university of the first author, based on countries recognized by the United Nations in 2024 (Nations, 2024).
- Materials and components studied, with each material or component separately if multiple were present in a single study.

3.5 Data Visualization

Figures were produced using Python, such as WordCloud (Mueller, 2024), Excel (Microsoft Corporation), and Photoshop ("Adobe Photoshop").

4. Results

4.1 Study Selection

In the identification phase, 323 articles were identified on the Scopus database and 85 on Google Scholar. After removing duplicate records (n= 11), 397 articles were screened based on their titles, abstracts, and keywords, leading to the exclusion of 108 articles, reducing the total to 289. Next, 278 articles were assessed based on their full text, as 11 were excluded due to inaccessibility. For the final eligibility stage, 143 articles were excluded based on the exclusion criteria. Consequently, 135 articles were included in the qualitative synthesis. The entire process is shown in Figure 1.

4.2 Characteristics of Included Studies

Out of a total of 135 articles, 98 (73%) were publications in scientific journals and 37 (27%) were conference papers. The journals with the highest number of articles were Sensors, Journal of Intelligent Manufacturing, and Journal of Manufacturing Systems, with 6, 5, and 4 articles, respectively. Following them, Applied Sciences, IEEE Access, and Materials each featuring 3 articles in this study. Several journals each scored 2 articles, including Aerospace, Composite Structures, Computers in Industry, Engineering Applications of Artificial Intelligence, International Journal of Advanced Manufacturing Technology, International Journal of Fatigue, International Journal of Production Economics, Journal of Studies, Journal of Manufacturing Science and Engineering, Machines, Robotics and Computer-Integrated Manufacturing, SAE International Journal of Advances and Current Practices in Mobility.

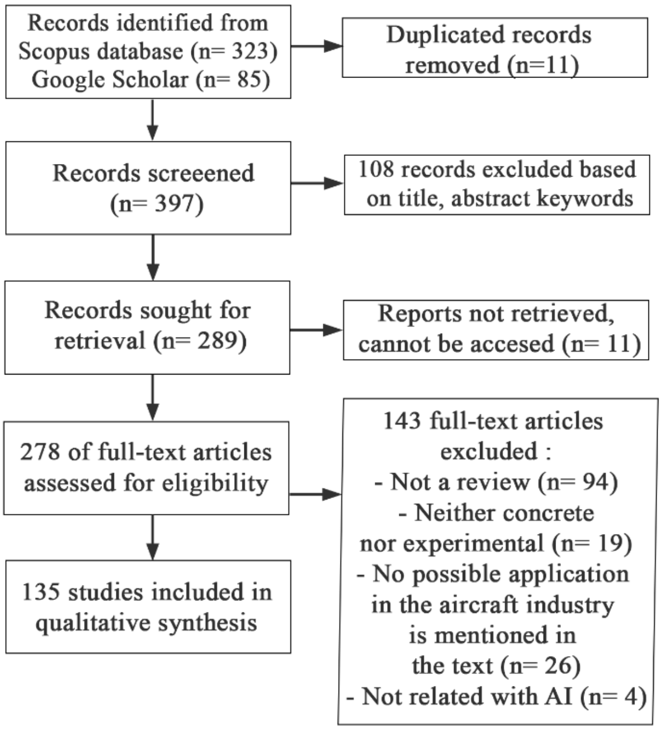


Fig. 1. Prisma flow diagram of this study

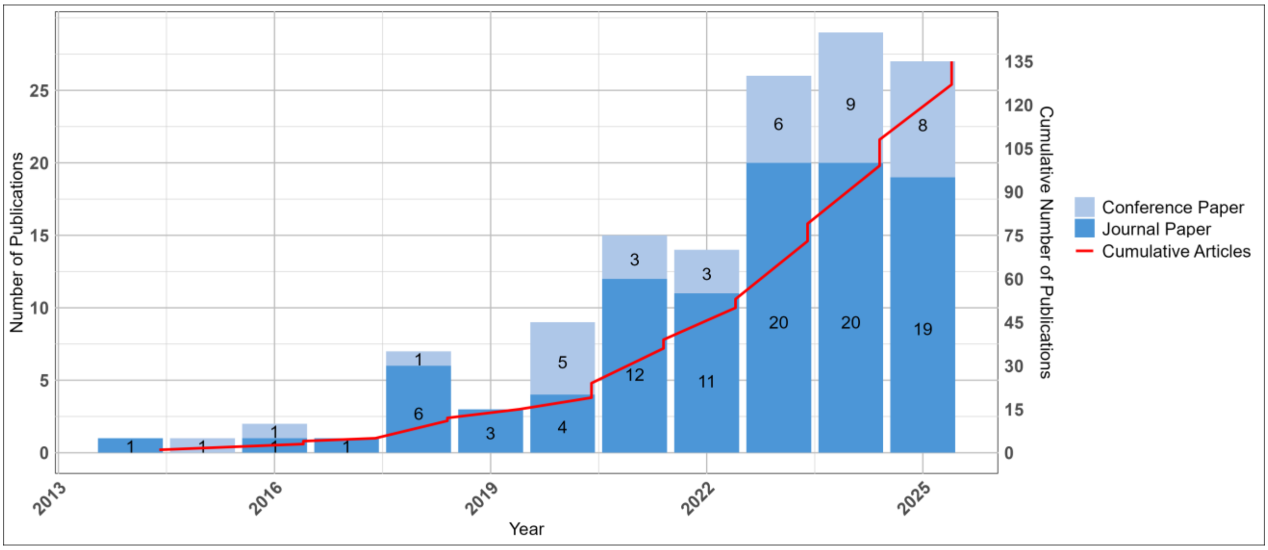


Fig. 2. Number of articles published over the years

International Journal of System Assurance Engineering and Management, Journal of Materials Engineering and Performance, Progress in Additive Manufacturing, and Scientific Reports. As shown in Figure 2, the number of articles has steadily increased over the years, with the first article published in 2014 and the highest number observed in 2024. This trend indicates a growing interest within the research community. To further analyze the content of these articles, a word cloud analysis was conducted.

4.3 Word Cloud Analysis

Figure 3 shows the most frequent keywords (those appearing at least twice) extracted from articles. Neural networks, namely artificial neural networks (ANN) and deep learning (DL), were the most studied machine learning models. Additionally, from a manufacturing perspective, keywords such as additive manufacturing, Industry 4.0, predictive maintenance, and wire electrical discharge machining were prominent domains that these articles focused on.

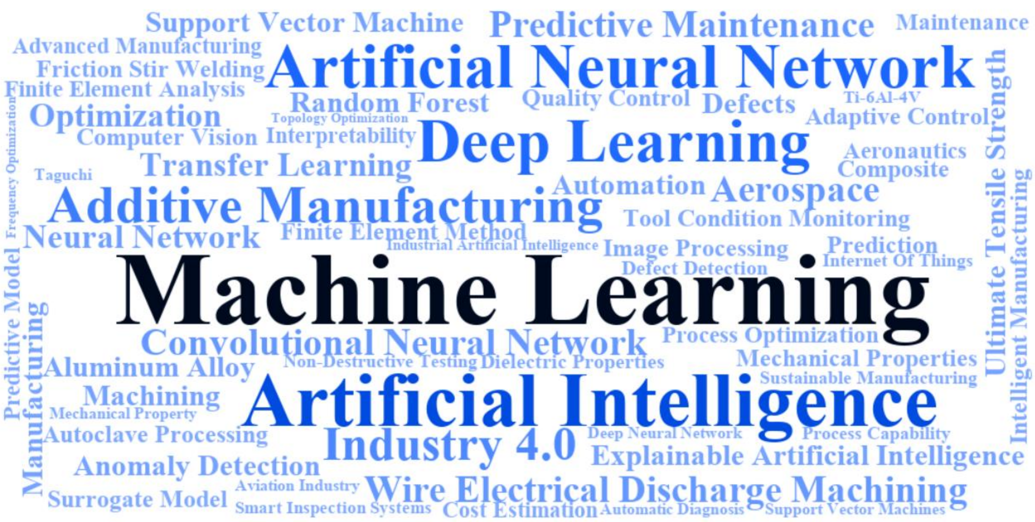
Next, the research's geographical distribution was investigated.

4.4 Country Distribution

Regarding country distribution, as shown in Figure 4, the main countries leading this research domain are the USA (24 articles), India (20 articles), China (16 articles), Spain (9 articles), Germany (7 articles), Canada (6 articles), Turkey and Italy (5 articles) then South Korea and United Kingdom (4 articles). To structure our analysis, we proposed a framework of AI/ML in aircraft manufacturing.

4.5 Structured Analysis Using the Proposed AI/ML Framework

In this review, after analyzing all the articles, a framework was established, as shown in Figure 5, to describe this research and the factors of AI/ML in aircraft manufacturing. As mentioned in the introduction, the deployment of AI/ML in companies is hindered by organizational factors. Additionally, aircraft manufacturing is characterized by several key features,



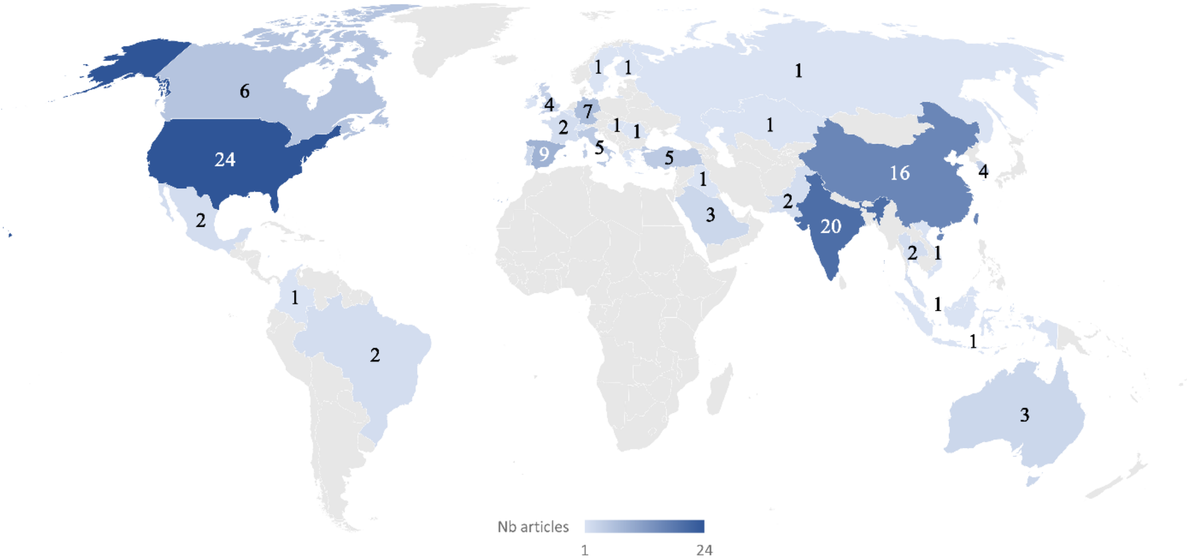


Fig. 4. Article distribution by country

namely its complexity, high level of customization, risk aversion, and relatively low production volumes. This leads to some challenges in leveraging data in this industry, for instance: (1) the lack of data; (2) the quality of the data; (3) the cost of gathering and/or labeling data; (4) the confidentiality of the data. One of the critical aspects of this framework is identifying data sources.

4.5.1 Data Sources Utilized

In this research field, 126 articles (93%) disclosed the data sources they utilized, which primarily include simulation data, company internal data, experimental data, and open-source datasets, as detailed in Table 2, in Appendix A. Simulation data can be derived from commercial software or methods, typically based on physics modeling. Specifically, 59 articles (47%) employed an experimental approach to construct their datasets, 31 articles (25%) utilized internal company data, and 24 articles (19%) used simulations, with 15 articles (12%) using software and 9 articles (7%) employing physics modeling. Additionally, 22 articles (17%) utilized public datasets, and, 11 articles (9%) reported a hybrid approach, combining multiple types of sources.

Among the commercial software, the following were identified: RAVEN ("RAVEN"), a software to model an autoclave cure process; Moldex3D ("Moldex3D"), a mold flow software; SolidWorks ("SOLIDWORKS"), a CAD software; ANSYS ("Ansys"), a finite element analysis software for structural engineering; ABAQUS ("Abaqus"), a finite element analysis software; Nektar++ ("Nektar++"), an open-source solver; ProDiMES (Simon, 2010), a software released by NASA to evaluate aircraft engine diagnostic methods; Sentaurus ("Sentaurus Device"), a multidimensional device simulator; nTop ("NTop"), a computational design platform for modeling and simulations; JavaFoil ("JavaFoil"), a program for airfoil analysis; and AnyLogic ("AnyLogic"), a process simulation software. After identifying data sources, the next step is data preprocessing.

4.5.2 Data Preprocessing Techniques

Next, the development of AI/ML solutions in this industry follows a common approach: data preprocessing, data analysis, model selection, training, and fine-tuning (Paleyes et al., 2023). Data preprocessing can be divided into several steps. First, data cleaning involves removing outliers, missing data, and duplicate records (Abidi et al., 2022; Liu et al., 2022). Then, data transformation, which refers to the process of converting data from one format or structure to another (Rahm et al., 2000), can be applied during data preprocessing to obtain data that are more distinctive across conditions. This can be done by applying transformations, for instance, Koch et al. (2022) and Knittel et al. (2019) used Fast Fourier Transform, Kim et al. (2022) used wave packet transformation (WPT), Hojjati et al. (2016), Akhavan et al. (2024), and Olowe et al. (2024) used a Short Time Fourier Transform, and Fernandes et al. (2018) used Discrete Fourier Transform, all, to transform time series data into the frequency domain, as this transformation shows clear evidence between two states or conditions (drill bit, milling diagnosis). Dasari et al. (2020) used polar transformations on images to improve performance. Akhil et al. (2020) employed first-order and second-order analysis using Gray-Level Co-occurrence Matrix (GLCM) and Neighboring Gray-Level Dependence Matrix (NGLDM) on images to obtain deeper information about texture features. Then, other transformations can be applied, such as frequency filtering (Alharbi et al., 2024), logarithmic transformations to reduce data skewness (Wu et al., 2024b), or converting into a numerical format (Abdulla et al., 2024; P et al., 2024). Otherwise, data transformation in this field can be achieved through data normalization, as reported by 53 articles (39%) of the articles reviewed. This operation typically transforms the data into a standardized range (B. Bala et al., 2024), for instance,

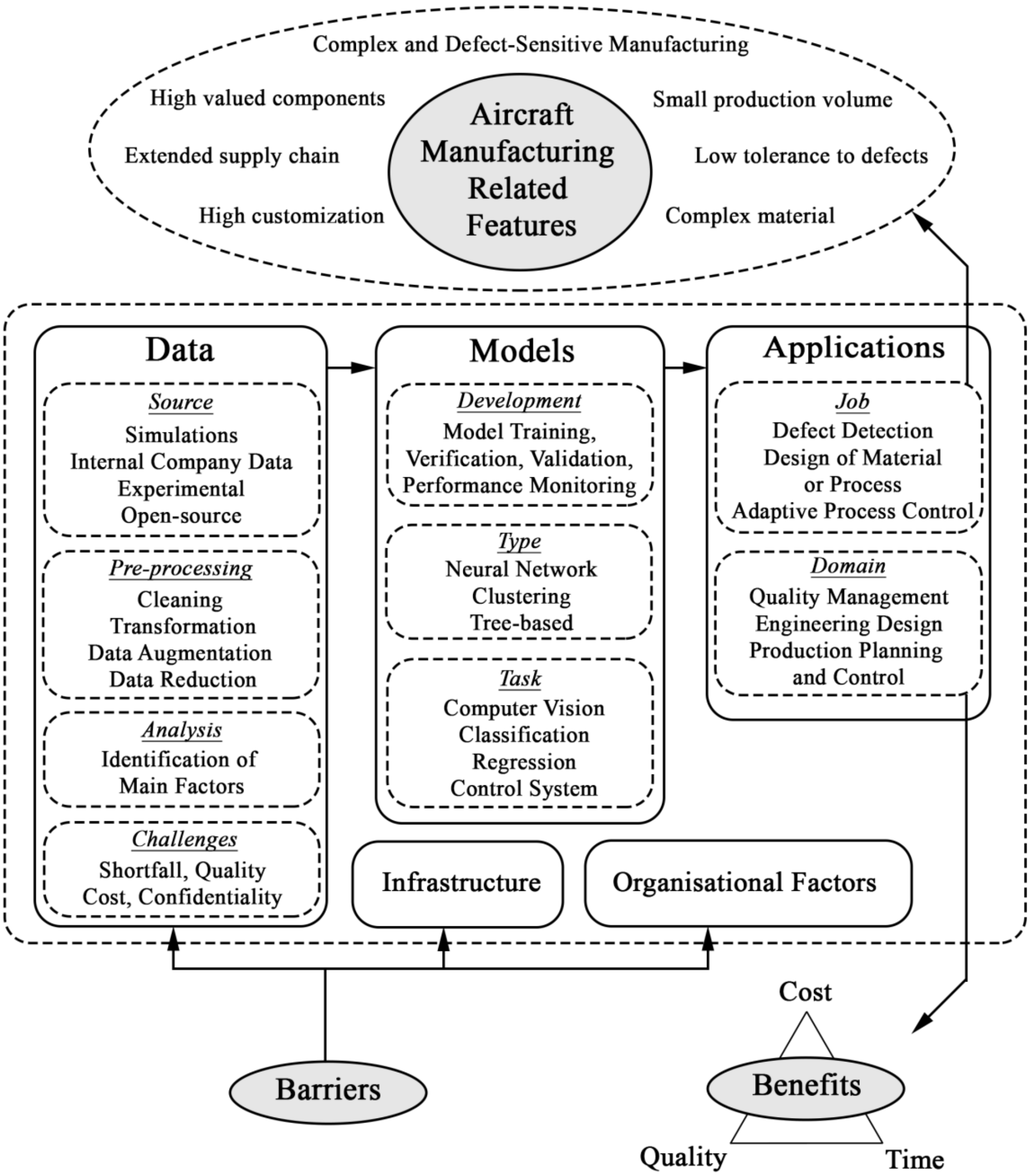


Fig. 5. Framework summarizing current research on AI/ML solutions in the aircraft industry, focusing on data sources, models employed, application domains, benefits, and challenges.

into a value range of [0, 1] (Liu et al., 2022; Martinez et al., 2021; Yang et al., 2020). Next, the last possible operation on data is augmentation or reduction. By analyzing the use of these techniques, 36 articles (27%) applied them in their methodology, as shown in Table 3, in Appendix A. After data preprocessing, the next crucial step is selecting and deploying machine learning models.

4.5.3 Machine Learning Model Employed

As shown in Figure 6 in Appendix A, the main learning paradigm was SL, and the main ML methods used were neural networks, tree-based methods, and clustering approaches, which share common tasks such as classification and regression (Plathottam et al., 2023). To understand the practical applications of these models, industry-specific applications were explored.

4.5.4 Industry-Specific Applications

In terms of applications, the two main domains addressed by the articles, as shown in Figure 7, were ED with 46 articles (34%) and QM with 45 articles (33%). Following these, MM with 20 articles (15%) and PPC with 18 articles (13%) were also important, while SCM with 5 articles (4%) and CS with 1 article (1%) were the least represented. The four main sub-

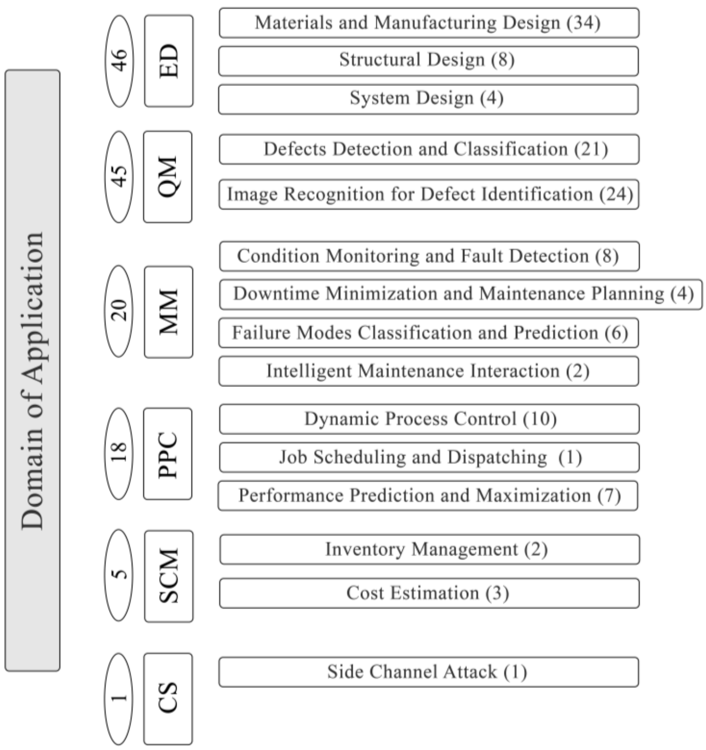


Fig. 7. Domain Distribution (number of articles)

categories of applications are material and manufacturing design with 34 articles (25%), image recognition for defect identification with 24 articles (18%), defect detection and classification with 21 articles (16%), and dynamic process control with 10 articles (7%). This can also be broken down by material or component studied, as shown in Figures 8 and 9, respectively.

Regarding the materials, 75 articles (56%) reported specific materials used in their papers. The main materials mentioned are aluminum alloys with 24 articles (18%), carbon fiber reinforced polymer/plastic (CFRP) composites with 22 articles (16%), polymer and plastics with 14 articles (10%), and titanium alloys with 13 articles (10%), as presented in Figure 8.

The distribution of the aircraft components over the articles, as shown in Figure 9, was mainly focused on engine and turbine components with 19 articles (12%), wing and structural components with 12 articles (9%), and assembly and fastening components with 8 articles (6%). The proportions of model types are balanced across the aircraft's sections. Figure 9 is adapted from Science Figures, licensed under the Open Design License 1.1, and has been modified to include all relevant information related to the focused parts and the AI/ML models used. More details on the main extracted features are provided in Table 4 of Appendix A. Another critical aspect to consider is the impact on manufacturing performance.

4.5.5 Impact on Time, Cost, and Quality

Finally, the impact of AI/ML on time, cost, and quality was assessed, as these are the key factors driving the manufacturing field (Kumar et al., 2022). The incentives to integrate AI/ML solutions in aircraft manufacturing should also align with these drivers. Therefore, as shown in Table 5 in Appendix A, 22 articles (16%) reported benefits that are primarily related to time savings. To conclude this section, a summary of the overall research is provided.

4.6 Summary

These results reveal several key findings that highlight the current state of AI/ML in aircraft manufacturing. The number of articles on AI/ML in aircraft manufacturing has steadily increased since 2014, with a peak in 2024, reflecting the growing interest and importance of this field within the research community. The USA, India, and China are the leading countries in this research domain, contributing significantly to advancing AI/ML applications in aircraft manufacturing. The main application domains are ED and QM, followed by MM and PPC, with a focus on material and manufacturing design, defect identification, and dynamic process control. AI/ML solutions in aircraft manufacturing align with the key drivers of time, cost, and quality, with many articles reporting time-saving benefits, highlighting the potential of AI/ML to enhance efficiency and productivity in this industry. Neural networks, particularly ANN and DL, are the most studied machine

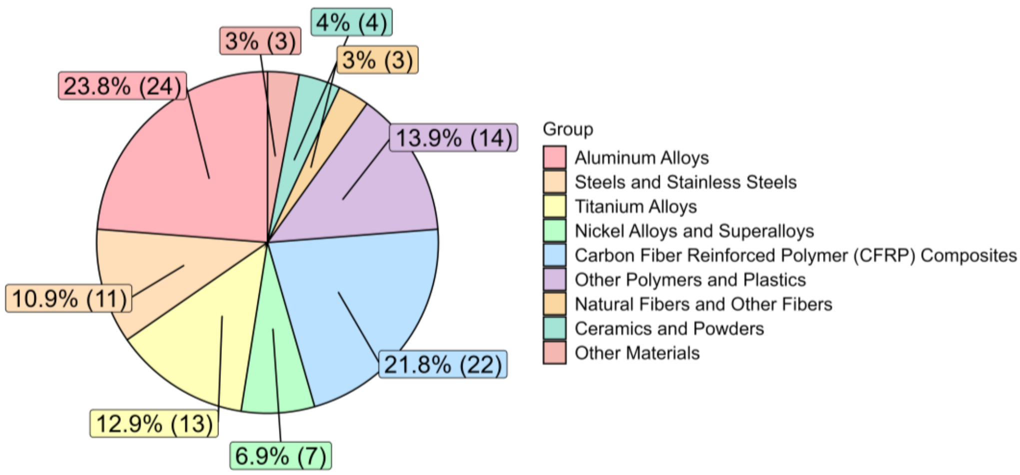


Fig. 8. Material distribution (one article can mention more than 1 material)

learning models. Four primary data sources are used: experimental data, company-internal data, simulation data, and open-source datasets. Data preprocessing techniques, such as data cleaning, transformation, normalization, and augmentation, are essential steps in preparing data for AI/ML models, enhancing data quality and improving model performance. A proposed framework outlines the factors and challenges of integrating AI/ML in aircraft manufacturing, considering organizational factors, data challenges, and the unique features of aircraft manufacturing, and provides a structured approach for future research and implementation.

5. Discussion

This study conducted a comprehensive review, employing both quantitative and qualitative analyses, to develop a framework and synthesize current research in this field. The discussion of results is structured to address each research question directly, fulfilling the objectives outlined in this paper. Following this, the study's limitations are examined, providing a balanced perspective on the research findings. The section concludes with a summary of major findings and their implications for future research.

5.1 RQ1 – What are the current trends in the application of AI in aircraft manufacturing operations in terms of technologies used and areas of application?

As shown in Figure 2, the field's incentive is showing significant growth over the years, indicating increasing interest from the research community. This result is consistent with previous research, which observed the same tendency but from an overall AI/ML perspective (Bertolini et al., 2021; Jan et al., 2023). One of the main manufacturing fields in this area of research is additive manufacturing, as shown in Figure 3. Research on additive manufacturing has been intensive over the past two decades, leading to the development of new processes (Prakash et al., 2018) and their rising utilization in manufacturing (Dilberoglu et al., 2017). The main advantages of additive manufacturing are its capacity to produce complex and large-scale geometries and its ability to reduce processing and fabrication time (Rasiya et al., 2021). Indeed, as previously mentioned, the aircraft industry is highly personalized, and additive manufacturing can tackle challenges such as faster prototyping (Prakash et al., 2018) and producing customized parts (Dilberoglu et al., 2017). Additionally, resource management is a key challenge in this industry (Ciano et al., 2025), and additive manufacturing has been reported to achieve higher material utilization while improving mechanical properties (Rasiya et al., 2021). Overall, the research analyzed in this review related to additive manufacturing presents techniques to improve its process and quality, and to predict the mechanical properties of parts produced with specific materials. The other trend in this field is the development of AI/ML solutions to detect defects using vision or sensors. Indeed, this industry is highly averse to defects in the manufacturing process, and automating inspection in aircraft manufacturing has already been identified in previous literature as a promising approach (Yasuda et al., 2022). This is truly relevant for aircraft manufacturers since it can significantly reduce production costs and resource use. For instance, as revealed by Shafi et al. (2023), who reported a comparison of 52.88% reduction in time and 34.32% reduction in cost for the wing section after the implementation of the AI defect detection model. Eventually, the latest trend identified in this review is simulation. Simulation is used in complex systems, such as aircraft, to anticipate performance, reliability, and safety before investing resources, based on numerical methods and mathematical modeling (Talib, 2023). In the aircraft industry, simulations can be used to explore material properties and manufacturing tolerances (Hu et al., 2016). The main incentive of integrating AI/ML into simulations is to gain computational time compared to traditional simulations and to reduce the need for experiments to find optimal parameters. For example, as shown in Table 5, Al-Haddad et al. (2024) deployed a ML solution that reduced computational times from around 5 hours with a regular tool simulator to 1 second to study the mechanical behaviors of aircraft landing gear during the landing phase. Similarly, Varol Özkavak et al. (2023) developed a solution to address the challenges of conducting many experiments to determine appropriate process parameters for aluminum heat treatment.

In terms of ML paradigms and techniques, SL and neural networks are ubiquitous in the research articles analyzed, as confirmed by Figures 3 and 6. Bertolini et al. (2021) also identified these two trends with a comprehensive literature review of AI/ML in manufacturing. However, in this review, a clear tendency for neural networks to be more widely employed than other techniques were observed. Neural networks are considered one of the most robust techniques to achieve tasks like regression, classification, computer vision, anomaly detection, control systems, generative models, and natural language processing (NLP) with UL, SL, and RF by simulating the human brain (Plathottam et al., 2023), and play an important role in manufacturing applications (Mumali, 2022). This could be explained by the fact that a neural network's features, namely its non-linear, non-limited, non-qualitative, and non-convex nature, allow self-learning and enable it to find an optimal solution to complex problems quickly (Wu et al., 2018). Additionally, neural networks can learn complex relationships within data (Rasamoelina et al., 2020), regardless of whether datasets are linear or non-linear (Kasar et al., 2016). So, its flexibility seems not only to provide the best performance across various complex settings but also to persuade the research community to adopt it.

5.2 RQ2 – What are the best practices and challenges encountered when implementing AI solutions in aircraft manufacturing?

We support the idea that deploying AI/ML solutions in the aircraft industry should be carried out while maintaining the core concepts of lean management, which involve producing at the highest quality, at the lowest cost, and with the shortest lead time (Kumar et al., 2022). Even if the gains are difficult to evaluate, this literature review can serve as a benchmark for similar applications, as shown in Table 5. We also invite the scientific community to indicate potential gains, even if estimated, so that actors in this industry can evaluate them before investing resources.

Another good practice is the identification of usable data for AI/ML applications, which depends on a combination of sector-specific knowledge and manufacturing processes, as well as examples that can be described in this research. Internal company data, for instance, offers better insights into real-world situations but is often anonymized in articles to maintain confidentiality, providing only a surface-level view of the datasets. Experimentation is another valuable method for generating data, particularly in manufacturing processes like additive manufacturing. Public datasets, available from sources such as NASA and data hosting platforms, are also a crucial data source.

Furthermore, we advocate for the importance of data operations, such as data augmentation, reduction, and transformation, as crucial best practices to address the specific data needs of the sector. The aspect of data augmentation and reduction is discussed in research question RQ5 of this section. Data transformation is mainly performed through data normalization. The main incentives of data normalization are: (1) to leverage data from different sources (B. Bala et al., 2024; Crawford et al., 2021; Fotovvati et al., 2022); (2) to increase the performance of the model (B. Bala et al., 2024; Filz et al., 2021; Hojjati et al., 2016). Data transformation can benefit this field by adapting and leveraging various data into AI/ML solutions, thereby multiplying the potential data sources or sensors.

Next, the choice of model is important for the deployment of AI/ML in this sector. Model selection involves a trade-off among the tasks at hand, the available infrastructure and hardware, computational cost, and privacy during the training phase (Paleyes et al., 2023). Moreover, the model choice is made based on: (1) the problem type, whether linear or non-linear, and its complexity; (2) data type: continuous, categorical variables, etc.; (3) the quantity of data to be processed (Gzar et al., 2022); (4) the desired complexity of the models (Paleyes et al., 2023). Further information on the capabilities of each model is provided in the work of Plathottam et al. (2023).

As shown in Figure 5, the main challenges in this industry concern the data that feed AI/ML models. Several solutions exist for producing data; however, the primary source is experimentation, as shown in Table 2. However, simulations offer a solution to these challenges by providing controlled and reliable data at a lower cost. We have observed that data simulation produces satisfactory results for applications predicting mechanical properties, whether of materials or components. Nevertheless, the effectiveness of these solutions depends on the quality of the simulations and the targeted application. For example, simulation data is an effective and powerful tool when the degree of variability is relatively low, as in the evaluation of physical constraints. Conversely, in aircraft manufacturing, assembly simulation remains marked by significant variability. This is why AI/ML process models generally use experimental datasets, especially from additive manufacturing. Nevertheless, a combination of data can also be considered for dataset production. We highlight a promising methodology by Zhu et al. (2024) who employed and merged simulation and experimental data. There are two main advantages of this approach: (1) data can be adapted to the work floor; (2) deeper variable predictions can be done, for example, with variables that are difficult to measure in the manufacturing process, while tackling challenges related to data collection. The other significant challenge is the available infrastructure for developing such models. Data confidentiality is a major concern in this industry, leading most models to be trained locally and limiting the use of complex models.

5.3 RQ3 – Which countries are leaders in research on AI applications in aircraft manufacturing?

As shown in Figure 4, the leading countries in this sector are the USA, India, and China. Surprisingly, the position of European countries is relatively weak, despite Spain coming right after China in the ranking. These results could be similar to the study by Dhamija et al. (2020) who conducted a bibliometric analysis of Scopus on AI in the operational field in 2018 and 2019. While major countries such as India, the USA, and China are also identified as leaders, results are different for the United Kingdom, France, Germany, Iran, Australia, and Brazil. Indeed, all of these countries are among the top 10 for operational AI research; however, in this study, Spain and Canada achieved better rankings, possibly indicating a recent increase in interest in this field from these two countries. Furthermore, these results were a bit different from those of Hassan et al. (2024), where the work was focused on the broad application of AI in aerospace engineering, identifying mainly the USA and China as leaders in aerospace engineering, with more than 170 articles for both of them, and then India as the third leading country with 57 articles. Thus, this literature review introduces new insights into the nation leading in this area, which is more focused on commercial aircraft.

5.4 RQ4 – What materials and aircraft components are primarily targeted by AI applications in this industry?

The main materials focused on by this field of research are aluminum alloys, CFRP composites, polymers and plastics, and titanium alloys. Aluminum alloys have historically been used mainly in structural components of aircraft (Raj et al., 2021), representing 60/80% of an aircraft's total weight (Li et al., 2023b). They are appreciated in the aircraft industry for their weight-strength ratio, corrosion resistance, ease of machining, and low cost in terms of material, manufacturing, operation, and repair, while maintaining high performance (Raj et al., 2021), which is sought after in this field (Jawalkar et al., 2015). Composite materials are widely used in commercial aircraft composition (Chatterjee et al., 2019; Chibane et al., 2021; Vieira et al., 2017), mainly because they possess better performances than other materials, such as a greater strength, stiffness, fatigue resistance, and corrosion resistance, improved manufacturing design and process, and a lower density (Shivi Kesarwani, 2017; Soutis, 2005). This material overall improves aerodynamic efficiency (Soutis, 2005), reduces fuel consumption, emissions, and maintenance costs for customers

(Shivi Kesarwani, 2017). CFRP is reported as a key material for the next generation of new commercial aircraft (Vieira et al., 2017). Both aluminum alloys and CFRP are recyclable materials that support sustainable development (Li et al., 2023b). Polymer materials are used by many aircraft manufacturers, for example, as insulation, but they also have broader aerospace applications (Lakatos et al., 2023). Some parts of an aircraft could be produced with polymer-based plastic materials, such as interior components, structural, propulsion, and navigational components, making this material promising for the future (Rahman et al., 2023). Its use is becoming more and more widespread in current mechanical engineering (Zolkin et al., 2021). The primary benefits include low weight, high-temperature resistance, and excellent corrosion resistance (Rahman et al., 2023). Among polymers, elastomers and fibers are considered the most promising (Zolkin et al., 2021), especially as alternatives to rubber or metallic alloys, enabling fuel savings (Rahman et al., 2023). Similarly, titanium alloys are valued in this industry for their features, such as a high strength-to-weight ratio, corrosion resistance (Pattanam Ramamoorthy et al., 2025), and their low weight, offering a promising alternative to steel components, for instance, in the aircraft structure (Mezher et al., 2024).

Overall, these materials already have, or are expected to have, key roles in the next generation of aircraft. The different solutions developed could bring several benefits. For instance, Huang et al. (2023) used machine learning to study composite fiber shapes and their impact on mechanical properties, such as the transverse modulus, providing an approach with good accuracy and low computational time. Román et al. (2023) developed a machine learning solution to compute the mechanical properties of natural rubber based on formulations, creating a tool that can be employed in reverse engineering to reduce the number of iterations needed to find a satisfactory formulation with desired performance. Additionally, Adizue et al. (2023) explored different models to predict the surface roughness of steel produced with high-precision CNC machining, which can improve process parameters, quality, and decrease manufacturing costs. Therefore, the research focus is consequently relevant for optimizing existing materials in terms of process, or for exploring new mechanical properties through the use of AI/ML, reducing the overall cost and time to design processes and materials, aligning with green manufacturing goals (Ciano et al., 2025).

Regarding the components targeted by this field of research, as shown in Figure 9, the focus is mainly on engine and turbine components. This aligns with the efforts of aircraft manufacturers to design better engines in order to make them quieter and less polluting, while increasing their performance in terms of operating distance (Chatterjee et al., 2019). Since an engine is a complex and expensive component (accounting for around 30% of the total aircraft price), engine manufacturers are major partners of aircraft manufacturers. Furthermore, there is intense competition among engine suppliers to meet aircraft manufacturers' requirements and enhance engine performance, particularly during new aircraft programs (Schmitt et al., 2016). In this review, we noticed that the main trends are to optimize manufacturing processes and to explore engine designs and maintenance. We stated that this is due to the high-pressure environment, which stimulates research interests. Indeed, disruptive technologies or improvements in engine design can create significant competitive advantages. For example, MTU Aero Engines, an engine manufacturer, implemented a new process that reduced the cost of one engine component by 50% and its weight by 40% while improving fuel efficiency (Singamneni et al., 2019).

So, all these research efforts, whether focused on materials or components, align with the concept of sustainable manufacturing in Industry 5.0 (Narkhede et al., 2024), share the common goal of reducing fuel consumption and, consequently, pollutant emissions. This aims to both lower fuel and engine costs, which make up a significant part of the expense, and to meet environmental standards set by authorities (Barbosa, 2020; Schmitt et al., 2016).

5.5 RQ5 – What are the different methods to tackle the lack of data for AI training?

According to Table 3, the main strategies to increase the dataset are: (1) using Euclidean geometric transformation (rotation, mirroring, flipping, cropping); (2) generating new data from a generative adversarial network (GAN) or via regression between variables and; (3) adding Gaussian noise; and using hardware during data acquisition to maximize the data points. While Euclidean geometric transformations and adding Gaussian noise are considered basic augmentation techniques for images (Chlap et al., 2021), techniques like GANs are viewed as more advanced (Chen et al., 2024). GANs can generate data directly from the data distribution, avoiding assumptions about the data distribution required by alternative methods (Chen et al., 2024). Another technique that does not increase the size of the dataset but instead reduces the need for having a large dataset is transfer learning, where the concept is to adapt pre-trained models to new tasks, reducing the need to collect data. Regarding methods to reduce the dimensionality of the data, the most observed techniques include principal component analysis (PCA) (Li et al., 2023c), robust principal component analysis (RPCA) (Manohar et al., 2018), or the use of autoencoders (Etem, 2025), as shown in Table 3. The most popular technique reported in the literature is PCA, which aims to filter and retain key information to reduce feature or sample size, thereby decreasing dataset complexity and improving the overall AI/ML solution (Zha et al., 2025). Thus, overall, the tactics screened in this review could be considered basic yet effective when employed.

5.6 RQ6 – What new models or approaches to artificial intelligence have recently emerged in the aircraft manufacturing industry?

New approaches, such as Federated Learning (FL) and Transfer Learning (TL), are promising for the future. FL aims to train ML models on different datasets across multiple agents without transferring data between agents (Yin et al., 2022). These various agents are managed by central servers, enabling the integration of multiple data sources (Li et al., 2020). The main benefits of FL are that this method keeps confidential user data and exchanges only aggregated model updates, and allows personalization of the model from the user since the training uses their local data (Banabilah et al., 2022), making FL relevant in cases where data is highly sensitive and private (Li et al., 2020). Its deployment can address challenges in deploying AI/ML applications, leveraging big data, and complying with data privacy regulations (Yin et al., 2022). However, some challenges remain, including privacy and security risks, data heterogeneity across clients, and significant communication costs due to the FL architecture (Wen et al., 2023). FL has been applied to language processing, image processing, and biometrics (Yin et al., 2022). For instance, in the healthcare field, this method is used to train AI/ML models on data from multiple clinics while preserving patient data privacy (Banabilah et al., 2022). In industrial engineering, FL is used to monitor, gather sparse data from multiple sensors to train ML/AI models, and perform visual inspection tasks, addressing data scarcity while ensuring data confidentiality for manufacturers (Li et al., 2020). In our literature, only one article applied this technique: Llasag Rosero et al. (2024), who introduced a FL method to address problems related to handling diverse data samples in terms of characteristics and size. They conducted two case studies, first on product inspection failures in Bosch factories, and second on aircraft component remaining useful life predictions. Therefore, due to the requirements of the aircraft industry, we point out that FL is promising, especially in manufacturing settings, where it can address data privacy issues, which are particularly prominent among entities in this field.

As for TL, this approach involves transferring knowledge from a source task to a sufficiently related target task (Zhuang et al., 2021). The method offers advantages by reducing the need for target-domain data, which may be unavailable, limited, or costly to gather and label, thereby potentially saving both time and cost (Farahani et al., 2020; Hosna et al., 2022; Weiss et al., 2016). However, to ensure these models perform correctly, the source and target tasks must be sufficiently compatible, otherwise, there is a risk of negative transfer (Farahani et al., 2020; Weiss et al., 2016; Zhuang et al., 2021). This technique can be found, for example, in the healthcare sector. It is mainly applied to tasks involving image and language processing (Farahani et al., 2020) in sectors such as medicine, bio-computing, transportation, recommendation, and e-commerce (Hosna et al., 2022). In our review, four articles employed a TL approach: Amini et al. (2022) employed TL to reduce the need for large datasets in defect detection; Dou et al. (2023) used a TL algorithm to recognize tools, avoiding the creation of a model from scratch; Ramezankhani et al. (2021a) and Ramezankhani et al. (2021b) applied TL to tackle data shifts in production by estimating process parameters. Alharbi et al. (2024) used a TL model for audio data since its training was related to the problem studied, instead of developing a new model. Thus, we claim that TL presents an opportunity in this field, as it helps address challenges in data collection and data shift, which can be difficult due to the potential to hinder production output and incur high costs from hiring experts for data labeling or from maintaining these systems on a dynamic factory floor.

5.7 Summary of Key Discussion Points

The discussion highlighted several key trends and insights regarding AI/ML in aircraft manufacturing, particularly in additive manufacturing, defect detection, and simulation. Additive manufacturing offers advantages such as producing complex geometries and reducing processing times, while defect detection using AI/ML solutions has shown promise for reducing production costs and resource use. Simulation has emerged as a crucial trend, enabling the anticipation of performance and reliability with significantly reduced computational time.

Best practices and challenges emphasize maintaining lean management principles to optimize quality, cost, and lead time. Identifying usable data and performing operations such as augmentation, reduction, and transformation are crucial. The choice of ML model is significant and requires a trade-off among task requirements, infrastructure availability, and computational cost. Challenges primarily revolve around data quality and infrastructure availability, with data confidentiality being a significant concern.

Research leadership in AI applications in aircraft manufacturing is dominated by the USA, India, and China, with Spain also showing a strong presence. The materials and aircraft components primarily targeted by AI applications include CFRP composites, aluminum alloys, polymers/plastics, and titanium alloys, to optimize processes and reduce overall costs. Engine and turbine components are the primary focus, aligning with efforts to design better, more efficient engines.

Data augmentation and reduction strategies to enhance AI model performance include Euclidean geometric transformations, generating data with GANs, adding Gaussian noise, and using hardware to increase the number of data points. Techniques like PCA are popular for reducing data dimensionality and improving model performance by filtering out key information.

New models and approaches to AI include FL and TL. FL allows training ML models on distributed datasets without transferring data, preserving confidentiality and enabling personalization. TL reduces the need for large target datasets by transferring knowledge from a source task to a related target task, saving time and cost. These approaches show promise for addressing data privacy issues and the challenges of data collection, as well as shifts in the manufacturing environment.

6. Research Opportunities and Future Direction

This systematic literature review not only highlighted various trends in this research area but also identified opportunities that could guide future research directions for the community. Unlike previous general reviews, our study employs a rigorous methodology, offering distinct results that provide a clearer framework of the field, as shown in Figure 5. The distribution of research across different aircraft components and materials was identified, as illustrated in Figures 8 and 9. Furthermore, in the following section, we will primarily identify future research directions by comparing Industry 5.0 concepts with those that are absent in the reviewed articles.

As stated in the introduction, aircraft manufacturing is highly personalized, which hinders the scaling up of AI/ML solutions. While some research can already be applied in real manufacturing settings, we argue that future solutions should prioritize human-AI collaboration, flexibility, and explainability to adapt to each aircraft manufacturer's requirements and align with stakeholders' comprehension. This is particularly crucial in a risk-averse environment, where human errors remain the major source of aircraft disasters (Baidzawi et al., 2019), affecting not only human life but also damaging a brand's reputation (Welch, 2021). The transition toward Industry 5.0, namely characterized by human-centricity, resilience, and sustainability (Ciano et al., 2025; Moenck et al., 2025), presents a real opportunity to address these challenges and reshape the industry.

First, the human-centric dimension encompasses both the call to integrate human factors and the need for human-AI collaboration. Given the inevitability of manual operations and human errors, workplaces should be designed to accommodate workers' limitations, including both their cognitive and physical constraints (Alogla et al., 2021; Kadir et al., 2019). Human-AI collaboration can be achieved by combining human intelligence and AI capabilities to leverage their respective strengths, namely creativity, expertise, and flexibility on the human side, and consistency and data analysis on the AI side (Dellermann et al., 2019). This synergy could achieve better overall performance than either stakeholder could alone, by allowing machines to handle redundant and tedious tasks and for humans to focus on their intuition (Hemmer et al., 2021). This is especially relevant in this field, where manual tasks such as inspection and assembly remain prevalent (Moenck et al., 2025). Additionally, domain experts need to understand how AI/ML solutions generate their outputs. However, a research gap remains regarding how to comprehend the algorithm without requiring deep AI/ML expertise (Yadam et al., 2020). Explainable AI (XAI), a subfield focused on making models understandable and explicable for human users (Oliveira et al., 2024), can be further explored in this industry, with only 6 articles (4%) related to this area. XAI can tackle challenges such as improving trust, understanding, and the ethical use of AI through transparency and post-hoc explicability (Mosqueira-Rey et al., 2023).

Second, ethical considerations must be considered in the design of AI/ML solutions. The high-stakes nature of the aircraft industry demands alignment with rigorous quality and certification standards. Some areas of exploration remain, such as the design of the human-AI collaboration framework, like human in the loop or AI in the loop (Dellermann et al., 2019), and the question of responsibility in cases of failure, including who ultimately bears that responsibility. Additionally, biases can emerge on the manufacturing floor, for instance, through human involvement in dataset creation or sensor drift (Pereira et al., 2018; Plathottam et al., 2023), directly threatening the resilience goal of Industry 5.0. Future research should focus on mitigating these risks to ensure a successful integration that protects both companies and employees.

Eventually, sustainability is recognized as one of the most actively studied themes in the research community, as mentioned in section 5.4. Current efforts primarily focus on reducing environmental impacts during the manufacturing stage and aircraft use. However, further efforts could explore how AI/ML technologies can enhance remanufacturing, repurposing, or recycling aircraft components, thereby aligning more closely with the Industry 5.0 paradigm. This holistic approach to manufacturing could benefit aircraft manufacturers and suppliers by identifying alternative materials or components, reducing the risk of supply chain disruption.

Another opportunity identified is the use of Large Language Models (LLMs) in this industry. LLMs are a branch of natural language processing (NLP) capable of performing tasks such as language translation, text summarization, and question answering (Liu et al., 2023). These models are trained on a large volume of data to leverage their statistical distributions to generate predictions of word sequences and can analyze both text and images (Birhane et al., 2023). LLMs in manufacturing can be applied in three main areas: engineering design, manufacturing, and mechanics. While they enhance conceptual design by aiding brainstorming and automating idea generation, they can also streamline prototyping, CAD modeling, and simulation tasks. Moreover, they contribute to the discovery of underlying knowledge, as well as to achieving intelligent predictive maintenance, digital twin, process automation, planning, and assisting human-machine interaction. Overall, LLMs have the potential to improve flexible decision-making and efficiency across engineering workflows (Liu et al., 2025; Mustapha, 2025). They are expected in the future to use real-time data to dynamically adapt to their environment and new scenarios autonomously, thereby improving performance and reducing the need for human supervision (Yutong et al., 2024). Therefore, we argue that these advantages can significantly benefit this field, especially by lightening workloads and reducing completion time for activities involving repetitive expertise and knowledge. Furthermore, domain experts and stakeholders could use LLMs as tools to explore and solve problems faster, leveraging their creativity and knowledge to identify multiple approaches to tackle complex issues. Indeed, among all papers analyzed, three used this AI technology; Auyeskhan et al., (2025) utilized a LLM integrated with Retrieval-Augmented Generation (RAG) to enhance decision-making in additive manufacturing, enabling users to access knowledge derived from research articles; Chandrasekaran (2025) combined a LLM with RAG to streamline the workflow of a defect diagnosis system, which typically requires human involvement and expert knowledge; and Wang et al. (2024), developed a domain-specific LLM tool tailored for aircraft maintenance. However, further research is needed to capitalize on these opportunities.

Eventually, the last opportunity identified relates to the supply chain. Surprisingly, as observed in Figure 7, research attention on the supply chain is significantly lower than in other domains of application. As stated in the introduction, the aircraft industry has a complex structure (Van Nguyen et al., 2023). Indeed, although some production stages are located close to the assembly factory, some suppliers remain based abroad, resulting in a global supply chain network (Mohib et al., 2017). Thus, we argue that further research could be conducted in this domain to tackle its complexity, particularly when a shortage of specific components can disrupt the entire production, or when knowledge is dispersed among multiple stakeholders.

7. Implications for stakeholders

This literature review presents several implications for stakeholders in this industry and policymakers. Firstly, this review helps identify and clarify a global framework for deploying these technologies, enabling decision-makers in this industry to understand their challenges, limitations, and opportunities. This understanding allows them to develop decision-making strategies tailored to the scale of their organizations and core business activities. The strength of this review lies in its analysis, which includes a broad range of aeronautical manufacturing stages, providing a multi-level perspective on the production process, which differs from current literature reviews.

Secondly, as stated in the introduction, this field is highly influenced by government policies. This review identifies both leading countries and mid-tier countries in this high-stakes research domain. Consequently, there are significant motivations to launch collaborative research projects between public institutions and private companies to overcome these challenges and produce research outputs that align with the interests of both actors. Given that this industry is highly reluctant to share collected data or developed technologies publicly, each project can have a critical impact in this highly competitive environment. Public policies can therefore play a significant role in supporting private actors.

8. Limitations

A PRISMA methodology has been used in this systematic literature review to fill the research gap of previous research conducted either in broader research areas or without a precise and rigorous procedure. Nevertheless, despite this meticulous method being applied, some limitations emerge, for example, that only two databases were analyzed. Indeed, including more databases would have provided a better overall perspective on this research field. However, it would have significantly increased the amount of required resources. Furthermore, one of the two databases screened could be considered somewhat weak in terms of transparency and quality of the papers. Thus, to alleviate these limitations, this database was combined with another one, deemed reliable for conducting systematic literature reviews, and a strict approach was adopted.

Additionally, the authors recognize that incorporating supplementary approaches, such as snowballing techniques or citation tracking, could strengthen the search strategy. However, integrating these methods posed challenges due to the specific combination of databases used. Moreover, the methodology of this review, particularly the screening and eligibility assessment of articles, was conducted by a single person, which introduces the possibility of reporting bias. Future reviews could benefit from involving multiple reviewers to minimize such biases and improve the reliability of the findings.

9. Conclusion

This study presents a comprehensive PRISMA literature review of 135 articles, providing an in-depth analysis of AI/ML applications in the aircraft manufacturing industry. It addresses the unique challenges of integrating AI/ML into a sector that has traditionally lagged in these technologies. Key findings highlight the focus on additive manufacturing, defect detection, and simulation, and identify gaps and opportunities, including FL, TL, human factors integration, the use of LLM, and supply chain applications.

Additionally, the review compiles data sources, enhancement techniques, research focus areas, and promising approaches to address challenges in AI/ML deployment in this industry. This study provides valuable insights for stakeholders by aligning with Industry 5.0 principles to leverage AI/ML technologies effectively. This research serves as a foundational resource, offering a roadmap for advancing AI/ML integration and highlighting the potential for transformative advancements through strategic application.

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Appendix

Appendix A

Table 2. Summary of dataset origins and their applications when mentioned.

Data Source Types	Articles	Data Sources	Prediction purposes
Experimental	(Wang et al., 2019; Wang et al., 2018a; Wang et al., 2018b); (Natarajan et al., 2023); (Sanchez et al., 2018); (Pattanam Ramamoorthy et al., 2025)	WEDM (Wire Electrical Discharge Machining) process data	Surface quality monitoring of fir-tree slots; Geometrical defect detection of fir-tree slots; Tolerance monitoring of disc turbine fir-tree slots; Alloy material performance; Defects detection; Surface roughness.
	(Hojjati et al., 2016); (Ernst et al., 2021); (Knittel et al., 2019); (Şap et al., 2025)	CNC (Computer Numerical Control) Milling	Reproducing printed components; Geometric characteristics of blades of a blisk; Surface quality diagnosis; Machining outcomes.
	(Adizue et al., 2023); (Adeniji et al., 2022)	CNC (Computer Numerical Control) Cutting	Surface roughness; Digital twin.
	(Akhil et al., 2020); (Fotovvati et al., 2022)	Selective Laser Melting (SLM)	Surface texture; Surface roughness.
	(Grozav et al., 2023); (Castro et al., 2023)	Fused Deposition Modeling (FDM)	Material properties; Compressive strength.
	(Massimo et al., 2023)	Powder Metallurgy	Mass and length of sintered workpieces.
	(Zhang et al., 2022b)	Robocasting	Adaptive control.
	(Caiazzo et al., 2018)	Laser Direct Deposition	Output geometric parameters.
	(Perani et al., 2023)	Laser Metal Deposition	Size of a track deposited.
	(Mueller et al., 2019)	Riveting	Online and offline inspection.
	(Verma et al., 2022)	Friction Stir Welding (FSW)	Ultimate tensile strength.
	(Salary et al., 2020)	Aerosol Jet Printing	Functional properties of printed electronics.
	(Nalajam et al., 2021); (Gain et al., 2025)	Wire Arc Additive Manufacturing (WAAM)	Detect porosity in microstructural images; Material properties.
	(Román et al., 2023)	Blending Process	Material properties prediction.
	(Kim et al., 2022); (Koch et al., 2022); (Lee et al., 2025)	Drilling	Burr types; Tool wear classification; Hole defects.
	(Kumar et al., 2024)	Single Point Incremental Forming	Maximal axial peak forces.
	(Fernandes et al., 2018)	Pulsed Thermal Ellipsometry	Assess fiber orientation of fiber-reinforced material.
	(Rabby et al., 2024)	Dielectric sensors	Quality inspection of fiber-reinforced polymer.
	(Yang et al., 2020)	Rotor System from Beijing Oriental Institute of Vibration and Noise Technology ("Beijing orient institute of measurement and test (boimt)") (branch of Chinese Academy of Space Technology (CAST) ("China academy of space technology")	Fault diagnosis.
	(Li et al., 2023c)	Microwave sensors	Real-time and non-destructive evaluation of coated composite structures.
	(Meister et al., 2021b); (Higgins et al., 2023)	Laser sensors	Explainable model for defect detection; Improve accuracy of industrial robots.
	(Prudviraj et al., 2021)	Thrusters	Mechanical properties.
	(Thanusha et al., 2024)	Wear setup	Wear and mechanical properties of nanocomposites reinforced with silicon carbide and jute fiber.
	(Doodi et al., 2023); (Bharat et al., 2025); (Auyeskhan et al., 2025)	3D Printing	Energy absorption of lattice structure; Compressive strength; Cost estimation.
	(Varol Özkavak et al., 2023)	Treatment Process	Mechanical properties.
	(Olowe et al., 2024)	Additive manufacturing printing process.	Print quality.
	(Akhavan et al., 2024)	Laser Directed Energy Deposition process.	Print head spatial localization.
	(Prasomthong et al., 2025); (Nargundkar et al., 2024)	Friction Stir Processing process.	Mechanical properties; Machining outcomes.
	(Raju Chekuri et al., 2025)	Hydraulic systems operations.	Fault detection.
	(M. A. Gorkavyy et al., 2024)	Painting process.	Real-time detection of aircraft components.
	(Ledesma et al., 2024)	Thermal cycles process.	Materials properties.
	(Mezher et al., 2024)	Resistance spot welding process.	Mechanical properties.
	(M et al., 2025)	Brazing process.	Process parameters adjustments.
	(Etem, 2025)	IR-based videos collected from welding.	Welding classification.
	(Shaban et al., 2017)	CNC (Computer Numerical Control) Cutting	Quality control of carbon fiber-reinforced polymer (CFRP).

	(Garcia-Perez et al., 2024; Liu et al., 2022)	CNC milling machines, Vertical lathe tool	Tool condition monitoring.
	(Isaza et al., 2024a)	Pictures	Nonconformities of trench-filling components.
	(Wang et al., 2020)	Internal Fault Tree Diagram	Fault diagnosis.
	(Hu et al., 2023)	Pictures & CAD models	Inspection of cable brackets of C919.
	(Bautista-Hernández et al., 2024)	Bill of material	Failures in manufacturing design process of electrical harnesses.
	(Loyer et al., 2016)	Description of components	Manufacturing cost of jet engine components.
	(Van Nguyen et al., 2023)	Material data, process data and market data (web crawling)	Aircraft structure, sub-assembly parts, components, and aircraft engine manufacturing cost.
	(Pereira et al., 2018); (Chen et al., 2023a); (Manohar et al., 2018); (Martinez et al., 2021)	Sensors in manufacturing processes	Quality control of a riveting machine; Real-time monitoring system for predictive maintenance of hot-pressing furnace; Shim gaps of Boeing; Quality control of aircraft seams of F-35 Joint Strike Fighter.
	(Shafi et al., 2023); (Ruiz et al., 2020); (Niccolai et al., 2021)	Images from manufacturing processes	Quality control of wing section; Quality control of aircraft fixation elements; Quality control using fluorescent penetrant inspection (FPI).
Company	(Siyaev et al., 2023)	Technical documents of Boeing 737	Maintenance operations.
	(Fysikopoulos et al., 2015); (Jwo et al., 2022)	Manufacturing process	Optimize production variables of military ramp hinge loading; Digital twin of autoclave curing process.
	(Merayo et al., 2021)	Material properties	Material properties.
	(Abdulla et al., 2024)	Supplier's data and internal decision-making criteria	Reduce complexity of input data for supplier selection.
	(Isaza et al., 2024b)	Expert knowledge from the aeronautical industry.	Defects classifications
	(Rosa et al., 2025)	Technical reports, company's production order database, interviews.	Estimating the duration for developing new products and forecasting the overall lead time for component manufacturing.
	(Yunker et al., 2024)	Fuselage production processes.	Defects classification.
	(Abdullah et al., 2025)	Collection of components utilized during the process.	Aerospace part recognition.
	(Hassan et al., 2025)	Historical autoclave data.	Temperature of autoclave process.
	(Sen et al., 2025)	Configuration of the product.	Prediction of the operational failures.
	(Wijaya et al., 2025)	Current sensors from autoclave process.	Fault detection.
	(Crawford et al., 2021; Ramezankhani et al., 2021a; Ramezankhani et al., 2021b)	Raven ("RAVEN simulation software | convergent")	Autoclave curing process.
	(Hsu et al., 2023)	Moldex3D ("Moldex3D | plastic injection molding simulation software")	Mechanical properties of woven fiber composite material.
	(Herrera et al., 2024)	ANSYS ("Ansys mechanical | structural fea analysis software")	Damage detection of wings.
	(Al-Haddad et al., 2024)	SolidWorks ("SOLIDWORKS") & ANSYS ("Ansys mechanical | structural fea analysis software")	Mechanical properties of aircraft landing gear.
Software	(Choi et al., 2023), (Wu et al., 2024a)	ABAQUS ("Abaqus finite element analysis | simulia - dassault systèmes")	Elastic moduli of short-fiber reinforced plastics; DoC curve of composite material
	(Frey Marioni et al., 2022)	Nektar++ ("Nektar++")	Low-pressure turbine properties.
	(Jaw et al., 2014)	ProDiMES (Simon, 2010) (NASA)	Fault diagnosis of aircraft engine.
	(Choudhary et al., 2025)	Sentaurus ("Sentaurus Device")	Single Event Transient pulse current.
	(Zhao et al., 2024); (Huang et al., 2023); (Zhang et al., 2022a)	Finite Element Method	Stress prediction of composite bolted joints; Transverse modulus of unidirectional composites; Deformation and progressive damage of open-hole laminates.
	(Zhan et al., 2021a; Zhan et al., 2021b)	Continuum Damage Mechanics	Elastoplastic fatigue damage.
Method	(Yüce et al., 2023)	FALSTAFF (Aicher et al., 1976)	Crack growth life of aircraft wing joints.
	(Bacciaglia et al., 2025b), (Bacciaglia et al., 2025a)	Bidirectional evolutionary structural optimization (BESO).	Topology optimization.
	(Mehrabi et al., 2025)	Combination of mathematical models.	Materials properties.
	(Abidi et al., 2022)	Github (Desai, 2025)	Predictive maintenance of aircraft engines.
Open-source	(Tong, 2023); (Yadam et al., 2020); (Azar et al., 2022; Azar et al., 2020); (Llasag Rosero et al., 2024)	NASA; C-MAPSS (Frederick et al., 2007); Dataset repository ("Prognostics center of excellence data set repository - nasa")	Engine performance features; Visual interpretable model for predicting airfoil noise; Fault diagnosis of aircraft engines; Remaining useful life of aircraft components.
	(Dou et al., 2023); (Jeung et al., 2025); (P et al., 2024)	"Mechanical Tools Classification Dataset" ("Mechanical tools classification dataset"); "Rotating Machinery Type AI Dataset"	Tool recognition; Classification of vibration of rotating equipment.

		(“Plateforme de fabrication kamp ai”); “Machine Predictive Maintenance Classification” (“Machine predictive maintenance classification”).	
	(Wang et al., 2024)	“MaintNet” (Akhbardeh et al., 2020)	Defect detection.
Open-source	(Dasari et al., 2020); (Wu et al., 2024b)	Public dataset; (Zhang et al., 2023)	Defect classification of selective laser melting.
	(Ali et al., 2022)	Compilation from published research papers	Mechanical properties of lattice structures.
	(Arora et al., 2024); (Dhrangdhariya et al., 2025)	“NEU-DET” (Wu) and “GC10-DET” (“GC10-det”); Compilation of online resources – “Fashion Pattern dataset” (“Fashion-pattern-images”) and “Kylberg dataset” (“Kylberg texture dataset”)	Machine state; Defects classification.
Experimental and Software	(Awd et al., 2025)	Selective Laser Melting (SLM) and ABAQUS (“Abaqus finite element analysis | simulia - dassault systèmes”)	Mechanical properties.
	(Abbas et al., 2025)	Fused Deposition Modeling (FDM) and nTop (“NTop | computational design software | formerly ntopology”)	Mechanical properties.
	(Chan et al.)	Autoclave process and Public dataset (Namilae et al., 2024)	Defect detection.
Experimental and Open-Source	(Zubair et al., 2024)	Dry Finishing Turning and Zubair et al. (Zubair et al., 2023)	Tool life and Surface Roughness.
	(Matitopanum et al., 2023b)	Friction Stir Welding (FSW) & (Shubham Verma et al., 2018) & (Matitopanum et al., 2023a)	Material properties.
Experimental and Method	(Zhu et al., 2024)	Additive Friction Stir Deposition (AFSD) and Computational Fluid Dynamics (CFD)	Thermal prediction.
	(Chandrasekaran, 2025)	Inspection process and reports made by technician. Open-source data (unavailable).	Defect analysis.
Company and Open-source	(Xie, 2024)	CNC lathe machines (process parameters); IoT sensors for condition monitoring; NASA’s Turbofan Engine Degradation Simulation Dataset (CMAPSS) (“CMAPSS jet engine simulated data - nasa open data portal”)	Prediction tool life; Condition monitoring; Degradation process of turbofan engines.
	(Alharbi et al., 2024)	Sensors in Manufacturing Process and Purohit et al. (Purohit et al., 2019)	Machine condition.
Company and Software	(Saadi et al., 2024)	Internal information and AnyLogic (“AnyLogic”)	Production line parameters.
Open-source and Software	(Eckley et al., 2025)	UIUC Airfoil Coordinates Dataset (“UIUC airfoil data site”) and JavaFoil (“JavaFoil”).	Airfoil Geometry

Table 3. Strategy of data augmentation or reduction utilized

Domain	Article	Strategy used
	(Zhao et al., 2024)	Use of a pre-trained SR-M-GAN network to enhance the resolution and quantity of simulation results obtained from finite element method simulations with coarse-grid meshing of stress.
	(Tong, 2023)	Creation of new data points by transforming the data through multiplying coefficients on certain variables considered to be linearly correlated.
ED	(Varol Özkavak et al., 2023)	Scaling up with 5 intermediate values by cross-linking the standard deviation and mean values in the dataset.
	(Bacciaglia et al., 2025b)	Use of the condition number κ method.
	(Wu et al., 2024a)	Restriction and utilization of 20 horizontal coordinates to define a curve's behavior.
	(Eckley et al., 2025)	Arbitrary data removal due to memory constraint.
	(Garcia-Perez et al., 2024)	Two data augmentation strategies were reported: hardware and software. Hardware: use of a specific camera to capture 9 different angles from a single image shot. Software: use of Generative Adversarial Networks (GANs) and Stable Diffusion (SD), two AI models to generate new images, as well as through Euclidean geometric transformations (rotation, mirroring, flipping, cropping, upscaling, shearing, and color shifts).
MM	(Liu et al., 2022)	Application of 3 random Gaussian noises to half of the dataset with a noise intensity of k = 0.1.
	(Jaw et al., 2014)	Use of kernel sliced inverse regression and principal component analysis.
	(Abidi et al., 2022)	Use of the Jaya-based Sea Lion Optimization (J-SLnO) algorithm for optimal feature selection of the data.
	(Xie, 2024)	Use of feature extraction (no information).
	(Alharbi et al., 2024)	Add of background noise, time stretching, picth shift and gaussian noise.
	(Chandrasekaran, 2025)	Removing data from insufficient classes. No information about the augmentation technique employed.
	(Raju Chekuri et al., 2025)	Use of Extra Trees Classifier for features extraction and Feature Importance Ranking to reduce the dimensionality of the data.
	(Crawford et al., 2021)	Using the Synthetic Minority Over-sampling Technique (SMOTE) for undersampling dominant labels and oversampling underrepresented labels.
	(Ramezankhani et al., 2021b)	Development of a framework called Active Transfer Learning (ATL) that integrates Transfer Learning (TL) and Active Learning (AL) to train a model to maximize information gain from manufacturing data and to create a robust model in response to the introduction of new data distributions (operational shifts).
	(Hu et al., 2023)	Reduce overfitting by integrating Augmented Reality into Mask R-CNN and then comparing it with the CAD model for more efficient image segmentation.
	(Meister et al., 2021a)	Use of a Deep Convolutional Generative Adversarial Network (DCGAN) to generate Laser Line Scan Sensor depth maps of Automated Fiber Placement layup defects.
	(Tyystjärvi et al., 2024)	Use of random flips and dataset image cropping.
	(Ruiz et al., 2020)	Use of three rotations of 90, 180, and 270 degrees and two symmetries (vertical and horizontal) on each dataset image.
	(Ruiz et al., 2022)	Use of rotations and symmetries on images to increase the dataset.
	(Mueller et al., 2019)	Use of rotation and mirroring on dataset images.
QM	(Meister et al., 2021b); (Arora et al., 2024)	No information about the method.
	(Amini et al., 2022)	Use of a pre-trained COCO model and application of transfer learning to reduce the need for a large dataset.
	(Isaza et al., 2024a)	Use of a pre-trained COCO model and application of transfer learning to reduce the need for a large dataset.
	(Fernandes et al., 2018)	Utilization of Principal Component Thermography to extract the most variable features of the data.
	(Herrera et al., 2024); (Li et al., 2023c)	Use of principal component analysis (PCA) to reduce the dimensionality of the data.
	(Manohar et al., 2018)	Use of robust principal component analysis (RPCA) to reduce the dimensionality of the data.
	(Etem, 2025)	Use of an autoencoder to reduce the dimensionality of IR image data.
	(Chan et al.)	Conversion of grayscale image into a three-channel color images.
	(Dhrangdhariya et al., 2025)	Geometric transformations, splitting images into quarters, distortions, various projections, stretching, perspective changes, and color intensity variations.
	(Yunker et al., 2024)	Use of signal flipping, reversing, and flipping-reversing.
	(Dou et al., 2023)	Use of several methods such as rotation and noise disturbances.
SCM	(Abdulla et al., 2024)	Manual selection of relevant variables to reduce data size. Use of multivariate feature imputation for data augmentation.

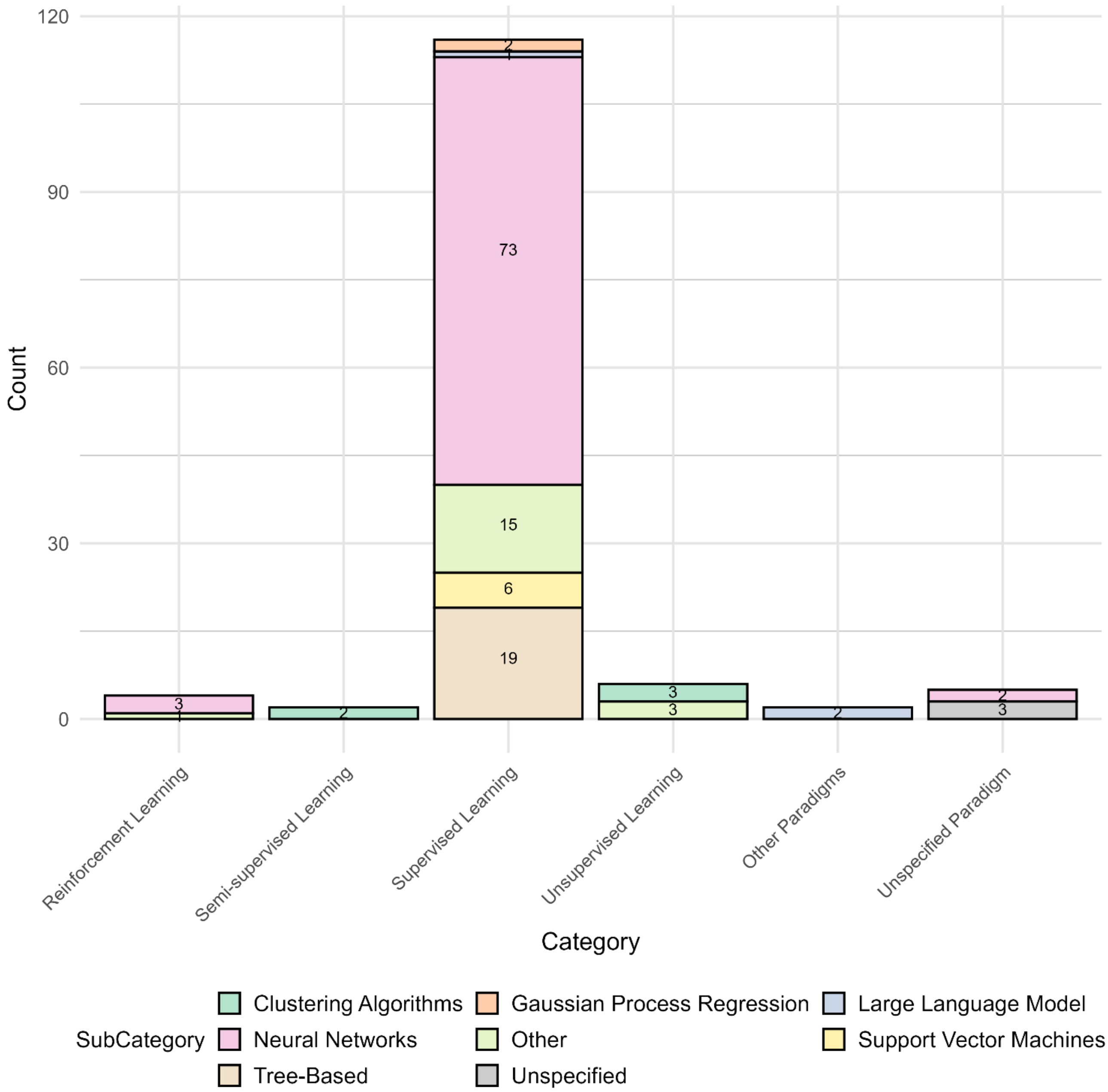

Fig. 6. Distribution of learning paradigms and models

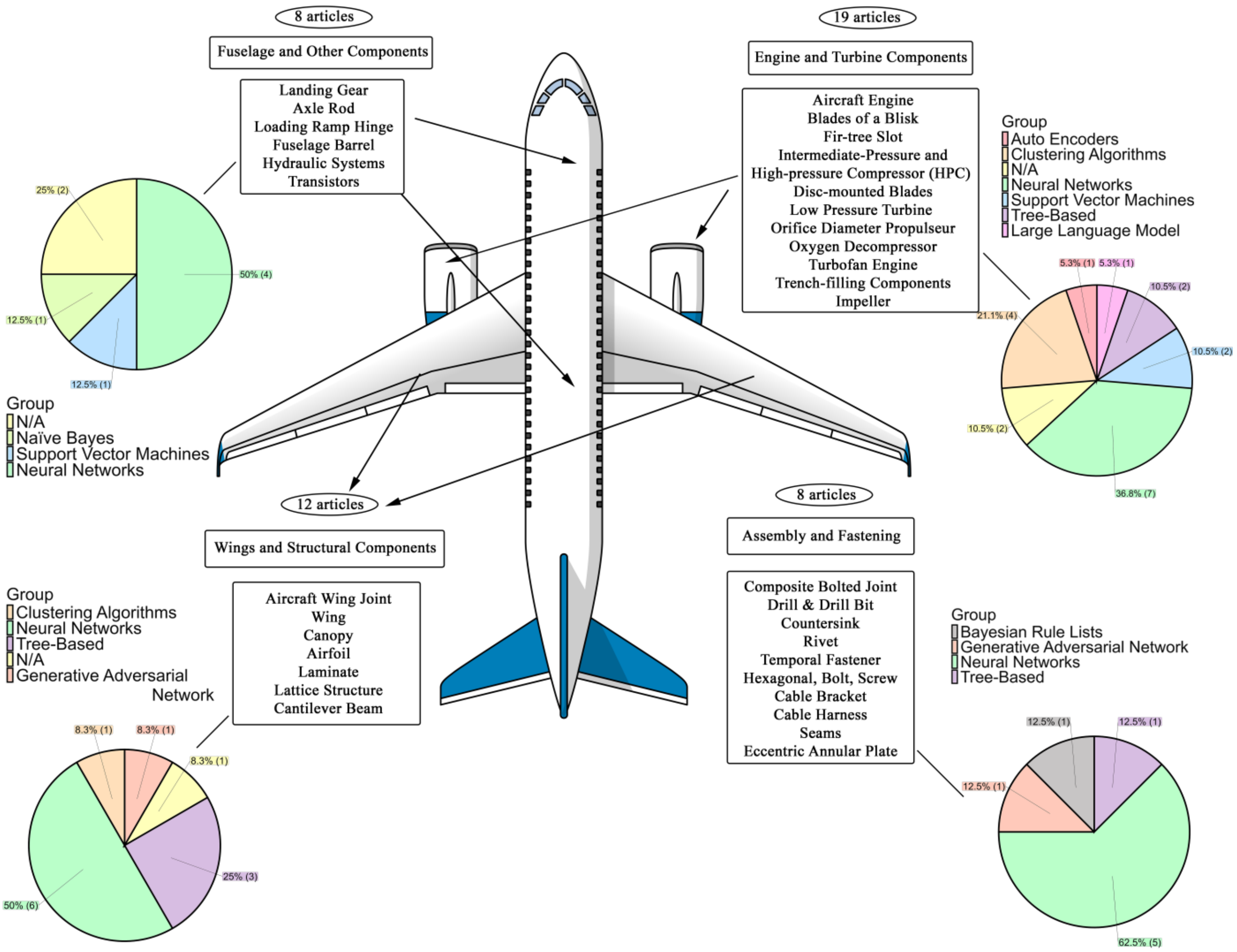

Fig. 9. Distribution of aircraft components focused and model used

Table 4. Details of main features

Main features	Articles
Supervised Learning	(Abbas et al., 2025; Abdulla et al., 2024; Abdullah et al., 2025; Abidi et al., 2022; Adizue et al., 2023; Akhavan et al., 2024; Akhil et al., 2020; Al-Haddad et al., 2024; Alharbi et al., 2024; Ali et al., 2022; Amini et al., 2022; Arora et al., 2024; Auyeskhan et al., 2025; Awd et al., 2025; Bacciaglia et al., 2025a; Bacciaglia et al., 2025b; Bautista-Hernández et al., 2024; Bharat et al., 2025; Caiazzo et al., 2018; Castro et al., 2023; Chan et al.; Chandrasekaran, 2025; Chen et al., 2023a; Choi et al., 2023; Choudhary et al., 2025; Crawford et al., 2021; Dasari et al., 2020; Dhrangdhariya et al., 2025; Doodi et al., 2023; Dou et al., 2023; Eckley et al., 2025; Eddy et al., 2023a; Eddy et al., 2023b; Ernst et al., 2021; Etem, 2025; Fernandes et al., 2018; Filz et al., 2021; Fotovvati et al., 2022; Frey Marioni et al., 2022; Gain et al., 2025; Garcia-Perez et al., 2024; Grozav et al., 2023; Hassan et al., 2025; Herrera et al., 2024; Higgins et al., 2023; Hojjati et al., 2016; Hsu et al., 2023; Hu et al., 2023; Huang et al., 2023; Isaza et al., 2024a; Isaza et al., 2024b; Jaw et al., 2014; Jeung et al., 2025; Jwo et al., 2022; Kim et al., 2022; Knittel et al., 2019; Koch et al., 2022; Kolozis et al., 2025; Kumar et al., 2024; Ledesma et al., 2024; Lee et al., 2025; Li et al., 2023c; Loyer et al., 2016; M. A. Gorkavyy et al., 2024; M et al., 2025; Martinez et al., 2021; Massimo et al., 2023; Matitopanum et al., 2023b; Mehrabi et al., 2025; Meister et al., 2021a; Meister et al., 2021b; Merayo et al., 2021; Mezher et al., 2024; Mueller et al., 2019; Nalajam et al., 2021; Nargundkar et al., 2024; Natarajan et al., 2023; Niccolai et al., 2021; Olowe et al., 2024; P et al., 2024; Pattanam Ramamoorthy et al., 2025; Perani et al., 2023; Pereira et al., 2018; Prasomthong et al., 2025; Prudviraj et al., 2021; Rabby et al., 2024; Raju Chekuri et al., 2025; Ramezankhani et al., 2021b; Román et al., 2023; Rosa et al., 2025; Ruiz et al., 2022; Ruiz et al., 2020; Saadi et al., 2024; Salary et al., 2020; Sanchez et al., 2018; Şap et al., 2025; Sen et al., 2025; Shaban et al., 2017; Shafi et al., 2023; Siyaev et al., 2023; Thanusha et al., 2024; Tong, 2023; Tyystjärvi et al., 2024; Van Nguyen et al., 2023; Varol Özkavak et al., 2023; Verma et al., 2022; Wang et al., 2018b; Wang et al., 2024; Wijaya et al., 2025; Wu et al., 2024a; Wu et al., 2024b; Xie, 2024; Yadam et al., 2020; Yüce et al., 2023; Yunker et al., 2024; Zhan et al., 2021a; Zhan et al., 2021b; Zhang et al., 2022a; Zhang et al., 2022b; Zhao et al., 2024; Zhu et al., 2024; Zubair et al., 2024)

Unsupervised Learning	(Eckley et al., 2025; Liu et al., 2022; Manohar et al., 2018; Wang et al., 2019; Wang et al., 2018a; Yang et al., 2020)
Reinforcement Learning	(Awd et al., 2025; M et al., 2025; Saadi et al., 2024; Veeramani et al., 2020)
Semi-supervised Learning	(Azar et al., 2022; Azar et al., 2020)
Unspecified Paradigm	(Llasag Rosero et al., 2024)
Unclassifiable and others	(Auyeskhan et al., 2025; Chandrasekaran, 2025)
Engineering Design (ED)	(Abbas et al., 2025; Al-Haddad et al., 2024; Ali et al., 2022; Awd et al., 2025; Bacciaglia et al., 2025a; Bacciaglia et al., 2025b; Bharat et al., 2025; Caiazzo et al., 2018; Castro et al., 2023; Choi et al., 2023; Choudhary et al., 2025; Doodi et al., 2023; Eckley et al., 2025; Frey Marioni et al., 2022; Gain et al., 2025; Grozav et al., 2023; Hassan et al., 2025; Hsu et al., 2023; Huang et al., 2023; Kolozis et al., 2025; Kumar et al., 2024; Ledesma et al., 2024; Matitopanum et al., 2023b; Mehrabi et al., 2025; Merayo et al., 2021; Mezher et al., 2024; Nargundkar et al., 2024; Pattanam Ramamoorthy et al., 2025; Prasomthong et al., 2025; Prudviraj et al., 2021; Ramezankhani et al., 2021a; Román et al., 2023; Şap et al., 2025; Thanusha et al., 2024; Tong, 2023; Varol Özkavak et al., 2023; Verma et al., 2022; Wu et al., 2024a; Wu et al., 2024b; Yadam et al., 2020; Yüce et al., 2023; Zhan et al., 2021a; Zhan et al., 2021b; Zhang et al., 2022a; Zhao et al., 2024; Zubair et al., 2024)
Maintenance Management (MM)	(Abidi et al., 2022; Alharbi et al., 2024; Azar et al., 2022; Azar et al., 2020; Chandrasekaran, 2025; Chen et al., 2023a; Filz et al., 2021; Garcia-Perez et al., 2024; Jaw et al., 2014; Jeung et al., 2025; Koch et al., 2022; Liu et al., 2022; Llasag Rosero et al., 2024; P et al., 2024; Raju Chekuri et al., 2025; Sen et al., 2025; Siyaev et al., 2023; Wang et al., 2024; Wijaya et al., 2025; Xie, 2024)
Production Planning and Control (PPC)	(Adeniji et al., 2022; Adizue et al., 2023; Akhavan et al., 2024; Fotovvati et al., 2022; Fysikopoulos et al., 2015; Higgins et al., 2023; Jwo et al., 2022; M et al., 2025; Massimo et al., 2023; Natarajan et al., 2023; Perani et al., 2023; Rosa et al., 2025; Saadi et al., 2024; Sanchez et al., 2018; Shaban et al., 2017; Veeramani et al., 2020; Zhang et al., 2022b; Zhu et al., 2024)
Quality Management (QM)	(Abdullah et al., 2025; Akhil et al., 2020; Amini et al., 2022; Arora et al., 2024; Bautista-Hernández et al., 2024; Chan et al.; Crawford et al., 2021; Dasari et al., 2020; Dhrangdhariya et al., 2025; Eddy et al., 2023a; Eddy et al., 2023b; Ernst et al., 2021; Etem, 2025; Fernandes et al., 2018; Herrera et al., 2024; Hu et al., 2023; Isaza et al., 2024a; Isaza et al., 2024b; Kim et al., 2022; Knittel et al., 2019; Lee et al., 2025; Li et al., 2023c; M. A. Gorkavyy et al., 2024; Manohar et al., 2018; Martinez et al., 2021; Meister et al., 2021a; Meister et al., 2021b; Mueller et al., 2019; Nalajam et al., 2021; Niccolai et al., 2021; Olowe et al., 2024; Pereira et al., 2018; Rabby et al., 2024; Ramezankhani et al., 2021b; Ruiz et al., 2022; Ruiz et al., 2020; Salary et al., 2020; Shafi et al., 2023; Tyystjärvi et al., 2024; Wang et al., 2019; Wang et al., 2018b; Wang et al., 2020; Yang et al., 2020; Yunker et al., 2024)
Supply Chain Management (SCM)	(Abdulla et al., 2024; Auyeskhan et al., 2025; Dou et al., 2023; Loyer et al., 2016; Van Nguyen et al., 2023)
Cybersecurity (CS)	(Hojjati et al., 2016)
Aluminums Alloys	(Ali et al., 2022; Auyeskhan et al., 2025; Awd et al., 2025; Caiazzo et al., 2018; Herrera et al., 2024; Kim et al., 2022; Koch et al., 2022; Kumar et al., 2024; Matitopanum et al., 2023b; Merayo et al., 2021; Nalajam et al., 2021; Nargundkar et al., 2024; Prasomthong et al., 2025; Ramezankhani et al., 2021a; Rosa et al., 2025; Van Nguyen et al., 2023; Varol Özkavak et al., 2023; Verma et al., 2022; Wu et al., 2024b; Yüce et al., 2023; Zhan et al., 2021b; Zhu et al., 2024; Zubair et al., 2024)
CFRP	(Ali et al., 2022; Amini et al., 2022; Bharat et al., 2025; Chan et al.; Choi et al., 2023; Crawford et al., 2021; Fernandes et al., 2018; Hsu et al., 2023; Isaza et al., 2024a; Jwo et al., 2022; Kolozis et al., 2025; Ledesma et al., 2024; Lee et al., 2025; Li et al., 2023c; Meister et al., 2021a; Meister et al., 2021b; Rabby et al., 2024; Ramezankhani et al., 2021a; Ramezankhani et al., 2021b; Shaban et al., 2017; Wu et al., 2024a; Zhao et al., 2024)
Other Polymers and Plastics	(Abbas et al., 2025; Ali et al., 2022; Bharat et al., 2025; Castro et al., 2023; Grozav et al., 2023; Ledesma et al., 2024; Olowe et al., 2024; Román et al., 2023)
Titanium Alloys	(Adeniji et al., 2022; Akhil et al., 2020; Al-Haddad et al., 2024; Ali et al., 2022; Auyeskhan et al., 2025; Awd et al., 2025; Fotovvati et al., 2022; Mezher et al., 2024; Natarajan et al., 2023; Pattanam Ramamoorthy et al., 2025; Zhan et al., 2021b; Zhan et al., 2021b; Zubair et al., 2024)
Steels and Stainless Steels	(Adizue et al., 2023; Akhavan et al., 2024; Ali et al., 2022; Auyeskhan et al., 2025; Mezher et al., 2024; Ramezankhani et al., 2021a; Sanchez et al., 2018; Wang et al., 2019; Wang et al., 2020; Zhan et al., 2021a; Zhan et al., 2021b)
Engine and Turbine Components	(Abidi et al., 2022; Adeniji et al., 2022; Auyeskhan et al., 2025; Azar et al., 2022; Azar et al., 2020; Ernst et al., 2021; Frey Marioni et al., 2022; Garcia-Perez et al., 2024; Isaza et al., 2024a; Isaza et al., 2024b; Jaw et al., 2014; Loyer et al., 2016; Prudviraj et al., 2021; Tong, 2023; Wang et al., 2019; Wang et al., 2018a; Wang et al., 2018b; Wang et al., 2020; Yang et al., 2020)
Wings and Structural Components	(Ali et al., 2022; Bacciaglia et al., 2025a; Bacciaglia et al., 2025b; Doodi et al., 2023; Eckley et al., 2025; Herrera et al., 2024; Manohar et al., 2018; Pereira et al., 2018; Shafi et al., 2023; Yadam et al., 2020; Yüce et al., 2023; Zhang et al., 2022a)
Assembly and Fastening	(Eddy et al., 2023a; Eddy et al., 2023b; Hu et al., 2023; Mehrabi et al., 2025; Mueller et al., 2019; Ruiz et al., 2022; Ruiz et al., 2020; Zhao et al., 2024)
Fuselage and Other Components	(Al-Haddad et al., 2024; Arora et al., 2024; Fysikopoulos et al., 2015; Koch et al., 2022; Salary et al., 2020; Yunker et al., 2024)

Table 5. Benefits measured and reported in articles included in this review

Articles	Type of benefits	Benefits reported
(Zhao et al., 2024)	Time	Decrease the simulation time from 4 hours to 6.1 seconds for stress composite bolted joint simulation.
(Hsu et al., 2023)	Time	Decrease simulation time from 90 and 600 minutes to 1 minute for mechanical property simulation of woven fiber composite material.
(Isaza et al., 2024a)	Time	Decrease the inspection time from 1 hour 30 minutes to 6 minutes for turbine trench-filler.
(Veeramani et al., 2020)	Time	Decrease the time from 54 seconds to 0.23 seconds to find the optimal robot path planning.
(Al-Haddad et al., 2024)	Time	Decrease the time from 4 hours and 42 minutes to 1 second to simulate mechanical properties of aircraft undercarriage landing gear during the landing phase.
(Massimo et al., 2023)	Time	Gain of time to adjust process parameters by providing a simulation which runs in approximately 1.7 seconds instead of 35 pieces per minute for mechanical properties of sintered workpieces produced by powder metallurgy.
(Fernandes et al., 2018)	Time	Reduction of the inspection time from 25 minutes to 30 seconds for fiber orientation of fiber-reinforced materials.
(Bacciaglia et al., 2025a; Bacciaglia et al., 2025b)	Time	Reduction of 55% of the simulation time, 83% of time saving to build the dataset.
(Isaza et al., 2024b)	Time	Reduction of the diagnosis time from 90 minutes to 6 minutes (150%). Increase of the expected operation efficiency by from 112 to 3500 units.
(Zubair et al., 2024)	Time	Reduction by of 26% experimental trials.
(Lee et al., 2025)	Time	Reduction of the inspection time from 20 seconds to 10 seconds (50%) for one drilling operation.
(Bautista-Hernández et al., 2024)	Time and Quality	Reduction by 93% in time and 90% of errors in the creation of the manufacturing process for electrical harnesses (estimation).
(Awd et al., 2025)	Time and Quality	Reduction of the design iterations by over 50%, improvement of the fatigue crack resistance by 20-30% with 15% weight reduction.
(Shafi et al., 2023)	Time and Cost	52.88% reduction in time and 34.32% reduction in the cost of rework for the wing section.
(Adeniji et al., 2022)	Time and Cost	Improvement of 93% in process queuing time, 84% in energy efficiency, 2% in scrap cost, and 93% in queuing cost.
(M et al., 2025)	Time, Cost, Quality	Reduction of 24.8% of brazing cycle time, decrease of 15.3% of maintenance cost reduction, 11% reduction of power consumption, decrease of 23.5% of defect rate, improvement of 14,2% of joint strength.
(Wang et al., 2020)	Quality	Improvement by: (1) 50% in the efficiency of the oxygen decompressor; (2) 60% in the troubleshooting accuracy of the oxygen decompressor.
(Sanchez et al., 2018)	Quality	Can predict thickness variation in wire electrical discharge machining at least 2 mm in advance, allowing for reparameterization of the process before defects occur.
(Li et al., 2023c)	Quality	Decrease of the error (root-mean-square error) from 15µm to 12µm for thickness measurement of thin coating on carbon fiber composites in comparison with the traditional technique.
(Zhang et al., 2022b)	Quality	Reduction in the standard deviation of ceramic robocasting print quality from 153.6µm to 28.7µm (average standard deviation across tests).
(Auyeskhan et al., 2025)	Cost	Improvement in cost estimation accuracy by 21%.