International Journal of Theoretical & Applied Computational Intelligence
https://ijtaci.com

Research Review

Application of Data-Based Artificial Intelligence in the Aviation Industry: A Conceptual-Analytic Review of Machine Learning and Deep Learning Methods

Morteza Narimanidehnavi

Graduate, Ulster University (London Campus), London EC1N 2TD, United Kingdom
*Corresponding Author: Morteza Narimanidehnavi Email: Mailnarimani63@gmail.com
https://orcid.org/0009-0004-4450-163X

Received: 03/01/2026; Accepted: 21/02/2026; Published: 23/02/2026
https://doi.org/10.65278/IJTACI.2026.3

Abstract: The aviation industry, as a complex and safety-sensitive technical-operational system, faces a huge volume of heterogeneous data, including flight time series, aircraft and engine health data, spatial and temporal air traffic data, meteorological data, textual safety and repair reports, and visual inspection data. This article provides a conceptual-analytical review that aims to explain the logic of "data-driven artificial intelligence" in aviation and describe how machine learning and deep learning methods can be purposefully utilized to produce "operational knowledge" and "actionable decisions." The present review approach, rather than simply comparing algorithms, focuses on the “problem-data-model-output” mapping framework and suggests that the choice of analytical method should be a function of the type of operational problem (prediction, anomaly detection, classification, image analysis, and sequential decision making), the nature of the available data, and the requirements of industrial deployment. The results of the review indicate that classical machine learning methods have greater advantages in more structured problems requiring interpretability, and deep learning models have greater advantages in large/complex or unstructured data (images, text, long time series). However, successful transition from a research environment to an operational environment faces challenges such as lack of labeled data, class imbalance and rare events, changing data scope, need for interpretability, and regulatory constraints. Finally, the paper suggests future directions in the form of multi-source learning, robust and adaptive learning, secure reinforcement learning, human-in-the-loop, and certification frameworks for sustainable deployment of AI in aviation.

Keywords: Data-driven AI; Aviation Industry; Machine Learning; Deep Learning; Flight Safety; Predictive Maintenance; Explainable AI Monitoring; Local Binary Patterns

1. Introduction

The aviation industry, as one of the most complex technical-operational systems in the world, inherently faces dynamic environments, high uncertainty, and extreme safety sensitivity. In such a system, operational decisions from flight planning and execution to maintenance management and air traffic control directly impact safety, cost, efficiency, and environmental sustainability. The rapid growth of digitalization and the development of sensing and data recording infrastructure have turned modern aviation into one of the richest data ecosystems. Data ranging from flight recorders and aircraft health systems to Automatic Dependent Surveillance-Broadcast (ADS-B) data, airport data, textual maintenance reports, and safety reports [1]. These conditions have paved the way for the emergence of a dominant paradigm: data-driven artificial intelligence. This paradigm aims to transform heterogeneous and voluminous data into “operational knowledge” and “actionable decisions” [2]. In line with this trend, more recent reviews indicate that data science and artificial intelligence have been increasingly integrated into the entire aviation lifecycle, from flight network management to ground operations [3]. Despite historical advances in physical models and statistical methods, the limitations of traditional approaches to the complexity of today's aviation industry have become increasingly apparent. Many key aviation problems are nonlinear, multi-causal, and time-dependent in nature, and are often associated with incomplete, noisy, and unbalanced data (especially for rare but critical events) [4]. In such a context, relying solely on fixed rules or simplified models does not meet the needs for fast and reliable decision-making. This has led to the emergence of machine learning and deep learning methods as the main tools for pattern extraction and prediction in aircraft dynamic systems, especially in scenarios where the goal is prediction or early detection rather than just posterior analysis [5]. Furthermore, more general reviews in recent years have shown that ML/DL in areas such as anomaly detection, predictive maintenance, route optimization, and operational resource management have strengthened the transition from reactive to predictive decision-making [6].

Understanding “how to use” ML/DL in the aviation industry requires a chain view. In a data-driven approach, the starting point is always a real operational problem: for example, reducing flight delays, reducing fuel consumption, increasing fleet availability, or reducing safety risk. The type of data that describes that problem is then identified: Multidimensional time series data such as FDR/QAR and engine parameters [7], spatio-temporal data such as ADS-B and traffic data, textual data (such as maintenance reports and safety reports), and image data (such as visual inspection of the airframe or components). After that, the data preparation stage and appropriate input construction (time synchronization, missing data correction, feature engineering, or representation learning) are crucial, because in many industrial projects, the failure or success of the model depends more on the quality of the data and the preparation process than on the complexity of the algorithm [2]. In this direction, the choice of method is also a function of the "data type" and the "decision-making goal": classical ML methods are often suitable in more limited data conditions and require higher interpretability, while DL has more advantages when faced with complex and voluminous data (images, text, long time series) [8-10].

Recent literature suggests that the application areas of AI in aviation can be categorized into several main areas, each with a specific mapping of “problem-data-model-output.” In the field of flight safety, the focus is on flight anomaly detection, identification of precursors of hazardous events, and multi-source analysis of human-environmental factors. Here, deep time series models, unsupervised/semi-supervised methods for anomaly detection, as well as NLP methods for analyzing safety reports, become important [11]. In the field of maintenance and repair (MRO), the main goal is to reduce sudden failures, prevent accidental grounding (AOG), and optimize the repair cycle; therefore, models such as random forest/gradient boost for failure prediction, recurrent networks and autoencoders for health monitoring and deviation detection, and remaining life (RUL) estimation frameworks are widely used [12]. In the field of air traffic management (ATM), the problem is tied to spatio-temporal data and network interactions, and models are usually structured around traffic prediction, route optimization, and delay reduction; systematic reviews have also shown that a significant portion of recent studies are dedicated to these goals[13]. In the areas of flight operations and fuel consumption, as well as airport and ground operations, models for delay prediction, resource allocation, and decision optimization are also proposed, often leading to combined "optimization + learning" or even reinforcement learning approaches for sequential decision making [14].

However, the successful transition from "research modeling" to "industrial deployment" in aviation requires overcoming technical and non-technical obstacles.

• First, data quality and availability are challenging: data can be fragmented, confidential, non-standardized, and fleet/company-specific.

• Second, critical events are often rare and cause class imbalance: hence, evaluating models solely by metrics such as overall accuracy is misleading, and metrics sensitive to error cost, type I/II error rate analysis, and robustness assessment in rare scenarios should be used [11].

• Third, in safety-sensitive systems, "interpretability" and "confidence" in the model are of critical importance: as a result, there has been an increasing trend towards explainable models and hybrid approaches that strike a balance between efficiency and explainability [15].

• Fourth, the issue of "domain shift" and performance degradation in new conditions, especially in operational data, is a serious obstacle to generalizability and highlights the need for continuous monitoring and controlled retraining [16].

The sum of these factors shows that the true value of AI in aviation is not limited to choosing an advanced algorithm, but rather in designing a complete lifecycle—from data to model and from model to decision and deployment [17].

Despite the large number of published studies and reviews, an important gap remains: many of the existing reviews either focus on a specific sub-domain, e.g., only safety or only ATM, or have a more "list-oriented" approach and less on how to provide an operational logic for method selection, data definition, evaluation design, and deployment path [18]. Therefore, a conceptual-analytical review can add value to both researchers and industry professionals by providing a framework that clarifies the relationships between "industrial problem, data type, appropriate ML/DL method, evaluation criteria, and deployment considerations." On this basis, this article attempts to show how machine learning and deep learning techniques can be used in a targeted and deployable manner in the aviation industry, while categorizing application areas and critically analyzing trends, and what challenges—from data and interpretability to generalizability and safety requirements—should be considered in the design of the solution.

In the following, the conceptual foundations of data-driven AI in the aviation industry and the logic of "problem-data-model-output" will be explained first, and deep learning and machine learning methods will be introduced. Then, the main application areas of safety, MRO, ATM, flight operations, and airports will be analyzed and compared based on data type and model family. Finally, key challenges for deployment and future directions of industrial research and development will be presented.

2. Basics of data-driven artificial intelligence

2.1.Artificial Intelligence

Artificial intelligence refers to a branch of computer science that deals with the design and development of systems capable of performing tasks that traditionally require human intelligence, including learning from data, pattern recognition, reasoning, and decision support. In recent decades, significant advances in artificial intelligence, especially in the field of machine learning and deep learning, have led to the expansion of the application of this technology in complex and data-driven systems. The aviation industry, as one of the most complex and sensitive industries in terms of safety, efficiency, and real-time decision-making, has provided a suitable platform for the application of these technologies [19, 20].

Machine learning, as a subset of artificial intelligence, focuses on developing algorithms that are able to extract hidden patterns and relationships using historical and operational data and improve their performance without explicit programming. In the aviation industry, this feature enables the analysis of diverse data such as flight data, aircraft health data, air traffic information, and airport operational data. Machine learning algorithms have played an effective role in applications such as flight delay prediction, operational risk analysis, predictive maintenance, and fuel consumption optimization, and help in data-driven decision-making at various operational levels [21].

Deep learning, as an advanced branch of machine learning, can model complex nonlinear relationships and automatically extract features from raw data by utilizing multilayer artificial neural networks. This capability is particularly important for the large and complex data generated in the aviation industry—such as multidimensional time series data from flight recorders, image data from aircraft inspections, and text data from safety reports. Deep neural networks can identify patterns that are difficult to detect with classical methods or human analysis [22].

Recent advances in deep learning architectures, including convolutional neural networks (CNN), recurrent neural networks (RNNs), and transformer-based models, have enabled more accurate analysis of complex aviation data. CNNs have been widely used in image data analysis, such as for automated inspection of aircraft fuselages and components [23, 24]. Recurrent networks and architectures such as LSTM and GRU have been applied to modeling flight time series data and aircraft health monitoring, while transformers have found an increasing role in analyzing textual maintenance and safety reports and fusing multi-source data. These architectures, relying on the computational power of modern hardware and access to extensive operational data, have led to significant improvements in the accuracy and stability of aviation AI systems.

2.2. General applications of artificial intelligence in the aviation industry

Data-driven AI has found wide applications in various operational and management areas in the aviation industry. One of the most important of these areas is flight safety, where machine learning and deep learning algorithms are used to detect flight anomalies, identify early warning signs of danger, and analyze aircraft and pilot behavior patterns. These systems are capable of analyzing a huge amount of flight and environmental data to provide early warnings and prevent unwanted events [25].

In the maintenance and repair (MRO) space, AI is playing a key role in the transition from time-based maintenance to predictive maintenance. By analyzing aircraft health data, repair history, and operating conditions, machine learning models can predict potential failures and suggest the optimal time to repair or replace parts. This approach reduces aircraft grounding, reduces maintenance costs, and increases fleet availability [26].

Also, in air traffic management and flight operations, artificial intelligence is used to predict traffic loads, optimize routes, reduce delays, and improve fuel efficiency. Analyzing spatio-temporal air traffic and meteorological data using advanced learning models enables smarter and more adaptive decision-making in air traffic control systems. Overall, AI plays the role of a key decision-support tool in the aviation industry by reducing dependence on purely empirical decision-making and increasing reliance on data analysis.

2.3.Deep learning and neural networks in aviation applications

Artificial neural networks are models inspired by the structure of the human brain, consisting of simple processing units (neurons) organized in successive layers. These networks have shown success, especially in solving complex problems involving large amounts of data and nonlinear relationships. In the aviation industry, neural networks play an important role in applications such as flight time series prediction, anomaly detection, inspection image analysis, and text report processing [27].

Convolutional neural networks (CNNs) are one of the most widely used deep learning architectures in aviation, designed for analyzing multidimensional data, especially image data. Using convolutional, fusion, and fully connected layers, these networks are able to extract low-level to high-level features of images and can be used for tasks such as detecting cracks, corrosion, or structural damage in aircraft inspection. The ability of CNN to automatically learn features makes it a suitable option for automating inspection processes [28, 29].

Alongside CNNs, recurrent neural networks and architectures based on them are used to model temporal dependencies in flight data and monitor system health. These networks can capture complex temporal patterns in multidimensional data and be used to predict future system behavior. Despite the widespread success of these architectures, there are still challenges such as interpretability, the need for high-quality data, and ensuring generalizability in real-world operational conditions that require further research [30].

A deep CNN model consists of a limited set of processing layers that can learn various features of input data (such as an image) with multiple levels of abstraction. The initial layers learn and extract high-level (lower abstraction) features, and the deeper layers learn and extract low-level (higher abstraction) features. The basic conceptual model of CNN is shown in Figure 1. The different types of layers are explained in the following sections.

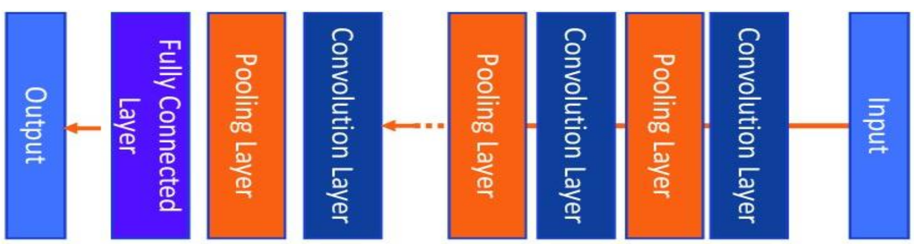
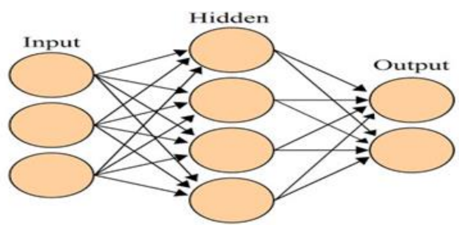


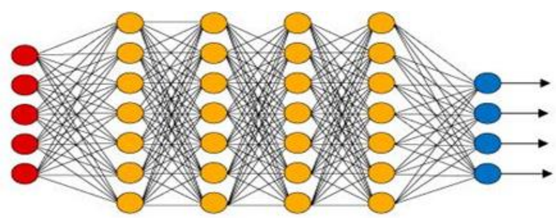
Figure 1: The main conceptual model of CNN

Deep learning techniques involve continuous transformations that map input vectors with training data to output. This means that the model can learn by sampling both the input and output datasets. Deep learning has been developed as an effective machine learning method that incorporates multiple layers of features or data representations and provides advanced results. The application of deep learning has shown impressive performance in various application areas, especially in security data classification in cloud computing systems, object segmentation and recognition, and time series prediction. Recent advances in deep learning techniques have yielded encouraging performance for time series forecasting, aiming to distinguish sub-level categories. Simple variants of this type of learning include multi-layer perceptron networks (MLPs) with a large number of hidden layers. These networks have an output layer, an input layer, and some hidden layers. Another type of supervisory method is recurrent neural networks (RNN), which have advantages such as accurate prediction capability, time series, high convergence speed, and high adaptability [31]. In this network, the outputs of the hidden layers have feedback to themselves. In other words, each neuron in the output layer has a feedback connection to itself, which is done through a buffer layer. This feedback in the output layer makes the RNN learn better, recognize better, and produce better instantaneous and instantaneous patterns. Each hidden neuron is connected to only one return neuron with a constant number with the value of one. So the recurrent layer is actually a copy of the seasonal state of the hidden layer in its previous state. The number of recurrent neurons is equal to the number of hidden neurons. Unlike a traditional recurrent neural network, where the content is rewritten at each time step, in an LSTM recurrent neural network, the network can decide whether to retain the current memory through the introduced gates. Intuitively, if the LSTM unit detects an important feature in the input sequence in the early steps, it can easily transmit this information over a long path, thus capturing and preserving such possible long-term dependencies. Hence, an LSTM neural network can be used in the buffer units in a recurrent network [32].

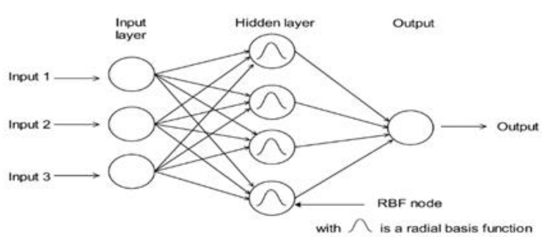
Deep neural network-based models are categorized as follows. These models are shown in Figure 3. Figure 2 demonstrates types of Deep neural networks (DBN): A) Multilayer perceptron feedforward neural networks (MLFNN), B) Deep neural network, C) Radial Basis Neural Networks (RBFNN), D) Structure of a WNN, E) Time-delayed neural networks (TDNN), F) Recurrent neural networks RNN, G) Recurrent neural LSTM, H) Convolutional Neural Networks (CNN).



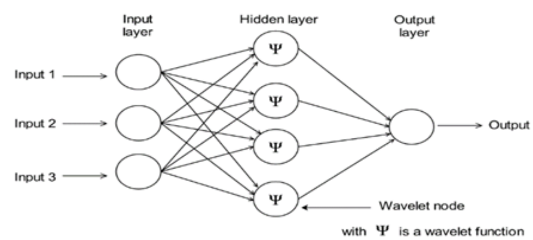
A) Three-layer perceptron neural network



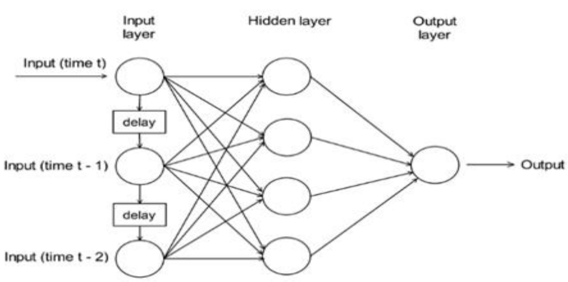
B) Deep perceptron neural network



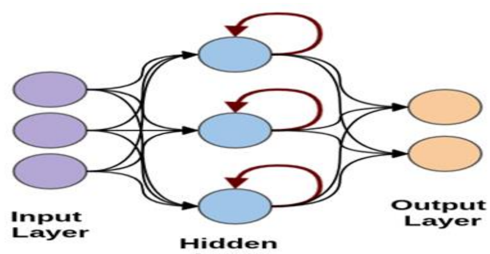
C) An RBFNN neural network



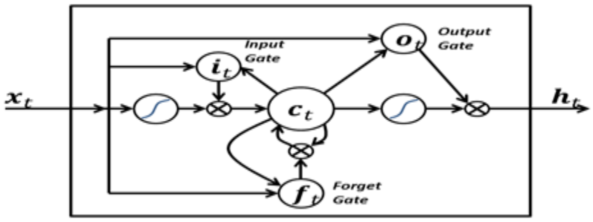
D) Structure of a WNN



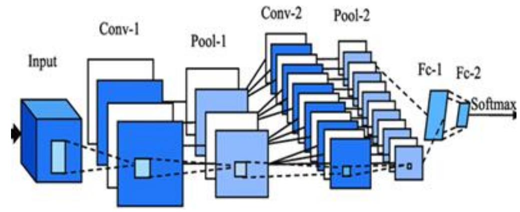
E) TDNN neural networks



F) Recurrent Neural Networks (RNN)



G) LSTM network



H) CNN neural network

Figure 2: Types of deep neural networks

To compare deep neural network-based methods, Table 1 is presented with key criteria such as network structure, main feature, application, and strengths/weaknesses.

Table1: Comparison of Neural Network and Deep Learning Types

Method	Strengths	Weaknesses	Application	Network Structure	Main Feature
MLFNN	Simple and fast, suitable for basic problems	Inability to model time-dependent data	Prediction and classification	Multi-layer feedforward networks	Processing data in linear and non-linear ways
Deep neural network	High performance in complex problems	Requires large datasets and heavy computation	Wide-ranging applications	Multiple processing layers	Ability to automatically extract features
RBFNN	High accuracy in problems with independent data	Does not perform well on sequential data	Prediction and classification	Radial basis	Using radial functions for modelling
WNN	Ability to extract fine and local features	High computational complexity	Prediction of non-stationary data	Combination of a neural network with wavelet transform	Simultaneous analysis of time and frequency domains
TDNN	Ability to model sequential data	Weakness in learning long-term dependencies	Analysis of cloud computing systems	Time-delay network	Considering the temporal dependency of data
RNN and LSTM	Managing sequential data and dependent patterns	Long training time and requires precise tuning	Prediction and classification in cloud computing systems such as endoscopy	Recurrent (with internal memory)	Modelling long-term temporal dependencies
CNN	Suitable for image and multi-dimensional data	Less suitable for security data in video cloud computing systems	Analysis of multi-dimensional data	Convolutional	Extracting spatial and local features
DBN	Ability to model high levels of complexity	Requires tuning many parameters	Prediction and complex analyses	Deep belief	Unsupervised learning to extract complex features

Table 1 provides a comprehensive view of the different structures and applications of methods based on deep neural networks. Deep neural network-based methods for attack classification and detection include architectures such as MLFNN, deep neural networks, RBFNN, WNN, TDNN, RNN and LSTM, CNN, and DBN. These methods apply to the analysis of existing data depending on their structure and characteristics.

For example, CNN is the most suitable option for analyzing cloud computing systems by extracting spatial and local features, while RNN and LSTM have high performance by modeling temporal dependencies for relevant data. Methods such as WNN and DBN are also capable of extracting detailed and complex features, but require more computational complexity. The choice of the appropriate method depends on the type of data, the detection goal, and the available computational resources.

2.4.Data-driven artificial intelligence in the aviation industry

Data-driven AI in the aviation industry should be seen as more than a set of algorithms or computational tools, but rather as a conceptual framework for decision-making in complex, safety-sensitive systems. In this framework, data is not simply an input to models, but is a central element of the value chain, starting from operational problem definition and leading to actionable system-level action. Recent reviews show that a significant portion of the failures of AI projects in the aviation industry stem from an over-focus on algorithm selection and a neglect of the design of this data-driven chain, especially in cases where the operational problem, available data, and decision output are not properly aligned [33].

From a conceptual perspective, a data-driven AI system in aviation is based on the dynamic interaction between several key components: the operational problem, data, analytical method, and decision-making output. Unlike traditional linear approaches, these components interact with each other in a feedback loop, meaning that the decision output can modify the problem definition or data requirement in subsequent cycles [34]. Review studies show that successful projects in this area generally started with defining a specific, measurable problem linked to an operational need, such as delay prediction, flight anomaly detection, or fuel consumption reduction, and then data and analytical methods were selected accordingly, rather than first selecting an algorithm and then imposing the problem on it [35].

In this framework, the nature of the data plays a decisive role in shaping the analytical path. Aviation industry data is inherently heterogeneous, multi-source, and multi-scale, and includes time-series flight recorder (FDR/QAR) data, engine and structural health data, spatiotemporal air traffic data (ADS-B), meteorological data, textual maintenance and safety reports, and visual inspection data. Each of these data has its own characteristics, limitations, and biases, and recent literature consistently emphasizes that the choice of machine learning or deep learning method should directly follow these characteristics. Ignoring this issue, especially in noisy or unbalanced operational data, has been reported to be one of the main reasons for the reduced generalizability of models in the real environment [36].

Accordingly, the role of classical machine learning methods in the aviation industry remains prominent. Algorithms such as decision trees, Random Forests, and Gradient Boosting methods have shown acceptable performance in many industrial applications, such as component failure prediction, flight delay analysis, and operational risk modeling, due to their lower need for large data sets, higher interpretability, and ease of deployment. Analytical reviews show that in many real-world scenarios, these methods not only compete with deep models in terms of accuracy, but also have a significant advantage in terms of industrial acceptance and user trust [37].

On the other hand, the increasing complexity of data and the need to extract deep nonlinear relationships have led to the expansion of the use of deep learning in specific areas. Recurrent and convolutional neural networks have played key roles in the analysis of long time series data and the detection of flight anomalies, 2D convolutional networks in the visual inspection of aircraft components, and Transformer-based models in the analysis of textual safety and maintenance reports. Recent reviews show that successful use of these models has usually occurred in situations where the complexity of the data or the need to learn automatic representations has been justified [38].

However, new literature emphasizes that distinguishing between prediction, diagnosis, and decision-making is essential to understanding the true value of data-driven AI. Many early studies have been limited to producing accurate predictions, while operational value is realized when the model output directly leads to a decision or action; for example, failure prediction is only meaningful when it leads to maintenance planning or optimal resource allocation. In this regard, the use of reinforcement learning for sequential decision-making problems such as flight path optimization or airport resource management has received increasing attention in recent years [39].

Performance evaluation also requires a conceptual rethink in this data-driven framework. In aviation systems, which deal with rare but costly events, metrics such as overall accuracy cannot provide an accurate picture of the actual performance of the model. Analytical reviews show that metrics sensitive to data imbalance, error cost analysis, and model stability assessment in novel conditions are essential for safety-sensitive applications [40].

Finally, industrial deployment is emerging as the final link in the data-driven chain. Even the most accurate models will fail in the operational environment if they fail to adapt to changing data scope, regulatory requirements, and the need for interpretability. For this reason, the new literature emphasizes hybrid approaches, the use of explainable models, and consideration of the full model life cycle from monitoring to retraining [41].

Overall, this integrated view shows that data-driven AI in the aviation industry is not an independent goal, but a means to improve decision-making in complex, safety-oriented systems. The most successful applications have been those that have created alignment between problem definition, data, analytical method, evaluation, and industrial deployment; precisely the point where a conceptual-analytic review can add value beyond descriptive reviews by clarifying it [42].

As shown in Table 2, the success of data-driven AI in the aviation industry depends not on the choice of a specific algorithm, but on the alignment between the problem definition, the nature of the data, the analytical method, the evaluation criteria, and the requirements of industrial deployment.

Table 2: Conceptual Summary of the Data-Driven Approach in Applying Artificial Intelligence in the Aviation Industry

Conceptual Component	Analytical Explanation	Sample Data	Dominant ML/DL Methods	Operational Output	Considerations and Challenges
Operational problem definition	The starting point of any AI system; the problem must be measurable and relevant to decision-making	Flight delays, component failure, fuel consumption, safety risk	–	Defining the KPI and decision objective	Incorrect problem definition → failure of the entire system
Nature of the data	Data are heterogeneous, multi-source, and multi-scale	FDR/QAR, ADS-B, weather data, text logs, inspection images	–	Understanding data limitations and capacity	Incomplete data, noise, class imbalance
Data preparation	A decisive stage in the model's success	Time synchronisatio,	Feature Engineering,	Model-ready usable data	High cost, need for domain knowledge

		cleaning, feature engineering	Representation Learning		
Model family selection	Depends on data type, objective, and the need for interpretability	Time series, text, image, tabular data	RF, XGBoost, LSTM, CNN, Transformers	Prediction/diagnosis model	Incorrect model selection for the data
Type of analytical problem	Prediction, anomaly detection, or decision-making	Failure, flight deviation, resource allocation	Supervised / Unsupervised / RL	Actionable output	Focusing only on prediction without decision
Performance evaluation	Beyond accuracy; sensitive to the cost of errors	Rare and critical data	Precision–Recall, ROC, Cost-sensitive metrics	Safety-oriented validation	Inappropriate metric → false confidence
Industrial deployment	Transition from the lab to real operations	OCC, MRO, ATM systems	Hybrid AI, XAI	Practical use of the model	Drift, regulation, organisational acceptance
Model life cycle	An AI system is dynamic and requires continuous monitoring	New operational data	Monitoring & Re-training	Performance stability	Decline in generalisation over time

3. Data in the Aviation Industry and Data-Driven Challenges

One of the fundamental differences between the aviation industry and many other areas of AI application is the nature of the data that is generated and used in the industry. Aviation data is not only very large in volume, but also highly complex in terms of variety, structure, production rate, and operational sensitivity. These characteristics make the design of AI systems in aviation more dependent on a proper understanding of the data landscape than anything else. Recent reviews show that a significant part of the difference between research results and the actual performance of AI systems in the operational environment is due to the neglect of these data-driven characteristics[43].

In terms of origin, aviation industry data can be divided into several main categories. Flight data recorded by systems such as FDR and QAR consist of a set of multidimensional time series parameters that describe the behavior of the aircraft, engine, and control systems during flight. These data are the basis for many applications related to flight safety, performance analysis, and aircraft health monitoring [44]. In addition, aircraft and engine health data obtained from condition monitoring systems provide accurate information about the technical condition of components and play a key role in predictive maintenance[45].

Another important category of data is spatiotemporal data related to air traffic management. Data such as ADS-B, radar, and flight planning information describe the current and historical state of air traffic and are used to predict congestion, optimize routes, and reduce delays. These data are often combined with meteorological data to analyze the impact of weather conditions on flight safety and efficiency. Systematic reviews show that combining traffic and meteorological data is one of the most challenging, yet effective, areas of machine learning applications in aviation[13].

In addition to numerical and time series data, a significant portion of the aviation industry's operational information is stored in the form of unstructured data. Textual safety reports, maintenance logs, and engineering technical reports are examples of this data, which contain valuable human and empirical knowledge. Advances in natural language processing and deep learning-based models have made it possible to extract key patterns and concepts from these sources, and recent literature points to the increasing role of these data in safety and maintenance analysis[46]. Also, image data from aircraft body and component inspections have paved the way for the use of convolutional neural networks in automating inspection processes.

Despite this data diversity, aviation data has common characteristics that pose specific challenges for data-driven analytics. One of the most important of these features is the severe imbalance of classes, so that critical events such as serious failures or safety incidents are very rare but very significant in terms of cost and consequence. This causes many standard machine learning models to perform misleadingly when used without adjustment. Analytical reviews show that in such situations, focusing solely on metrics such as overall accuracy can be dangerous and that metrics that are sensitive to rare events are needed[40].

Another important challenge is data quality and integrity. Aviation data is typically generated from different sources, at different sampling rates, and in disparate formats. Data synchronization, missing data management, and noise removal, especially in real operational data, is a costly and expertise-intensive process. Reviews show that many successful industrial projects have spent a significant portion of their time and resources on data preparation rather than developing more sophisticated models[47].

Furthermore, the issue of changing data ranges is particularly important in the aviation industry. Fleet changes, changes in operating procedures, or even changing environmental conditions can alter the distribution of data over time, leading to a degradation in the performance of models that were trained in the past. This suggests that aviation AI systems should be designed as dynamic systems requiring continuous monitoring and retraining, rather than static models that are trained once and used forever [48].

Overall, the aviation industry data landscape shows that choosing a machine learning or deep learning approach without considering the nature of the data, its limitations, and challenges cannot lead to reliable results in the operational environment. Understanding these characteristics is essential not only for designing more accurate models but also for interpreting results, evaluating performance, and safely deploying AI systems. This data-driven analysis sets the stage for the next section of the article, where the relationship between the problem, the type of data, and the choice of machine learning and deep learning methods will be explored in a structured manner.

As seen in Table 3, the diversity and complexity of aviation industry data mean that the selection of machine learning and deep learning methods is not based on algorithmic superiority, but rather on the nature of the data, the type of problem, and operational constraints.

Table 3: Types of Aviation Industry Data, Applications, and Analytical Implications for Artificial Intelligence

Data Type	Main AI Applications	Common ML/DL Methods	Key Challenges	Implication for Model Design	Nature and Characteristics	Data Source
Flight data (FDR/QAR)	Flight safety, anomaly detection, performance analysis	LSTM, GRU, Autoencoder, XGBoost	Noise, missing data, synchronisation	Need for models robust to noise and temporal dependencies	Multivariate time series, high sampling rate	Flight recorders
Aircraft and engine health data	Predictive maintenance, remaining useful life estimation	Random Forest, Gradient Boosting, LSTM	Class imbalance, rare failures	Use of metrics sensitive to rare events	Long-term time series, dependent on operating conditions	Aircraft Health Monitoring
Air traffic data	Traffic prediction, route optimisation	LSTM, Graph Neural Networks, Transformers	Scalability, domain shift	Need for scalable and adaptive models	Spatio-temporal, networked, dynamic	ADS-B, Radar

Weather data	Flight safety, delay reduction	Regression ML, Deep Neural Networks	Uncertainty, temporal alignment	Combining predictive models with uncertainty	Spatio-temporal, stochastic	Stations, forecasting models
Text data	Safety analysis, extraction of experiential knowledge	NLP, Transformers, BERT-based models	Linguistic ambiguity, lack of labels	Need for pre-trained language models	Unstructured, natural-language based	Safety reports, MRO logs
Image data	Damage detection, inspection automation	CNN, Vision Transformers	Lack of labelled data	Use of transfer learning	Image-based, high resolution	Airframe and component inspection
Airport operational data	Delay prediction, resource allocation	Classical ML, RL	Data heterogeneity	Combining ML with optimisation	Tabular, multi-source	Airport systems

3.1. Problem-Data-Model-Output Mapping in the Aviation Industry

One of the fundamental challenges in applying AI in the aviation industry is the gap between the development of analytical models and their practical use in real-world environments. This gap is mainly due to the lack of a structured logic to connect the operational problem to the type of data available, the appropriate analytical method, and ultimately the output that can be used in decision-making. In many studies, the main focus has been on comparing algorithms, while successful industrial experiences show that choosing a model without considering the nature of the problem and data leads to unstable and unsustainable results. Therefore, providing a mapping framework that coherently connects these elements is essential for understanding and developing data-driven AI applications in aviation [49, 50].

The starting point for this mapping is the definition of the operational problem. Aviation problems can be broadly classified into three main categories: prediction-based problems, diagnosis-based problems, and decision-making problems. Prediction-oriented problems include things like flight delay prediction, component failure prediction, or fuel consumption estimation, which aim to estimate the future state of a variable or system. Diagnosis-oriented problems focus on identifying anomalies, deviations, or unusual patterns, such as detecting unusual flight behaviors or identifying early signs of failure. Finally, decision-making problems involve resource allocation, route optimization, or operation scheduling, the output of which leads directly to operational action or policy. The precise distinction between these types of problems determines the direction of data and model selection.

Once the problem is defined, the type and structure of the data play a decisive role in the rest of the process. For example, prediction and diagnosis problems related to flight safety and aircraft health typically rely on multidimensional time series data extracted from flight recorders or health monitoring systems. In contrast, air traffic management issues are more based on spatial-temporal and network data, while safety and maintenance analysis often requires combining numerical data with textual data from human reports. These data differences mean that a single analytical method cannot answer all questions, and the choice of model must be directly related to the data characteristics [51].

In this framework, classical machine learning methods are usually efficient in problems where the data is more structured, its volume is more limited, and higher interpretability is required. For example, in flight delay prediction or operational risk analysis, models such as Random Forest or Gradient Boosting can extract effective relationships between variables with appropriate accuracy and acceptable transparency by using engineered features. This feature makes the model output understandable to operational users and facilitates its organizational adoption.

In contrast, deep learning shows its true advantage when the data is complex, large, or unstructured. Analyzing long-time series data with complex dependencies, processing aircraft inspection images, or extracting concepts from safety text reports are examples of applications where deep neural networks excel. However, this algorithmic advantage only translates into operational value when coupled with appropriate strategies for data preparation, evaluation, and output interpretation. Otherwise, deep models may become untrustworthy “black boxes” in safety-sensitive environments.

The next key element in this mapping is the definition of the output and its role in decision-making. Many studies are limited to simply producing a prediction or label, whereas in the aviation industry, the model output must be directly linked to a decision or operational action. For example, predicting the probability of a component failing is only valuable if it can lead to maintenance planning, spare parts allocation, or flight plan changes. For this reason, in recent years, the focus of research has increased from mere prediction to the design of decision support systems; systems that present the model output in the form of recommendations, warnings, or operational policies.

In this regard, reinforcement learning has been considered as a suitable approach for sequential decision-making problems. In problems such as flight path optimization, air traffic queue management, or airport resource allocation, decisions are made sequentially and dependent on the state of the system.

Reinforcement learning allows modeling of this dynamic decision-making process, but its successful use requires a precise definition of the environment, reward function, and safety constraints. This again demonstrates that model selection without a deep understanding of the operational problem cannot lead to reliable results.

Another important point in problem-data-model mapping is performance evaluation in the application context. Evaluation criteria should be selected according to the type of problem and the consequences of errors. In safety-oriented problems, rare but critical errors can have very serious consequences; therefore, criteria sensitive to rare events and error cost analysis are more important than general criteria. These evaluation choices directly affect user confidence and the model's deploy ability in the real environment.

Ultimately, this mapping is only complete when industrial deployment considerations are also taken into account. Changing operating conditions, changing fleets, or changing traffic patterns can cause data distributions to shift and model performance to degrade. Therefore, aviation AI systems should be designed as dynamic systems with a defined life cycle that includes continuous monitoring, controlled retraining, and periodic performance evaluation. This cyclical perspective strengthens the link between academic research and industrial application.

In summary, the Problem-Data-Model-Output mapping provides a conceptual framework through which diverse applications of AI in the aviation industry can be analyzed in a coherent manner. This framework demonstrates that success in the application of machine learning and deep learning depends not on the complexity of the algorithms, but on the logical alignment between the problem, the data, the analytical method, and the operational decision. This analytical perspective provides a basis for examining specialized applications in different areas of the aviation industry in the following sections of the article [52].

As shown in Table 4, the choice of machine learning and deep learning methods in the aviation industry is a direct function of the type of operational problem, the nature of the available data, and the expected level of decision-making, not simply the complexity of the algorithm.

Table 4: Conceptual Mapping of Problem–Data–Model–Output in AI Applications in the Aviation Industry

Type of Operational Problem	Sample Aviation Problems	Suitable ML/DL Methods	Type of Model Output	Role of Output in Decision-Making	Dominant Data Type
Prediction	Flight delay prediction, component failure prediction, fuel consumption prediction	Random Forest, XGBoost, LSTM	Numerical value / probability	Preventive planning, cost reduction	Time series, tabular data
Anomaly detection	Detecting abnormal flight behaviour, identifying engine performance deviation	Autoencoder, Isolation Forest, LSTM	Alert / anomaly label	Early warning, increased safety	Multivariate time series
Classification	Classifying system health status, analysing safety reports	SVM, Neural Networks, NLP Models	Class label	Operational decision support	Tabular, text data
Image analysis	Detecting airframe damage, cracks, or component corrosion	CNN, Vision Transformer	Detection / damage region	Automating inspections	Image data
Sequential decision-making	Flight path optimisation, airport resource allocation	Reinforcement Learning	Decision policy	Optimising system performance	Spatio-temporal, system state
Hybrid analysis	Multi-source data-driven predictive maintenance	Hybrid ML/DL Models	Operational recommendation	Integrated decision-making	Numerical + text + image

3.2.Specialized applications of artificial intelligence in the aviation industry

After explaining the conceptual foundations and framework of the problem-data-model mapping, this section examines specialized applications of data-driven artificial intelligence in key areas of the aviation industry. The purpose of this section is not to simply list applications, but rather to analyze how machine learning and deep learning methods can be applied to address real-world operational and safety issues. The literature review shows that research is largely focused on a few main areas, each with different data characteristics, safety requirements, and decision-making objectives.

3.2.1 Flight safety

Flight safety is one of the most important and sensitive areas of application of AI in the aviation industry. In this area, the main goal is to identify potentially dangerous conditions early and prevent serious accidents or incidents from occurring. The data used in these applications mainly include multidimensional time series data from flight recorders (FDR/QAR), spatio-temporal flight data, meteorological data, and textual safety reports. The complexity and heterogeneity of this data have made classical machine learning methods alone unable to meet analytical needs, and the use of more advanced deep learning models has been considered [53].

One common application in this area is flight anomaly detection, where models attempt to identify unusual patterns in aircraft or system behavior that may be a precursor to a dangerous situation. Unsupervised and semi-supervised learning methods, such as autoencoders and recurrent networks, have shown good performance, especially in situations where labeled incident data is limited. These models learn normal behavior patterns, identify significant deviations, and provide them as early warnings to decision support systems.

Another important application is the analysis of precursors to accidents and near-accident events. In this context, AI is used as a tool to simultaneously analyze technical, environmental, and operational factors. Machine learning models are able to extract nonlinear relationships between variables such as weather conditions, system status, and flight parameters, which are often overlooked in traditional analyses. These analyses allow for the identification of high-risk scenarios and modification of operational procedures [54].

In addition to numerical data, analysis of textual safety reports has also played an increasing role in improving flight safety. Voluntary reports from pilots and engineers contain valuable empirical knowledge that is too time-consuming to extract manually. The use of deep learning-based natural language processing models, especially pre-trained language models, has made it possible to extract key concepts, recurring patterns, and hidden risk factors. Combining text analysis results with flight data creates an integrated approach to safety management.

Despite its significant benefits, the application of AI to flight safety also comes with serious challenges. The most important of these challenges includes the scarcity of real-world incident data, the high sensitivity of decisions, and the need for interpretability of model output. Therefore, many recent studies have focused on developing explainable models and combining data-driven methods with expert knowledge to gain the trust of users and regulatory bodies.

3.2.2 Maintenance and Repair (MRO)

Maintenance is one of the areas that has benefited the most from data-driven AI. The main goal in this area is to move from time-based or reactive maintenance to predictive and condition-based maintenance. The data used includes aircraft and engine health data, flight operational data, maintenance history, and technical reports. These data allow for continuous monitoring of the status of systems and prediction of potential failures [55].

In predictive maintenance applications, machine learning models are used to predict component failure and estimate remaining useful life (RUL). Classical machine learning algorithms, such as Random Forest and Gradient Boosting, have been successful in many industrial applications due to their robustness and interpretability. At the same time, recurrent neural networks and deep architectures for analyzing long and complex time series data have shown better performance in detecting gradual failure patterns.

One of the major challenges in this area is the severe data imbalance, as serious failures are relatively rare. This has led to an increased research focus on anomaly detection methods and multi-source data fusion. Also, the use of textual data from maintenance reports alongside numerical data, as an emerging approach, has enabled a more comprehensive analysis of the status of systems.

Successful application of AI in MRO has significant economic implications, including reduced aircraft unexpected grounding (AOG), reduced repair costs, and increased fleet availability. However, industrial deployment of these systems requires ensuring performance stability, interpretability of results, and compatibility with existing operational processes [56].

3.3.3 Air Traffic Management (ATM)

Air traffic management is one of the most complex areas of application of artificial intelligence in the aviation industry, dealing with dynamic spatio-temporal data and network interactions. The main goal in this area is to increase capacity, reduce delays, and maintain safety in dense traffic conditions. ADS-B data, radar, flight plans, and meteorological data are the main sources of analysis in this area.

Machine learning and deep learning methods have been used in ATM to predict traffic congestion, identify bottlenecks, and optimize routes. Time series models, neural network graphs, and transformer-based models are among the methods that have the ability to model complex relationships between flights and the network structure of airspace. In addition, reinforcement learning has been considered as a suitable approach for dynamic decision-making problems in the design of traffic flow management policies.

Despite these advances, the operational adoption of AI in ATM faces limitations such as stringent safety requirements, the need for human-machine interaction, and the necessity for decision transparency. For this reason, much research has been directed towards developing decision support systems that serve as an augmentation for air traffic controllers, rather than a complete replacement for them [57].

3.3.4 Airport Operations and Resource Management

As critical nodes of the air transport network, airports are complex environments with multiple operational interactions. AI is being used in this area to predict delays, allocate gates, manage ground resources, and improve passenger flow. Airport operational data, flight schedules, and passenger data are the main sources of analysis in these applications.

Machine learning models have been used to predict delays and identify factors affecting them, while reinforcement learning and hybrid optimization methods are used to dynamically allocate airport resources. These applications are directly related to increasing operational efficiency and improving the passenger experience, but require careful integration with existing systems and consideration of operational constraints [58].

As shown in Table 5, specialized applications of AI in the aviation industry have a specific mapping between the type of problem, the nature of the data, the family of analytical models, and the decision-making output, and their success depends on the alignment of these components.

Table 5: Summary of Specialised Applications of Data-Driven Artificial Intelligence in the Aviation Industry

Application Domain	Dominant Data Types	Common ML/DL Methods	Model Output	Operational Value and Decision-Making	Main Problems
Flight safety	Multivariate time series (FDR/QAR), spatio-temporal, weather, text	Autoencoder, LSTM/GRU, Isolation Forest, DL-based NLP	Alert, anomaly label, risk index	Early warning, reduced safety risk, procedure improvement	Flight anomaly detection, near-miss analysis, identifying risk precursors
Maintenance and Repair (MRO)	Aircraft and engine health data, operational time series, maintenance logs	Random Forest, XGBoost, LSTM, temporal CNN, hybrid models	Remaining time/cycles, failure probability	Reducing AOG, optimising maintenance, cost reduction	Failure prediction, remaining useful life (RUL) estimation, health monitoring
Air Traffic Management (ATM)	Spatio-temporal (ADS-B, radar), weather	LSTM, Graph Neural Networks, Transformers, Reinforcement Learning	Optimal route, control policy	Increased capacity, reduced delays, maintaining safety	Congestion prediction, route optimisation, delay reduction

Airport operations	Airport operational data, flight schedules, passenger data	Classical ML, Deep Neural Networks, RL, Optimisation + ML	Allocation recommendation, delay prediction	Increased efficiency, improved passenger experience	Delay prediction, gate allocation, ground resource management
Multi-source analysis ()	Numerical + text + image	Hybrid ML/DL, Multimodal Learning	Comprehensive operational recommendation	Coordinated system-level decision-making	Integrated operational and safety decision-making

4.Challenges, limitations, and research gaps in the application of artificial intelligence in the aviation industry

Despite significant advances in the application of artificial intelligence, machine learning, and deep learning in the aviation industry, a comprehensive literature review shows that this field still faces a set of fundamental challenges and limitations that prevent the widespread and sustainable deployment of intelligent systems in real-world operational environments. These challenges are not only technical in nature but also related to data, organizational, regulatory, and human aspects, and therefore, examining them is essential to understanding the existing research gaps.

One of the most fundamental challenges is data quality and availability. Aviation industry data is often fragmented, confidential, and company- or fleet-specific. In many studies, the data used have been limited to specific or simulated datasets that are not necessarily representative of real-world operating conditions, making the generalizability of research results to different operating environments questionable. Furthermore, the lack of labeled data, especially in the areas of safety and critical failures, which are considered rare events, is one of the main obstacles to the development and evaluation of supervised learning models.

Another important challenge is the severe data imbalance and the rarity of critical events. In many aviation applications, the goal is to identify or predict events that occur infrequently but have very serious consequences. Standard machine learning models may perform well in such situations, but may be ineffective in identifying critical events. This indicates a research gap in developing appropriate evaluation and learning methods for imbalanced and safety-sensitive data.

Interpretability and trust in models are another key limitation in deploying AI in the aviation industry. Many deep learning models, despite their high accuracy, are considered "black boxes," and their decision-making logic is difficult to explain. In safety-sensitive systems, lack of model transparency can be a serious barrier to adoption by operational users, engineers, and regulators. Although research into explainable AI has been conducted, there are no industry-accepted, standardized frameworks for widespread use of these methods in aviation. From an operational deployment perspective, changing data scope and model performance stability over time are significant challenges. Changing operating conditions, fleet changes, software updates, or changing traffic patterns can alter the data distribution and lead to performance degradation of previously trained models. Many existing studies have addressed this issue in a limited manner, and most models have been evaluated in a static format, while the aviation operational environment is dynamic in nature.

Finally, the gap between academic research and industrial needs remains significant. A significant portion of research focuses on improving the accuracy of algorithms, without considering deployment requirements, integration with existing systems, implementation costs, and regulatory considerations. This gap demonstrates the need for interdisciplinary approaches and closer collaboration between researchers and industry to develop deployable solutions.

4.1. Future research directions and prospects for the development of data-driven artificial intelligence in the aviation industry

Analysis of existing trends and gaps identified in the literature indicates that future research directions in the field of data-driven AI in the aviation industry should move beyond the development of more accurate algorithms and towards the design of reliable, deployable systems aligned with safety requirements. One of the most important future directions is to develop learning methods that are robust to imbalanced and sparse data. Focusing on unsupervised, semi-supervised, and simulation-based methods can help reduce the dependence on labeled data.

Another important research direction is to integrate high-performance interpretability into deep learning models. The future of this field will be towards developing models that can simultaneously provide high accuracy and meaningful explain ability. Such models will play a key role in increasing user trust and regulatory acceptance and can bridge the gap between research and industrial application.

From a data perspective, future research is expected to focus more on multi-source and multi-state modeling. Combining time-series, text, image, and spatio-temporal data can provide a more comprehensive understanding of the state of aviation systems, but this requires the development of coherent frameworks for aligning, weighting, and interpreting heterogeneous data.

Adaptive learning and model lifecycle management will also be a key focus of future research. Designing systems that can detect changes in the data domain, safely retrain, and maintain their performance over time is critical for operational applications. These approaches are directly related to the concept of “sustainable AI” in the aviation industry.

In the area of decision-making, the use of safe reinforcement learning and human-in-the-loop (HIL) is expected to expand. Rather than completely replacing humans, future systems will act as decision support tools that allow for human interaction, monitoring, and intervention. This approach can both increase the efficiency of systems and reduce safety and ethical concerns [59].

Ultimately, the future of research in this area will move towards integrated data-model-decision-deployment frameworks that consider operational, regulatory, and human requirements from the earliest stages of design. Such an approach could elevate the role of data-driven AI from a limited analytical tool to a key component in the digital transformation of the aviation industry.

As shown in Table 6, future research directions in the field of data-driven AI in the aviation industry should move beyond a focus on improving algorithms and towards developing reliable, deployable systems that are aligned with safety and regulatory requirements.

Table 6: Future Research Directions and Corresponding Challenges in Developing Data-Driven Artificial Intelligence in the Aviation Industry

Future Research Axis	Current Issue or Limitation	Proposed Research Approaches	Potential Implications for the Aviation Industry
Learning from rare and imbalanced data	Lack of data on accidents and critical failures	Unsupervised and semi-supervised learning, data augmentation, simulation	Improved safety and more accurate prediction of high-risk events
Model interpretability ()	Lack of transparency in deep models	XAI, hybrid ML/DL models, explainable models	Increased user trust and regulatory acceptance
Multi-source learning ()	Separation of numerical, textual, and image data	Multimodal models, data alignment	More comprehensive understanding of aviation system conditions
Generalisation and domain shift	Decline in model performance under new conditions	Domain Adaptation, Transfer Learning	Stable performance across fleets and different conditions
Model life-cycle management	Static models that cannot be monitored	Model Monitoring, safe re-training	Sustainable deployment in operational environments
Safe reinforcement learning	Risk of automated decision-making	Safe RL, constraint-based RL	Intelligent decision-making with safety guarantees

Human-in-the-loop ()	Resistance to replacing humans	Interactive decision support systems	Improved human–machine collaboration
Integration with existing systems	Incompatibility with operational infrastructures	Hybrid, API-based architectures	Facilitating industrial implementation
Regulatory and certifiability considerations	Lack of AI standards in aviation	AI-certification-ready frameworks	Accelerating formal adoption of AI
Sustainable and trustworthy AI	Exclusive focus on algorithmic accuracy	Robust AI, Ethical AI	Developing safe, stable, and responsible systems

5. Conclusion

This article aims to provide a conceptual-analytical review of the role and application of data-driven artificial intelligence in the aviation industry and shows that the success of this technology in such a complex and safety-sensitive industry depends not only on the advancement of algorithms, but also on the coherent alignment between the operational problem, the nature of the data, the analytical method, and the requirements of decision-making and industrial deployment. Unlike many existing reviews that focus primarily on comparing algorithm performance, this study adopted a problem-oriented and data-driven approach to explain the rationale for the effective use of machine learning and deep learning in aviation systems.

The results of the literature review showed that aviation industry data is inherently heterogeneous, multi-source, and dynamic, and these characteristics present challenges to the design of AI systems, such as severe data imbalance, rarity of critical events, changing data scope, and the need for interpretability. These challenges indicate that the choice of machine learning and deep learning methods should directly follow the characteristics of the data and the type of operational problem, and algorithm-based approaches will have limited generalizability and deployment regardless of the data and operational context. Analysis of specialized applications in areas such as flight safety, maintenance and repairs, air traffic management, and airport operations showed that the greatest value of AI is realized when the output of models leads to specific operational decisions and actions. Therefore, the transition from mere prediction to the design of decision support systems and sequential decision-making frameworks is considered one of the key trends in recent literature. Meanwhile, combining classical machine learning methods with deep learning models and utilizing domain expertise has been proposed as a realistic approach to increase trust, interpretability, and industrial acceptance.

This article also identified existing challenges and research gaps, showing that the future of research in the field of aviation AI should move towards developing systems that, in addition to analytical accuracy, have performance stability, interpretability, generalizability, and alignment with regulatory requirements. Focusing on multi-source learning, model lifecycle management, safe reinforcement learning, and human-in-the-loop approaches can play an important role in bridging the gap between academic research and industrial applications.

Overall, this conceptual-analytical review shows that data-driven AI in the aviation industry is not a standalone solution, but rather part of a complex decision-making ecosystem that requires a systems-oriented and interdisciplinary approach. The framework presented in this paper can be used as a basis for future research as well as conceptual guidance for industry professionals in designing and deploying secure, reliable, and efficient AI systems.

Funding Statement: "The author(s) received no specific funding for this study."

Conflicts of Interest: "The authors declare no conflicts of interest regarding this study."

Data Availability statement:" There is no data in use in this study."

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