Archives of Computational Methods in Engineering
https://doi.org/10.1007/s11831-024-10105-7

REVIEW ARTICLE

Application of Artificial Intelligence in Aerospace Engineering and Its Future Directions: A Systematic Quantitative Literature Review

Kamal Hassan[1] · Amit Kumar Thakur[2] · Gurraj Singh[3] · Jaspreet Singh[4] · Lovi Raj Gupta[5] · Rajesh Singh[6]

Received: 9 November 2023 / Accepted: 5 March 2024

Abstract
This research aims to comprehensively analyze the most essential uses of artificial intelligence in Aerospace Engineering. We obtained papers initially published in academic journals using a Systematic Quantitative Literature Review (SQLR) methodology. We then used bibliometric methods to examine these articles, including keyword co-occurrences and bibliographic coupling. The findings enable us to provide an up-to-date sketch of the available literature, which is then incorporated into an interpretive framework that enables AI's significant antecedents and effects to be disentangled within the context of innovation. We highlight technological, security, and economic factors as antecedents prompting companies to adopt AI to innovate. As essential outcomes of the deployment of AI, in addition to identifying the disciplinary focuses, we also identify business organizations' product innovation, process innovation, aerospace business model innovation, and national security issues. We provide research recommendations for additional examination in connection to various forms of innovation, drawing on the most critical findings from this study.

1 Introduction

Artificial Intelligence (AI) is a computer science branch focusing on building smart machines. An intelligent system can do tasks with the same level of sophistication as a human. Artificial Intelligence (AI) originated in antiquity but gained significant momentum during World War II. It has overcome hurdles and successfully addressed issues for acceptance in several fields. Some sectors, such as safety–critical engineering, have advanced in incorporating AI. Home service robots, software applications, and self-driving cars have developed technologies that are now part of daily life. Noncritical engineering solutions often feature non-real-time information processing or no human involvement. The latter needs safety assurance and certification to protect human life [1].

By using AI, we can create machines with the capacity for abstract thought. The science of artificial intelligence (AI) has expanded to include almost every other academic discipline, such as astronomy, flight management, healthcare, gaming, finance, data security, social media, the automotive industry, the transport sector, robotics, entertainment, agriculture, e-commerce, and education. The aerospace sector is a large, complicated enterprise with numerous stakeholders, regulations, and safety concerns.

The sector has been steadily progressing over the past year in optimizing its operations and enhancing the safety of the passengers. The history of AI in aerospace goes back to 1950 when it was involved in the research into knowledge- based systems and handling various tasks on aircraft design and navigation. Multiple applications of AI are currently employed in aerospace industries for innovation and efficiency. Integrating artificial intelligence (AI) into the aerospace sector is revolutionizing several facets of aviation and space exploration, fostering advancements and augmenting safety, efficacy, and productivity. Artificial intelligence (AI) plays a significant role in determining the future of the

✉ Amit Kumar Thakur
amitthakur3177@gmail.com

1 School of Mechanical Engineering, Lovely Professional University, Phagwara, India

2 Department of Aerospace Engineering, Lovely Professional University, Phagwara, India

3 Department of Industrial and Production, Dr B R Ambedkar National Institute of Technology, Jalandhar, India

4 School of Civil Engineering, Lovely Professional University, Phagwara, India

5 Lovely Faculty of Technology and Science, Lovely Professional University, Phagwara, India

6 Uttaranchal Institute of Technology, Uttaranchal University, Dehradun, India

Published online: 16 April 2024

aircraft industry, with applications ranging from enhancing flight control and fuel conservation to reinventing autonomous systems. Within the domain of flight control, systems empowered by artificial intelligence (AI) are furnishing pilots with immediate aid and a comprehensive understanding of their surroundings. These systems do this by scrutinizing sensor data, weather updates, and traffic patterns to promptly notify pilots of prospective dangers and propose the most advantageous routes for their flights.

Implementing this advanced decision-making support system plays a significant role in enhancing safety and efficiency within the aviation industry. Artificial intelligence (AI) is also transforming the field of aviation maintenance by facilitating predictive maintenance. This approach leverages machine learning algorithms to evaluate sensor data and forecast possible equipment malfunctions. This proactive method enables the prompt execution of maintenance interventions, mitigating expensive failures and maintaining aircraft safety. Furthermore, artificial intelligence (AI) is currently being utilized to enhance fuel efficiency by analyzing extensive flight data. This process involves the identification of trends and the subsequent recommendation of appropriate routes and flight profiles. In addition to its impact on aviation, artificial intelligence (AI) plays a transformative role in space exploration. Artificial intelligence (AI) algorithms are now employed to augment spaceship navigation and control systems, facilitating accurate maneuvering and successful rendezvous with space stations or celestial entities. Artificial intelligence can assess sensor data, comprehend intricate orbital mechanics, and make prompt judgments to enhance spacecraft trajectories. The incorporation of artificial intelligence (AI) into unmanned aerial vehicles (UAVs) and air traffic management (ATM) systems is significantly influencing the trajectory of unmanned aircraft. Using AI-driven decision-making and collision avoidance systems would facilitate the secure and effective functioning of unmanned aerial vehicle (UAV) fleets, diminishing dependence on terrestrial air traffic control networks. Artificial intelligence (AI) is pivotal in expediting the design and testing processes of novel aircraft and spacecraft within aerospace research and development. Artificial intelligence (AI) algorithms can evaluate intricate simulation data, optimize aerodynamic designs, and forecast performance characteristics, hence facilitating the development of more efficient and novel designs. The integration of artificial intelligence (AI) inside the aerospace sector catalyzes a surge of inventive advancements and profound changes, augmenting safety, efficacy, and productivity in diverse aviation and space exploration domains. The rapid progression of AI technology is expected to significantly influence the aerospace industry, leading to substantial advancements in flying capabilities and space exploration.

The following are the key contributions of the study:

- The study discussed various components of antecedents and consequences of AI acceptance/adoption in Aerospace from the available literature that define the requirement and need for monitoring and controlling the components.
- Integration of industry 4.0 tools (Artificial Intelligence) for monitoring Aircraft navigation, Simulation, Autonomous flight, Aircraft communication, Space exploration, Aircraft maintenance, Air traffic control, Drone based applications, Air quality, Optimization of Aircrafts Operations, and Aircraft fuel efficiency have been discussed. The requirement of monitoring and controlling for various purposes according to the needs of different components, with the help of Artificial intelligence, has been evaluated and discussed.
- The study also addressed some challenges and recommended some suggestions for the future enhancement of monitoring techniques by the use of Artificial Intelligence in various components of the aircraft. This comprehensive review outlines the most anticipated research questions with detailed answers in the applications of artificial intelligence. It distinguishes this review article from all other recent reviews on similar studies.

The article is structured as follows: Results of bibliometric analysis are covered in Sect. 2; the framework of artificial intelligence is covered in Sect. 4; Sect. 5 covers Discussion, conclusion, and future research; and Sect. 6 discusses the limitations.

2 Methodology and Data Collection

A comprehensive investigation of the subject matter was undertaken, utilizing a systematic quantitative literature review (SQLR) approach to systematically examine and evaluate the pertinent literature in line with established scientific literature [2, 3]. The data utilized in this study was obtained by collecting documents from two prominent databases, namely Scopus and Web of Science (WOS). As mentioned earlier, the data sources were selected due to their ability to aggregate a comprehensive collection of the most pertinent scholarly contributions within the application of artificial intelligence in aerospace. Both databases facilitate the structuring and integration of data collected from diverse sources, such as articles, conference papers, and book chapters, into readily usable bibliometric formats. (Fig. 1) illustrates the methodology employed in this investigation. In the initial phase, a comprehensive search was conducted on the Scopus database to identify titles "artificial intelligence in aerospace," abstracts, and keywords that encompassed the specified parameters, such

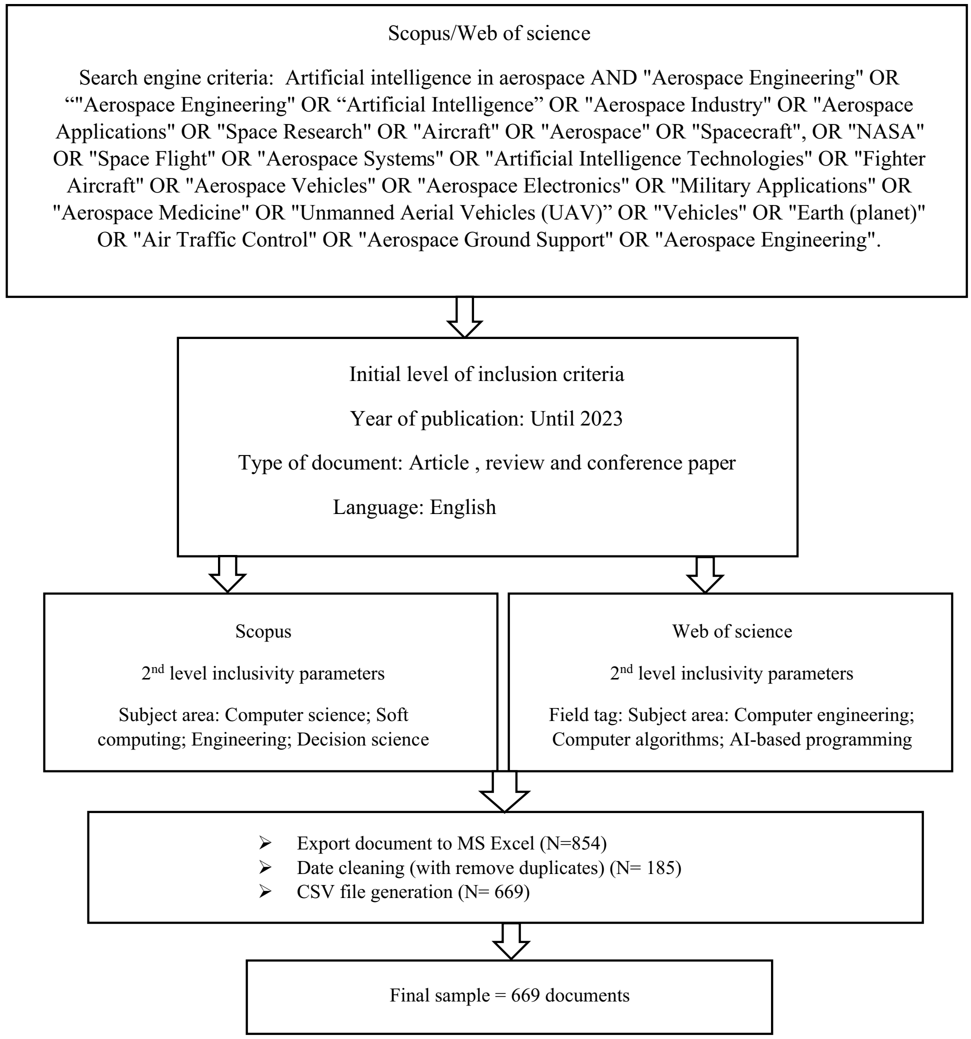


Fig. 1 Selection criteria of articles on artificial intelligence in aerospace

as other keywords "Aerospace Engineering," "Artificial Intelligence," "Aerospace Industry," "Aerospace Applications," "Space Research," "Aircraft," "Aerospace," "Spacecraft," "NASA," "Space Flight," "Aerospace Systems," "Artificial Intelligence Technologies," "Fighter Aircraft," "Aerospace Vehicles," "Aerospace Electronics," "Military Applications," "Aerospace Medicine," "Unmanned Aerial Vehicles (UAV)," "Vehicles," "Earth (planet)," "Air Traffic Control," "Aerospace Ground Support," "Aerospace Engineering". It led to 854 documents, and according to SQLR, we focused on articles and review papers in various subject domains like "Engineering," "Physics and astronomy," "Mathematics," "Earth and Planetary science," and "Environmental science" and written in the English language. By removing the duplicates and merging the documents from the two sources, it produced 769 documents. Finally, metadata was extracted for the articles containing the author's name, country, source, overall number of publications, citations, and publication year.

3 Results of Bibliometric Analysis

3.1 Geographical Study

According to the findings of the geography study, the top thirteen countries that have made significant contributions to the scientific production of articles on the applications of artificial intelligence in the aerospace industry are as follows: United States with 256 articles, China with 173 articles, United Kingdom with 63 articles, India with 57 articles, Germany with 35 articles, Italy with 31 articles, Canada with 30 articles, Spain with 26 articles, Russia with 17 articles, Australia with 16 articles, Brazil with 15 articles, Turkey with 13 articles, and South Korea with 11 articles as depicted in (Fig. 2).

The last decade has witnessed a significant increase in the allocation of funds by governmental and non-governmental funding bodies worldwide towards the research and development of disruptive technologies in several aerospace domains [3, 4].

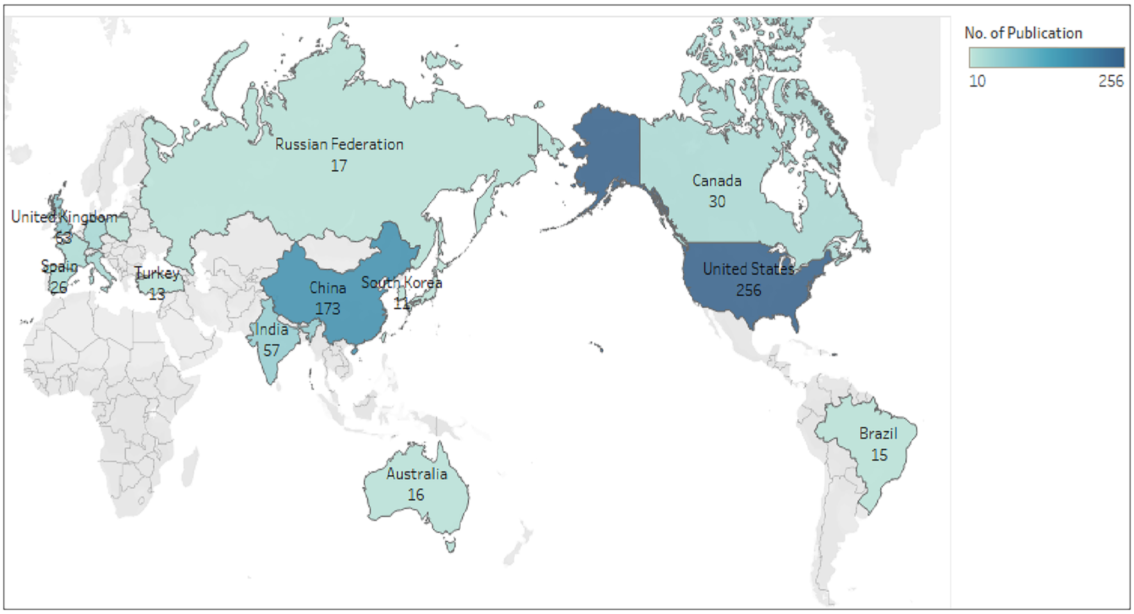


Fig. 2 Country-wise research output on applications of AI in aerospace

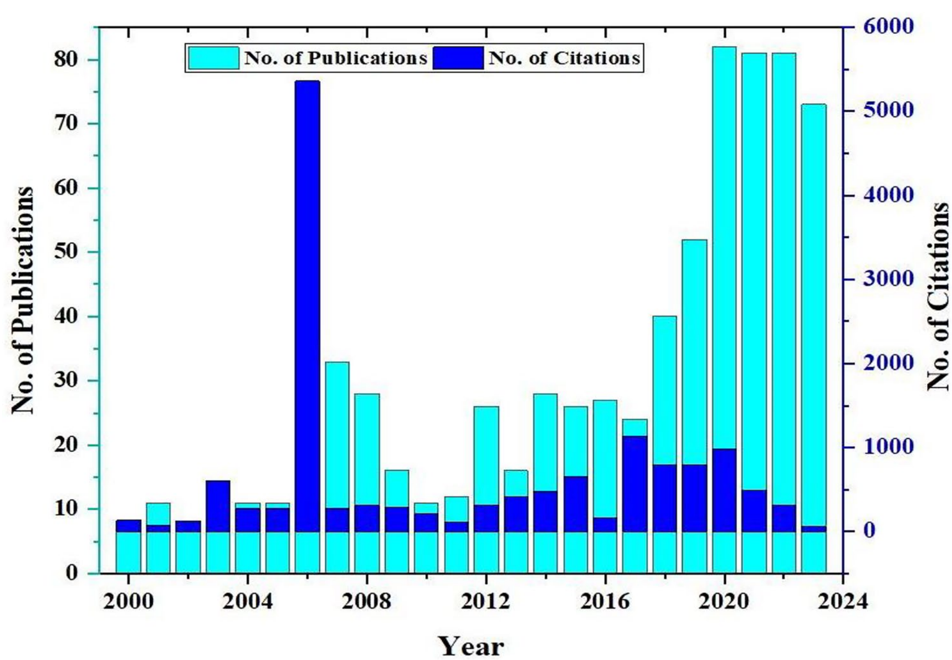
3.2 Analytical Description

We tracked the publications on applications of AI in aerospace till November 2023 on various engineering and astronomy aspects. Years (2007–2018) embark upon almost constant work on the usage of AI in aerospace. The pattern analysis has revealed an upward trend in focused research on artificial intelligence since early 2020. However, some preliminary studies were published on AI in the early 2000s. Consequently, citations increased drastically in 2006 (Fig. 3), as this disruptive technology took the world by storm [5].

3.3 Bibliometric Analysis: Keyword Co-occurrence Study

Bibliometric analysis is a field of research that uses mathematical and statistical methods to examine the relationships

Fig. 3 Country-wise research output on applications of AI in aerospace



between scholarly publications, authors, and institutions. It is a quantitative study of scholarly publishing that uses statistical methods to analyze publication patterns, citations, and other types of scholarly activity [6]. The effect of research may be measured with bibliometrics, as can the evolution of scientific areas and the identification of emerging trends. To offer an overview of AI application research and map it, VOS viewer was used since it is open source and is on its way to becoming a standard [7]. To determine the state of the art in the focus area, we performed an evaluation of co-citation networks, a study of journal co-citations, and bibliographic coupling. These three methods were used to analyze the links between essential researchers in the field. In addition, one may make assumptions about subject similarity by analyzing papers frequently mentioned simultaneously in another publication through bibliographic coupling.

This method enables us to show the intellectual structure of a study field. There is a lower potential for bias when using this approach of analysis. We used co-citation clusters to determine the relationships between the papers that were referenced, enabling us to mimic the development of different study fields. It was decided to generate bibliometric maps in addition to pictorial representations [8]. To identify active relationships between different subjects and ideas, we carried out a study based on the co-occurrence of specific keywords.

The methodology of keyword co-occurrence analysis was utilized to reveal the associations between conceptual objects and subjects. The methodology assumes that words that co-occur are linked through a thematic association. Furthermore, we depicted the advancement of abstract entities and pivotal terms, as evident in (Fig. 4). (Table 1) illustrates the research gap of artificial intelligence in aerospace applications with potential research areas.

4 Research Gap of Artificial Intelligence in Aerospace Applications

5 A Framework of Artificial Intelligence

A conceptual framework was devised to categorize applications of artificial intelligence into two clusters, with the categorization being based on findings from the study: (i) antecedents of artificial intelligence acceptance in aerospace and (ii) consequence of artificial intelligence implementation in aerospace (Fig. 5). Section 5.1 discusses these framework antecedents of AI in aerospace and the consequences of AI adoption in 5.2.

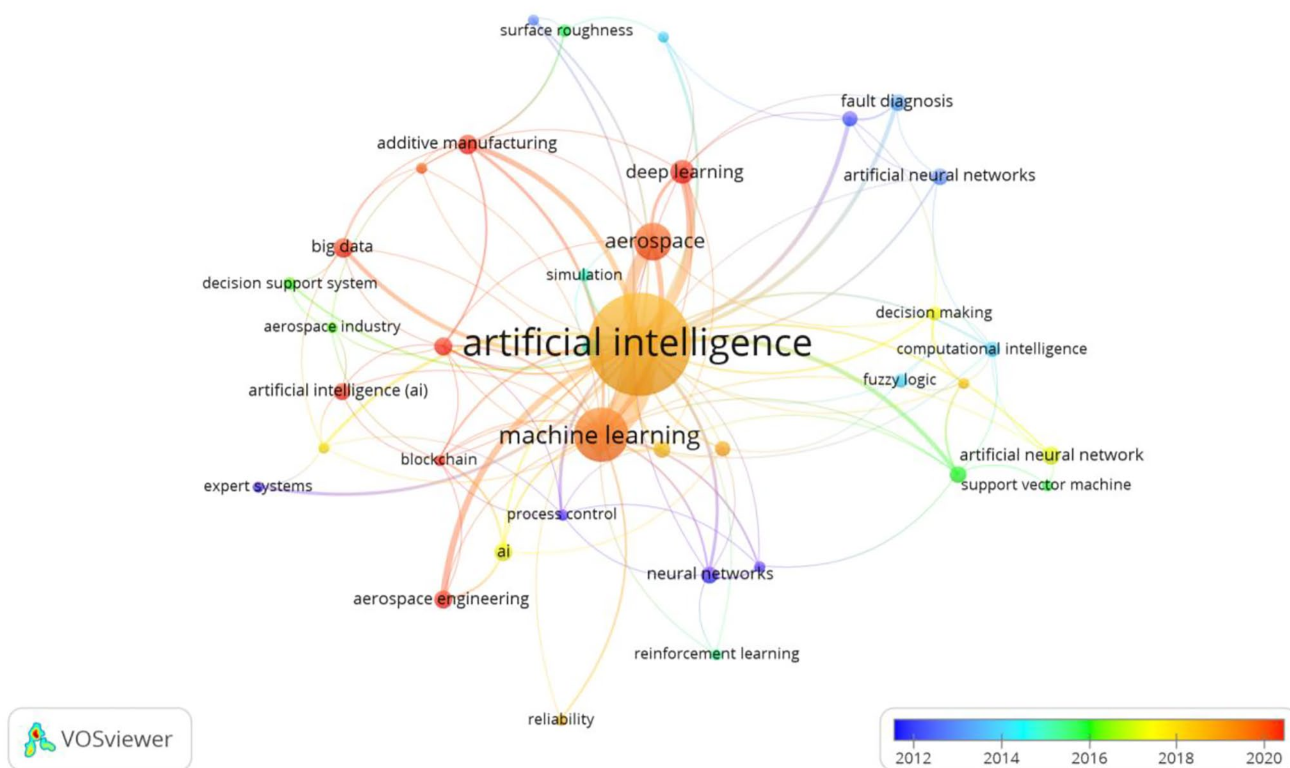


Fig. 4 Key co-occurrence analysis

Table 1 Research gap of artificial intelligence in aerospace applications with potential research areas

Application area	Research gaps	Potential research areas
Autonomous Flight Systems	a) The transparency and explicability of AI decision-making in critical situations are severely limited b) Inadequate performance in a variety of challenging conditions (such as severe weather or space radiation) c) Ensuring the security and safety of AI-controlled systems is difficult	Regulatory obstacles, a higher chance of mishaps and incidents, and a decline in trust in autonomous systems
Maintenance and Repair	a) Not enough information to validate and train AI-based predictive maintenance models b) Problems integrating AI with current workflows and instruments for inspection and repair c) Issues integrating AI with the inspection and repair procedures and tools used today	The potential for component failures increased downtime and maintenance costs, and missed opportunities for preventative maintenance are all potential consequences
Design and Optimization	a) Limited investigation of unusual and bio-inspired AI design ideas b) Difficulty in optimizing for multiple competing goals (such as performance, fuel efficiency, and noise reduction, for example)	Innovational constraints, suboptimal solutions, and inefficient resource utilisation
Air Traffic Management	a) Difficulty in efficiently managing situations that are both dynamic and unpredictable (for example, emergencies and weather disturbances) b) Concerns about bias and unfairness in air traffic control decisions made by AI c) Secure and dependable data sharing across systems is hindered by an absence of standard protocols and infrastructure	Problems with scalability and efficiency, possible accidents, and congestion
Space Exploration	a) The creation of fully autonomous exploration robots equipped with manipulative dexterity b) Powerful AI systems for managing resources and detecting anomalies in harsh and inaccessible places c) Conquering the obstacles of data transmission and long-distance communication for space missions powered by artificial intelligence	Reliance on ground control increased, scientific opportunities were missed, and the mission's scope was limited
Air-craft navigation	a) Due to their complexity and opacity, many AI navigation algorithms make it challenging to comprehend how they make decisions and spot any biases b) A common aspect of airplane navigation is communication with other aircraft and ground systems. One of the biggest challenges in AI is creating agents that can cooperate to make decisions and resolve conflicts in complicated aerospace situations c) Real-time dynamic scenarios such as sudden weather disasters or air traffic shifts are typically difficult for current AI algorithms to handle. AI algorithms that are flexible and fast to respond are required to optimize flight trajectories and fuel economy	The use of AI in airplane navigation is significant and has the potential to revolutionize aviation. Artificial Intelligence (AI) has the potential to revolutionize air travel by improving safety, efficiency, and sustainability with thoughtful development and conscientious use
Air-craft simulation	a) Limited precision for intricate aerodynamic processes (ground effects, turbulence), challenges integrating real-time sensor data into models b) Lack of natural and intuitive interfaces for pilots interacting with AI copilots c) AI's limited capacity to justify its choices and advice	Data-driven adaptive modelling combined with online learning can boost huge efficiency of aircraft simulation
Air-craft communication	a) Limited understanding of aviation-specific jargon and terminology, Difficulty handling ambiguous instructions and implicit communication b) Failure to include weather, flight plans, and air traffic data from outside sources in communication analysis	Enhanced automation and pilot-AI interaction, heightened situational awareness in AI and pilots

Table 1 (continued)

Application area	Research gaps	Potential research areas
Drone-based applications	a) Limited ability to withstand complicated settings with occlusions, dynamic lighting, and shadows b) Inability to deal with unforeseen circumstances (such as bird strikes and abrupt weather shifts)	Use probabilistic planning techniques and reinforcement learning to improve your ability to adapt to unforeseen circumstances
Air-quality monitoring	a) Absence of comprehensive, high-quality data on air quality, particularly in countries with low incomes and close to emission sources b) Extremely conceivable that models developed using particular datasets won't function effectively in other situations or with shifting circumstances	Adaption of reliable techniques for handling outliers and missing data, Examine strategies for domain adaptation and transfer learning
Air–fuel efficiency	a) Issues regarding safety arising from using AI to make crucial flying choices, Absence of precise rules and certification processes for air–fuel efficiency systems driven by AI b) Restricted access to real-time, high-resolution data from many operational sources (weather, air traffic control, engines, etc.)	Provide effective and safe systems for exchanging data.—Invest in sensor technology to collect more precise information

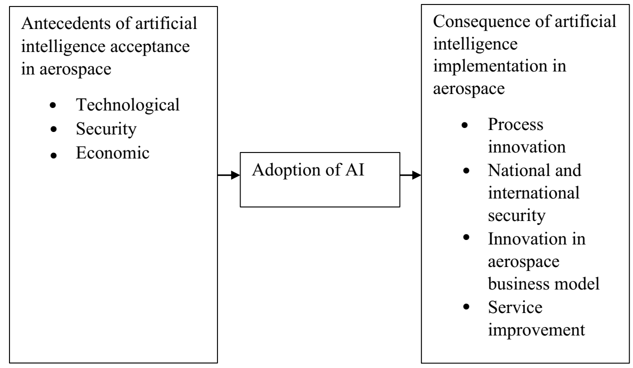


Fig. 5 Framework of antecedents and consequence of AI acceptance/adoption in aerospace

Table 2 Antecedents of artificial intelligence acceptance in aerospace

Type	Technology used	Potential Authors
Technological antecedents	Machine learning	[7, 31, 32, 41, 42]
	Deep learning	[35, 43–45]
	Neural network	[46–48]
	Big data	[49–51]
	Digital twin	[51–54]
	Fuzzy logic	[55–57]

5.1 Antecedents

(Table 2) represents a classification of research outputs about the antecedents mentioned above into three clusters: technological, security, and economic, which will be addressed elaboratively in the sections below. (Table 3) provides a picture of the most widely recognized researchers who engaged with applications of AI in aviation by using citations as a kind of acknowledgment and endorsement through bibliographic coupling. Journal-level citation analysis helped us pinpoint the best outlets for publishing research in our area of interest.

Technological antecedents The literature analysis reveals that machine learning tools [9–13], deep learning [14–17], neural networks [18–21], big data [22–24], fuzzy logic [25, 26], and digital twins [27–30] are often mentioned technological antecedents for the successful implementation of artificial intelligence in diverse aerospace applications.

The aerospace industry is undergoing an essential shift due to the fast growth of machine learning (ML) technologies. Machine learning algorithms can evaluate vast data sets and detect intricate patterns and trends that could present challenges or be unattainable through human examination. This technology can potentially enhance several aspects of aircraft development, production, upkeep, and functionality [31, 32]. For instance, machine learning (ML) is now

Table 3 Prominent researchers

Authors	Article Title	Journal/Proceedings	Cited by
[51]	Digital Twin Shop-Floor: a New Shop-Floor Paradigm Towards Smart Manufacturing	IEEE Access	809
[58]	Future Directions in Control in an Information-Rich World	IEEE Control Systems	309
[59]	High-Performance and Rapid-Response Electrical Heaters Based on Ultra flexible, Heat-Resistant, and Mechanically Strong Aramid Nanofiber/Ag Nanowire Nanocomposite Papers	ACS Nano	278
[60]	Real-Time Assessment of Mental Workload Using Psychophysiological Measures and Artificial Neural Networks	Human Factors	274
[61]	Variable-Temperature Electron Transport and Dipole Polarization Turning Flexible Multifunctional Microsensors beyond Electrical and Optical Energy	Advanced Materials	270
[62]	Very-high-resolution airborne synthetic aperture radar imaging: Signal processing and applications	Proceedings of the IEEE	237
[63]	A machine learning strategy to assist turbulence model development	53rd AIAA Aerospace Sciences Meeting	214
[64]	Review of aerospace engineering cost modeling: the genetic causal approach	Progress in Aerospace Sciences	201
[65]	A survey on artificial intelligence trends in spacecraft guidance dynamics and control	Astrodynamics	152
[66]	New approaches in turbulence and transition modeling using data-driven techniques	53rd AIAA Aerospace Sciences Meeting	145

employed in aerospace engineering to enhance aircraft aerodynamic efficiency, anticipate and mitigate problems in aircraft components, create predictive maintenance systems, optimize flight trajectories, and innovate autopilot systems. Machine learning (ML) can significantly transform the aerospace industry by automating various operations, enhancing operational efficiency, and auguring safety measures.

Deep learning, a type of machine learning, is revolutionizing the aerospace industry by simplifying previously intractable issues in areas like aircraft design [33], production [34], upkeep, and operation [35]. Aerodynamic improvements, predictive and preventative maintenance systems, optimized flight routes, and brand-new autopilot systems are some areas where deep learning is being used in the aerospace industry. Deep learning can change the aerospace industry by automating activities, boosting efficiency, and decreasing risk.

Neural networks are a specific machine learning algorithm that takes its cues from how the human brain operates [36]. Nodes of a neural network are coupled to one another and carry out a single function. Neural networks may learn to execute complicated tasks like image recognition, natural language processing, and machine translation by connecting nodes in various ways [37]. We may anticipate even more cutting-edge uses of neural network technology in the years to come as its development proceeds.

Using big data, new methods for predicting and avoiding bird attacks [38] are being developed. These systems can predict where bird attacks will occur by analyzing data from several sources, such as radar readings [38], weather reports, and bird movement patterns. Big data is being used to develop new strategies for forecasting and evading bird assaults. By evaluating data from several sources, including radar readings, weather reports, and bird movement patterns, these systems can forecast where bird assaults will occur.

Moreover, Digital twins are digital representations of physical systems that may be used to imitate and evaluate the behavior of the actual systems [39]. Because they are versatile and can be put to several different uses, they are gaining growing traction in the aerospace industry. Aircraft and spacecraft virtual prototypes [40] can be developed with the help of digital twins and then tested and improved in a simulated environment before any actual hardware is produced. This can speed up the development process, cut costs, and enhance the final product.

Security Antecedents The aerospace sector, particularly security, is changing quickly due to artificial intelligence (AI). The detection, prevention, and response to various aerospace security risks are all enhanced by AI-powered systems [67]. Regarding protecting aircraft assets, cybersecurity is one of AI's most promising uses. Monitoring aviation [68] and spacecraft systems for hostile behavior, detecting malware, isolating it, and fixing flaws are all possible uses for AI systems. Airbus, for one, is working on AI-driven systems that can monitor for and counteract cyberattacks on aircraft systems in real-time.

AI is also being utilized to improve the physical security of airports, planes, and other aerospace infrastructure. Artificial intelligence (AI)-powered systems may be used to monitor the health of airplanes [69] and other equipment, detect and track illegal immigrants, and prevent smuggling. Boeing, for one, is using AI-enabled devices to monitor its factories for any signs of unwanted entry. In addition to cybersecurity and physical security, AI is also being utilized to increase the safety of aeronautical goods. Aircraft and spaceship components that are defective can be repaired or replaced using AI-powered systems, and future maintenance issues can be anticipated and avoided. Space agency NASA uses AI to create systems that foresee and avoid spaceship maintenance issues [70].

Economic Antecedents Many economic variables have contributed to the aerospace industry's adoption of AI, including the increasing price of aerospace R&D and manufacturing, the expanding demand for aerospace products and services, the availability of data, and the decreasing price of computer power. In the aerospace industry, AI may assist in reducing costs and increasing productivity by taking over manual activities like component design, optimization, and factory automation.

The rising demand for aeronautical goods and services may be met with this. Aircraft sensors [71], flight data recorders [72], and maintenance records [73] are just a few examples of the types of data that are readily available to aerospace industries, allowing them to design and implement AI systems. This information may be used to teach AI systems to do things like anticipate maintenance issues and spot cyberattacks [74]. As the price of computers has decreased, aerospace businesses have found it easier to put them into use.

Design and engineering, production, operations [75], and security are just some of the aerospace applications now using AI. With its already substantial impact on the aerospace industry's bottom line and public safety, AI is only expected to grow in importance in the years ahead. Cost reduction, shorter product development cycles, increased productivity, and better decision-making are just a few reasons why the aerospace sector should implement AI technology. To save money, many firms are turning to artificial intelligence (AI) technologies to help them reduce manufacturing costs [76], allowing them to provide their wares and services at cheaper rates and increase productivity. In addition, AI enables research-driven internet platforms to test novel goods and services at minimal cost [77].

Moreover, AI systems enable companies to foster the creation of new, inexpensive automated services, offering social value to a larger audience at low-cost, decreasing expenses, and enhancing services. Incorporating AI technologies boosts corporate output by simplifying processes, boosting quality, and shortening turnaround times. Automated technology also helps organizations improve their ability to tailor their offerings to individual customers. Cognitive analytics encourages the automation of processes using AI, helping businesses save time when extracting information from unstructured data to cut time in new product creation. If AI algorithms are widely adopted, they might help managers make better decisions and boost the efficiency of their businesses.

5.2 Consequence of Artificial Intelligence Adoption

Our study findings show that the utilization of aerospace consequences encompasses four principal domains: Process innovation, National and international security, Innovation in aerospace business models, and Service improvement. The corresponding discussions are explained below.

Process Innovation Industry-wide, process innovation propelled by AI is reshaping businesses. It facilitates the development of new products and services and increases productivity and standards while decreasing expenses. Nevertheless, this phenomenon further exacerbates inequality, increases competition, and disrupts established industries. AI is becoming an obvious choice to automate manufacturing automation [51], quality control [78], and assembly line management. AI also boosts productivity by personalizing the customer experience and demand forecasting. The utilization of AI-driven unmanned aerial vehicles (UAVs) [79] has facilitated the execution of duties that were once undertaken by human operators, notably including aircraft inspections [80]. The emergence of new prospects in the business landscape has necessitated a need for current firms to adapt to remain competitive. To maintain competitiveness in the job market, workers must acquire and cultivate new talents.

National and International Security The aerospace sector is undergoing a rapid transformation due to the advancements in artificial intelligence (AI), which has significant consequences for national and international security. Artificial intelligence (AI) is now being employed in the advancement of novel and enhanced weaponry systems [68], the augmentation of intelligence collection and analytical skills, and the mitigation of cybersecurity vulnerabilities [81]. The above developments can instigate a fresh iteration of an arms race, diminish state transparency and trust, and exacerbate societal inequity. Artificial intelligence (AI) deployment in national security [82] carries notable ramifications, particularly concerning the heightened advancement of novel and potent weaponry systems. The potential utilization of AI-driven autonomous drones [83] and hypersonic missiles [84] can significantly transform the nature of warfare, facilitating enhanced capabilities for nations to assert their influence and discourage acts of aggression. Artificial intelligence (AI) has the potential to be utilized in the creation of novel strategies for information warfare, including the production of deep fakes and the manipulation of social media platforms.

One significant consequence is artificial intelligence's enhanced capacity for information collecting and analysis. Artificial intelligence (AI) has the potential to facilitate the collection and analysis of vast quantities of data obtained from various sources such as satellites [85], drones, and social media platforms. This capability can give nations a substantial edge in comprehending their opponents and the overall global environment. It can result in enhanced decision-making processes and heightened efficacy of military actions. Artificial intelligence (AI) has the potential to mitigate cybersecurity risks through the advancement of novel solutions aimed at safeguarding essential infrastructure from cyber threats [86]. Nevertheless, it is worth noting that this very technology has the potential to be utilized for the creation of novel offensive cyber capabilities.

Integrating artificial intelligence (AI) inside the aerospace sector may exert a substantial influence on global security dynamics. The proliferation of novel weapons systems [87] empowered by artificial intelligence (AI) can heighten the likelihood of interstate conflicts due to their superior capabilities and enhanced usability compared to conventional weaponry. Moreover, using artificial intelligence (AI) in intelligence collecting and analysis can diminish transparency and erode trust among states. Verifying the correctness of intelligence obtained and evaluated by artificial intelligence (AI) may provide challenges, potentially resulting in misunderstandings and miscalculations [88].

Ultimately, the advancement and implementation of AI-driven technologies may potentially exacerbate global disparities since nations endowed with the necessary resources to engage in AI research and development will likely be able to create more sophisticated AI-powered technology. The potential outcome of this situation may result in an asymmetry of power among nations, exacerbating geopolitical tensions.

Innovation in Aerospace Business Model Artificial intelligence (AI) is facilitating the advancement of new products and services, as demonstrated through the development of AI-driven drones [89] and predictive maintenance systems [90]. Those advancements are causing significant disruptions within the aerospace sector, generating creative opportunities for many enterprises. Artificial intelligence (AI) is enhancing operational efficiency through the optimization of aircraft flight routes [91], resulting in reduced fuel consumption [92] and improved on-time performance [83]. The use of this approach has the potential to yield substantial financial benefits for aerospace enterprises and enhance levels of customer contentment. Artificial intelligence (AI) is also facilitating innovative ways to earn income, like data-driven services [44, 93, 94] and leasing drones equipped with AI capabilities. It facilitates the diversification of business models for aerospace businesses and mitigates their dependence on conventional aircraft and aviation components sales. Artificial intelligence (AI) is also revolutionizing how aerospace enterprises engage with their clientele.

AI-driven chatbots [95] can offer round-the-clock customer care and tailor client experiences to individual preferences. It has the potential to enhance consumer satisfaction and foster customer loyalty within the aerospace industry. Artificial intelligence has facilitated the emergence of novel business models, exemplified by adopting pay-per-use services as an alternative to conventional airplane sales. This has the potential to enhance cost-effectiveness for enterprises seeking access to aerospace products and services, potentially stimulating heightened demand and yielding advantageous outcomes for the aerospace sector. Adopting artificial intelligence (AI) in the aerospace industry holds significant potential for transforming its business model. However, it is crucial to acknowledge and tackle the associated challenges. These challenges encompass the requirement for substantial investment in AI research and development, the establishment and enforcement of industry-wide standards governing the utilization of AI, and the ethical considerations arising from AI adoption. These ethical concerns include the possibility of job displacement and the imperative of safeguarding data privacy and security.

5.3 Service Improvement

Due to recent breakthroughs in artificial intelligence (AI), the aerospace sector is going through a fast change in how services are provided. This new information has significant repercussions for the business tactics employed by companies operating in this area, particularly those concerned with revenue creation [93]. Current applications of artificial intelligence (AI) include the automation of a variety of processes, the improvement of quality and consistency, the reduction of expenditures [96], the personalization of user experiences, and the promotion of the development of unique and inventive services. Artificial intelligence is being used to automate various activities in the aviation industry, including aircraft maintenance and inspection [97–99], flight planning, and customer assistance. This frees up the team to concentrate on more strategic and creative endeavors, such as the design and development of aircraft and relationships with customers.

Artificial intelligence can analyze vast amounts of data and identify patterns and trends that humans cannot [100]. These data could make it possible to improve aviation services and guarantee uniformity for all customers. Artificial intelligence (AI) has the potential to aid businesses in the aerospace industry in lowering operating costs by improving the efficiency of their operations [101] and streamlining any unnecessary steps. For instance, artificial intelligence (AI) possesses the potential to be utilized in the development of supply chain management, the reduction of fuel consumption [102], and the optimization of aircraft flight patterns [73]. Artificial intelligence (AI) has the potential to provide significant financial benefits to aerospace companies by assisting these companies in the discovery and mitigation of defects in aircraft components [103]. The application of artificial intelligence (AI) is now being utilized in the development of predictive maintenance technologies. These technologies are designed to aid airlines in identifying and resolving any issues relating to their aircraft, hence reducing the number of instances in which failures occur. Artificial intelligence (AI) is now being utilized to develop cutting-edge methods for the provision of aerospace services.

5.4 Related Work Done by Other Researchers Across the Globe

One such application is the artificial guidance of aerial vehicles in which the power and auto-pilot controller is driven by sophisticated algorithms run by artificial intelligence technology [104]. Aircraft industries use artificial intelligence to test aerodynamic chambers and permit new design techniques and real-time product inspections on boundary conditions [105]. [106] uses AI for corrosion detection and prevention in aircraft fuselage by machine learning algorithm on the data sets generated by images of lap joints of Boeing and Airbus aircraft. AI also holds vital applications for risk mitigation applications in aircraft flight control. [107] applied artificial intelligence in unmanned aircraft systems for safety assurance.

Another study conducted by [97] shows that AI can significantly enhance the efficiency of the decision-making process during the first phases of aircraft design. The study further demonstrates the potential use of artificial intelligence (AI) in the context of light business aircraft, substantiating these approaches' efficacy. The findings show the effectiveness of the artificial intelligence methodology in the first stages of aircraft design. The observed and estimated values for the take-off wing loading and the take-off thrust loading exhibit a satisfactory level of concurrence, with a discrepancy of no more than ten percent. Advanced design tools have shown their efficacy in reducing the duration of the aircraft design cycle. [108] analyzed the digital economy's mechanisms from the perspective of increasing key performance indicators influencing the efficacy of high-tech businesses. The need for analysis is necessitated by the inherent inertia of industry relative to other sectors of the economy. The introduction of tools and a complex of innovative technologies of the digital economy by high-tech companies necessitates the organization and consideration of several enterprise-specific factors, such as the analysis and evaluation of production processes and the structural composition of production assets. [26] described how a fuzzy logic technique is used in a case-based design for pilot trending to address the sub-problem of heterogeneous data fusion. The study uses a neuro-fuzzy system for predicting aircraft trajectories dealing with large amounts of data noise. It has generated more accurate predictions than those obtained using other methods.

Another vital application of artificial intelligence in aviation is cybersecurity, which addresses aviation security issues and their possible resolutions, including anomaly detection for avionics, data connection security, and security certification. [109] outline an actionable strategy for the integration of established machine learning cybersecurity techniques into the discipline of aviation security engineering and airworthiness. The proposed roadmap encompasses the following key areas: (i) the application of autonomous and semi-autonomous cybersecurity techniques to enhance the security of autonomous flight operations and (ii) the application of game theory models to address adversarial scenarios and uncertainty in the aviation sector. [110] presented a systematic review on understanding the evolution of cyber-attacks and attack surfaces in the aviation sector over the past 20 years that will help guide future frameworks designed to protect the growth of a crucial industry (Table 4). Companies and airports worldwide are beginning to realize that the application of AI has several significant benefits. Using machine learning, it is possible to give algorithms the ability to improve their performance over time [111]. Companies in the aviation industry can train their machine learning algorithms to consider a wide variety of data sources and variables with the help of big data [112]. A summary of the latest work done using machine learning and other AI technologies is given in (Table 5).

Computational Fluid Dynamics (CFD) methods have become popular in flow field simulation calculations. These approaches have demonstrated their ability to create exact aerodynamic data models [41]. Consequently, they have facilitated the integrating of dynamic characteristics study into the initial phases of aircraft design. The aircraft design scheme satisfies given requirements in multidisciplinary numerical optimization, combining aerodynamic, structural, strength, and stability analysis and using dynamic characteristics specification requirements as constraint conditions [127]. (Table 6) provides a comprehensive summary of the work done by the research community using AI-based simulation in aircraft simulation.

Autonomous flight is one of aviation's most popular and contentious topics. While the aviation industry is actively striving to develop utterly autonomous aircraft, current endeavors mainly concentrate on enhancing the overall safety of flight operations rather than replacing pilots in the cockpit. (Table 7) highlights some of the notable studies done by various investigators in recent years.

Artificial intelligence significantly contributes to the transformation of aircraft communication systems, resulting in notable enhancements in aviation efficiency and safety. The developments above involve using artificial intelligence (AI) for speech recognition and natural language processing [142]. This allows for more efficient and seamless interactions between pilots and air traffic controllers (ATCs) through voice commands and immediate transcription of conversations. Artificial intelligence (AI) algorithms are utilized in predictive communication to

Table 4 Research directions on AI-enabled aerospace applications

Research directions	Research questions
Antecedents of artificial intelligence acceptance in aerospace	ReQ1. To what extent do aerospace workers and firms differ in their acceptance of different AI technologies, including machine learning, deep learning, and big data?
	ReQ2. What impact can the automation of AI systems have on their overall acceptance?
	ReQ3. How do aerospace companies evaluate the benefits and hazards associated with the use of AI?
	ReQ4. What are the most efficacious strategies for mitigating vulnerabilities and threats?
	ReQ5. In what manner do the economic ramifications of implementing AI in the aerospace sector differ across industry segments (e.g., space, aviation, defense)?
Consequence of artificial intelligence implementation in aerospace	ReQ6. What are the most effective strategies for aerospace companies to integrate artificial intelligence to attain process innovation?
	ReQ7. What ethical issues should be considered while utilizing artificial intelligence (AI) in the aerospace industry for national security?
	ReQ8. In what ways may artificial intelligence (AI) be employed to enhance the safeguarding of critical infrastructure against aircraft threats?
	ReQ9. What are the growing economic models in the space tourism and space exploration sectors resulting from the use of artificial intelligence (AI)?
	ReQ10. How can artificial intelligence be utilized to create new aircraft products and services?

effectively and efficiently handle radio frequency congestion [143]. These algorithms are designed to proactively manage communication channels, aiming to improve them to guarantee enhanced clarity and dependability. Autonomous aircraft employ artificial intelligence (AI) to engage in autonomous talks with air traffic control (ATC) and other aircraft, successfully mitigating the pilots' workload. In addition, artificial intelligence enhances cybersecurity protocols by promptly identifying and reducing possible risks. The integration of advanced communication technologies and the utilization of artificial intelligence (AI) for optimizing routes and predicting maintenance needs jointly enhance the safety and efficiency of the aviation sector. A summary of experimental findings on aircraft communication is given in (Table 8).

A substantial body of evidence demonstrates that artificial intelligence (AI) has become an invaluable asset in space exploration. Autonomous robots, such as NASA's Perseverance rover, powered by artificial intelligence, have successfully traversed substantial distances on Mars, conducting scientific investigations and acquiring samples [157]. The efficiency of this technology allows for the processing of extensive datasets. A notable example is the James Webb Space Telescope, which is anticipated to produce a substantial amount of data, around 60 terabytes per hour. The accuracy of solar flare forecasting in space weather prediction has been enhanced by 45% with the utilization of artificial intelligence (AI) models [68]. The International Space Station employs artificial intelligence to consistently monitor astronauts' health, accumulating substantial health data across several hours. Artificial intelligence (AI) in land-cover categorization, deforestation detection, and climate modeling dramatically enhances the efficacy of Earth-observing satellites [153]. Within the field of astronomy, artificial intelligence (AI) algorithms, as demonstrated by the Transiting Exoplanet Survey Satellite (TESS), have successfully identified several prospective exoplanets.

Furthermore, the function of artificial intelligence (AI) in managing the progressively congested space environment has significant importance [158]. More than 27,000 monitored objects are in Earth's orbit, and the number of operating satellites is around 2,800. The stats above highlight the significant influence of artificial intelligence (AI) in space exploration, encompassing several aspects such as data analysis and mission safety [159]. A few critical studies done by various researchers on space exploration are given in (Table 9).

Artificial intelligence (AI) is driving a profound transformation in aircraft maintenance worldwide, leading to substantial improvements in operational efficiency and reliability [169]. Through predictive maintenance, AI leverages extensive datasets to anticipate component failures, significantly reducing unscheduled downtime. In the United States, implementing predictive maintenance can reduce maintenance costs by up to 30% and boost aircraft availability by 10% [170]. India is also witnessing the growing prominence of AI-driven aircraft maintenance, delivering cost efficiencies of approximately 20% in maintenance operations [72]. In China, aviation maintenance is increasingly adopting AI, with predictions indicating potential cost reductions of up to 25%. The United Kingdom has achieved noteworthy reductions in maintenance costs, ranging from 15 to 20%, through AI-enabled predictive maintenance [171]. In Germany, AI-powered robotics play a pivotal role in inspection tasks, while France has streamlined inventory management, leading to substantial financial benefits for airlines.

AI extends its capabilities to real-time condition monitoring, swiftly detecting anomalies, and precision-enhancing

Table 5 Recent applications of artificial intelligence in aircraft navigation

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[113]	2023	Machine learning	Improve the fault tolerance of the processor architectures used by Autonomous Landing Guidance Assistance Systems' (ALGAS) predecessors	To guarantee safety, equity, and privacy in aviation, responsible AI development and use are essential	Lowering fatigue for pilots while improving situational awareness	Enormous volumes of precise data must be collected for operation and training
[114]	2023	Deep reinforcement learning	The proposed IFHER algorithm improves the convergence speed by 28.99% and the convergence result by 11.57% compared to the state-of-the-art Twin Delayed Deep Deterministic Policy Gradient (TD3) algorithm	Carry out dynamic target-tracking tasks in vast, uncharted areas	The model is efficient in a dynamic environment	To create a more accurate simulation of combat situations, the simulation environment requires more accurate data sets
[115]	2023	Deep reinforcement learning (DRL	The collision rate decreases by 14.99% compared to existing navigation methods in successful formation without colliding with the other UAVs	AIoT-based navigation and formation control	The system can manage the situation where an actuator malfunctions and a leader fails	The reduction in collision rate is only 19%
[116]	2023	Reinforcement learning technique	The research generates a solution for intelligent formation of air combat in the future and guidance for manned or unmanned aircraft cooperative combat	Hierarchical maneuver decision architecture is used	Produces a plan for the future's intelligent creation of air combat	The same Model cannot be applied to three aircraft formation
[117]	2023	Internet of Things	Comprehensive automation in executing flight routes involving complex sequences with high precision has been successfully achieved	a new decision support system model for ATCos	The most efficient route achieved with 55 scenarios	The model will become on abnormal data sets
[118]	2023	Semantic segmentation	Our system becomes cost-effective and reduces inspection downtime by 87%, eliminating the need for human intervention	Suggested a drone-based automated inspection system that is driven by AI from start to finish	eliminates the requirement for human involvement by 87% during inspection downtime	A decrease in the down position also decreases the system's efficiency
[119]	2022	Hierarchical reinforcement learning	Results show that the built AI agent can simultaneously guide 16 aircraft safely and efficiently through Sector 01 of Nanjing Terminal	Application of hierarchical reinforcement learning method	Safe guidance of 16 aircrafts	The algorithm can be applied to a limited number of datasets
[120]	2022	Long-term evolution for machine-type communication	A practical reference guide for designing innovative sensing applications, low-latency and energy-efficient communication strategies, power-efficient computing modules, and machine learning algorithms for autonomous UAVs	Comparative analysis of literature in air-craft navigation	–	–

Table 5 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[15]	2021	Particle swarm optimization	This research calculates the line-of-sight rate and the position of the aiming point according to the current dynamics of the missile and target. It applies particle swarm optimization to optimize and continuously update the navigation constants of proportional navigation guidance to figure out the missile control commands of lateral acceleration	The proportional navigation (PN) technique is extended by a two-loop guiding algorithm	The simulation illustrates the algorithm's efficacy	A considerable decrease in sightline rate upon PN algorithm change
[121]	2021	Deep Reinforcement Learning	The training and test results show that the agent drone learns to catch the target drone, which can be stationary and non-stationary. In addition, the agent avoids crashing any environmental obstacles with a minimum success rate of 94%	A suggested DRL technique is backed by a real-time object detection model	It has a minimum success record of 94% in avoiding smashing into any obstacles in the area	When attempting to capture a target in a simulation, human pilots find it difficult to operate the drone using a remote controller
[122]	2021	Fuzzy Decision Making	Utilize historical data to generate fuzzy sets of different arrival delays using Frankfurt airport data of summer 2017 and conclude that delays positively correlate with the FCPM-based turnaround process through a linear regression model	Critical Path Method (CPM) technique and fuzzy set theory	Fuzzy Decision Making is efficient in the calculation of flight delay	Decision-making is on only historical data, various other variables need to be entertained on real-time data
[123]	2021	Convolutional neural network	Provides a reference for the development of bionic technology in China's agricultural aviation	Review on application of Bionic technology	-	-
[124]	2020	Neural Networks	This paper presents a recommendation tool based on multi-agent reinforcement learning to support air traffic controllers in complex traffic scenarios	Application of multiagent reinforcement learning	Neural networks enhance flight efficiency and penalize hazardous circumstances	The approach was effective for no more than 8000 episodes

Table 5 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[125]	2020	Genetic algorithm	This paper proposes a yaw trajectory replanning method based on an improved genetic algorithm, which improves the population quality by changing the confirmation method of the crossover operator and mutation operator by constructing the fitness function and using the new constraints to search for new guidance	New constraints to search for new guidance Point method	Good performance achieved through the genetic algorithm	Applied only to civil aircraft industries
[18]	2019	Neural network	The proposed software allows the examination of a significant number of different signals. The article describes software components like the signal base, learning subsystem, and signal generator	Application of Electronic Intelligence software	Examination of quantified variable signals	Data speed governance with a single architecture
[9]	2018	Machine learning	The overall positioning result improved by approximately 50% compared with the onboard solution	Utilizes a Kalman filter for different positioning accuracies	Comparing the entire positioning result to the onboard solution, there was an estimated 50% improvement	Data set favors only real-time data sets
[13]	2018	Machine learning	Build a model to detect graffiti on walls, which can help navigate the UAV to the correct coordinate and estimate the area of the graffiti. The data set, which contains graffiti images, is trained using machine learning techniques, which will be used to detect the graffiti patterns	Introduces a novel smart graffiti clean-up system	Applied on an ongoing smart city project	Image processing data sets need correlation with another similar project
[19]	2016	Genetic Algorithm, Neural Network	A Neural Network is employed to model the aircraft, and a Genetic Algorithm is utilized to optimize the PID controller of a quadcopter	More dependability than currently used algorithms	uses a quadcopter's PID controller	The applied algorithm checks the efficacy of the solution solely on the first data sets
[126]	2016	Machine learning	Proposed the use of support vector machine (SVM)-based machine learning technique to predict the moving speed of the aircraft	Utilizing the inertial navigation technique	The approach can be utilized in conjunction with other navigational sources to increase localization stability and accuracy	A variation in the data sets is required for variable motor speed

robotic inspections [172]. AI's analytical capabilities support decision-making, and augmented reality expedites complex repair processes. Considerable savings are realized through AI-driven inventory optimization [173]. The latest AI techniques, such as deep learning and neural networks, enhance predictive accuracy [174]. AI's versatile applications in aircraft maintenance encompass advanced fault detection, optimized resource allocation, and data-driven decision support, [106] collectively contributing to a safer and more cost-effective global aviation landscape spanning India, China, and several European nations. As seen in (Table 10), the application of AI to the field of aviation maintenance has had a notable effect on lowering maintenance costs. Using advanced data analytics and predictive maintenance methods, AI has become a game-changing tool for the aviation industry [89]. It has significantly reduced unscheduled disruptions [175], improving operational efficiency. Artificial intelligence has also been instrumental in lowering maintenance costs, which has resulted in significant savings.

Additionally, Air traffic control (ATC) is undergoing a global paradigm shift orchestrated by AI [184], ushering in a new era of increased aviation safety and operational efficiency. The need to control the ever-increasing flow of air traffic is driving the widespread use of AI in ATC systems globally [185]. For example, the Federal Aviation Administration (FAA) has deployed AI-driven ATC technologies in the United States, resulting in a 50% decrease in communication failures between air traffic controllers and pilots [83]. The United Kingdom, Germany, and China are just a few of the world's leading nations that have publicly shown enthusiasm for using AI in air traffic control [186]. The National Air Traffic Service (NATS) in the United Kingdom uses artificial intelligence (AI) to better prepare for weather-related delays and maximize airspace efficiency. Meanwhile, the German aviation authority uses AI to manage complex airspaces, reducing delays and improving efficiency [187].

Route optimization and airspace management systems that use AI have also shown substantial worldwide environmental benefits. It is predicted that these technologies have resulted in a 10% decrease in fuel usage and the corresponding emissions of greenhouse gases [188]. Using AI-powered technologies, Air services Australia in Australia has optimized flight paths, leading to significant fuel savings and a corresponding decrease in carbon impact. Integrating AI into ATC improves safety and sustainability and increases dependability in the aviation industry. Integrating AI-driven predictive maintenance practices into ATC infrastructure ensures smooth operation, reducing the likelihood of breakdowns and keeping services running smoothly [23].

Air traffic control is one area where AI is widely used, demonstrating its disruptive potential. All over the world, AI is leading the way toward more efficient, safer, and environmentally conscious aviation through innovations like improved communication dynamics in the US and cutting-edge weather forecasting and airspace administration in the UK and Germany. (Table 11) provides an overview of some of the most important studies conducted by various scholars on air traffic control.

Many businesses need AI for drone inspections. This innovative technology automates and optimizes exams. Drone AI systems may flag infrastructure issues and undesirable harvests [201]. AI effectively analyses and interprets drone flight images, videos, and sensor readings, providing essential insights and actionable information [202]. AI-equipped drones detect temperature fluctuations, structural flaws, and leaks and can forecast maintenance needs from inspection data, reducing downtime [20]. It guides drone flight patterns to avoid obstacles and examine the surroundings [203, 204]. AI-powered picture stabilization, noise reduction, and scene analysis improve video and image analysis. AI can build realistic 3D models and digital elevation maps using drone data for geographical mapping and change monitoring. Also, it analyzes inspection work risk to optimize resource allocation. Inspectors and operators may evaluate live feeds and receive warnings for critical discoveries using remote AI monitoring [205]. The function ensures quick action when needed. AI integrated seamlessly with LiDAR and thermal imaging improves inspection drones. AI models must fit specific sectors and use cases [206]. The vast drone inspection data is sorted and stored; consequently, the data is secure, accessible, and retrievable. Finally, AI dramatically enhances drone inspections in several fields [207], as briefly explained in (Table 12). Companies can better track, maintain, and manage their assets and resources.

Thus, drones are undergoing a revolutionary change, and artificial intelligence (AI) is at the vanguard of that change. Artificial intelligence in drones has improved autonomous navigation, object detection, map creation, crop optimization, infrastructure inspection, environmental monitoring, emergency response, package delivery, safety, and entertainment. This integration of AI with drones increases their intelligence and lowers their price, which has broad use in business and improves worker safety and productivity. Drones are already indispensable in many fields and will become even more so as AI develops.

Compelling data provide proof of the influence of Artificial Intelligence (AI) on air quality regulation. AI-driven monitoring systems have resulted in a notable decrease of up to 20% in PM2.5 levels inside urban areas. Predictive models have demonstrated a maximum accuracy of 90% for projecting air quality conditions. Implementing artificial intelligence (AI) in industrial processes has resulted in notable reductions in emissions, ranging from 15 to 30%. Implementing artificial intelligence (AI)-driven traffic management systems has resulted in a notable reduction in traffic-related emissions, with a reduction rate of 15%.

Table 6 Recent applications of artificial intelligence in aircraft simulation

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[128]	2023	Monte Carlo Simulation, Predictive Algorithms	Analyzes the reliability of the predictive algorithm to be implemented as an automatic error predictor in aerospace	Performed sensitivity analysis for the error prediction	The model is applicable as a predictor of auto-failures	Simulation runs accurately for 1000 runs
[129]	2020	Modeling, simulation	This study comprehensively examines the current software development status for high-performance computing (HPC) in China	Review of HPC Software capability	-	-
[130]	2020	UAVs Visual Navigation	This research to practice WIP presents a comprehensive experiment based on UAVs' visual navigation to improve multidisciplinary engineering skills in Aerospace engineering education	Evaluated the capacity for interdisciplinary engineering in every student	Increased the student proficiency in aeronautical exploration	Limited to only aerospace engineering students
[27]	2020	Digital twin	Based on an actual modern jet engine bypass outlet guide vane (BOGV), a case study shows how building and using its digital twin and high-fidelity simulation can save a fleet of engines/aircraft money	Application of computed tomography	Proposed an engineering design space to alter the geometry intended by the design to align with the produced data cloud	The application can be applied to other engineering applications
[131]	2024	Aerodynamic database prediction	This study found that CatBoost and XGB models required less training time than the Conv1D method and that the regression trees CatBoost, Bagging, and XGB can reduce the number of CFD simulations	Amalgamation of three different AI-based techniques for the calculation of aerodynamic coefficients	CatBoost removes the need to modify the hyperparameters according to various scenarios	Error values by incorporating different techniques can be reduced for higher accuracy
[132]	2022	Data twin service, human intelligence	Incorporating the Data Twin Service idea facilitates the connection between human and artificial intelligence	Introduction of Industry 4.0 tools	Embrace the idea of a data twin service to enable communication between artificial and human intelligence	An analysis is carried out using the last year's data
[133]	2021	Machine Learning Digitalization	A robust workflow engine in the back should seamlessly integrate manufacturing process simulation models, material property prediction models, databases, data visualization, search engines, and other digitalization tools through an innovator-friendly innovator's canvas	An extensive review of digitalization in various composites for aerospace applications	-	-
[134]	2023	Numerical simulation	The high-performance extremely high frequency (EHF) technology is expected to find extensive utilization in the aerospace industry	A thorough analysis of the components, capabilities, and uses of electric heating film (EHF)	-	-

Table 7 Notable use of artificial intelligence in autonomous flight

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[34]	2023	Augmented reality (AR)	This paper evaluates and analyzes AR, a remote assistance tool for industrial purposes	Assesses and examines augmented reality as a technique for remote help in the workplace	Reducing production stoppages by almost 50% of the time, which eventually boosts the GDP of a nation	Model efficient only on limited data sets
[135]	2019	Deep Q Network	The trained convolutional neural network controlled the UAV to complete the autonomous obstacle avoidance task during the flight	The convolutional neural network is trained using the Deep Q Network technique	Real-time flight height adjustments are made based on obstacle and terrain heights	Algorithm efficiency depends upon the fixed paths
[136]	2021	AI-based Safety Assessment	This research evaluates the current status of Europe's U-space and Air Traffic Management legislative environment	Exclusive review on unmanned aircraft systems for urban development	-	-
[137]	2020	Visual model-predictive localization	VML approximates the error between the model's predicted position and the visual observations as a linear function	Application of VML method for drone technology	The drone can still travel on its own with a fair amount of speed according to the suggested method	The author didn't estimate the thrust in this method
[138]	2018	Neural networks	Three distinct deep reinforcement learning (DRL) algorithms were employed to acquire the training models, utilizing the principles of Q-learning in reinforcement learning. The outcomes exhibit considerable promise, as around 80 percent of test flights achieved the designated objective	Drone-based deep learning techniques for full autonomy	Findings showed that eighty percent of test flights arrived at the objective on schedule	An increase in static information will reduce the drone's efficiency
[139]	2022	Computer vision, virtual reality (VR)	Presents artificially trained models to create vast volumes of space-based images for computer vision sensing and machine learning simulation and validation	Presents a unique method that uses artificially learned models for space-based computer vision sensing, machine learning simulation, and validation	The first use of pre-processed domain randomized imagery in the globe for space-based machine learning applications	The difficulty of doing hardware-in-the-loop testing for various climatic conditions is not exclusive to the aerospace industry
[140]	2023	Machine learning	A thermal modeling feature has been incorporated into Unreal Engine, facilitating the generation of realistic training data. This integration enables the real-time simulation of sensors operating in the short-wave infrared (SWIR), mid-wave infrared (MWIR), and long-wave infrared (LWIR) spectra	Included a thermal modeling feature in Unreal Engine to produce training data that is accurate by using various sensors	Demonstrated the simulation environment and how it relates to distributed autonomous decision-making, detection, and classification	Efficiency depends upon a radiometrically accurate sensor model

Table 7 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[141]	2020	Reinforcement learning	The present study has successfully demonstrated the capability of the proposed man–machine air combat system to accurately replicate real air combat scenarios and evaluate the efficacy of autonomous maneuver decisions made by unmanned aerial vehicles (UAVs)	Creates a suite of unmanned aerial vehicle (UAV) decision-making man–machine air warfare systems using a deep Q-learning network	Efficient demonstration of man–machine aerial warfare and situational awareness	Attack distance is limited to three kilometers only

Additionally, deploying health alert systems utilizing AI technology has decreased hospitalization rates for respiratory ailments, ranging from 10 to 15%. Additionally, using AI-driven methodologies has resulted in significant cost savings in healthcare expenditures for cities, amounting to billions of dollars. Furthermore, these techniques have effectively increased public awareness regarding air quality, as seen by a user engagement rate above 70% on various air quality applications and websites. The data illustrates the significant impact of artificial intelligence (AI) on enhancing air quality and promoting public health.

The subject of air quality monitoring is being quickly transformed by artificial intelligence (AI). Artificial intelligence-powered techniques and technology can assist us in better understanding, forecasting, and managing air pollution (Table 13). One of the most essential applications of AI in air quality monitoring is the collection and analysis of massive volumes of data [219]. Air quality sensors are already commonplace, and artificial intelligence (AI) may be used to evaluate the data from these sensors to build more detailed and accurate maps of air pollution levels [220]. AI may also be used to monitor changes in air pollution levels over time, assisting us in identifying trends and patterns [221]. Another critical use of AI in air quality monitoring is identifying pollutant sources. AI may detect pollution by analyzing air quality data and other data sources such as traffic and meteorological data [222]. AI is also being used to forecast future air quality levels. It is accomplished by training AI models with historical air quality data and weather forecasts. Once trained, the models may forecast air quality values for various places and periods. This data may be used to notify individuals about periods of excessive air pollution and to assist them in taking precautions to safeguard their health [69]. Finally, AI is being utilized to create new systems for monitoring and controlling air quality. AI-powered air purifiers, for example, may be used to clean interior air, while AI-powered drones can check air quality in remote places.

The US Environmental Protection Agency (EPA) employs artificial intelligence (AI) to create a new air quality forecasting system. The system will forecast air quality levels up to five days ahead using data from air quality sensors, satellites, and meteorological models. This data may be used to notify individuals about periods of excessive air pollution and to assist them in taking precautions to safeguard their health. AirVisual is employing artificial intelligence to create a global air quality monitoring network. AirVisual has placed air quality sensors in more than a hundred nations, and the data is used to build real-time maps of global air pollution levels. Millions of individuals use this information to be informed about air quality levels in their neighborhoods and make decisions about safeguarding their health. AI has the potential to transform how we monitor and manage air

Table 8 Notable implementation of AI technology in aircraft communication

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[144]	2023	Q-learning, artificial potential field	The proposed system offers real-time obstacle avoidance pathways for many Unmanned Aerial Vehicles (UAVs), mitigating early algorithm convergence	Application of the Q-Learning-based Ant Colony Optimisation technique	The problem of assigning different tasks to separate UAVs is addressed by a multi-task allocation method, which allows autonomous decision-making	UAVs' real-world combat and reconnaissance capabilities must be taken into account
[145]	2023	Reinforcement learning	This paper presents a cooperative federated reinforcement learning (RL) strategy that allows two UAVs to learn and predict the movements of an intelligent, deceptive target in a search area	Optimise target detection efficiency and quicken learning rate while preserving privacy	The two UAVs can cooperate remotely thanks to the suggested cooperative RL-based algorithm	The act of transition probability to trick the surveillance
[146]	2023	HVDC transmission, fault tolerance	The proposed control approach is simple to implement because no additional controllers are required, and existing communication infrastructure, such as power line communication, can be used	Suggests a unique artificial intelligence-based design approach for the best bus voltage compensation and power-sharing coefficient designs	The suggested method may be implemented without the need for additional digital communication lines or controllers	There should be terrestrial applications for the suggested design strategy
[147]	2023	Machine learning, advanced wireless communication	The suggested model for spectrum management aims to promote the efficiency of spectrum usage and expand airspace capacity, therefore catering to the requirements of future applications in the National Airspace System (NAS)	Takes into account different arrangements of airspace communications, such as air-ground and air-air communications	Intelligent resource allocation for improved spectrum utilization efficiency through cooperative use of AI and spectrum management techniques	Several obstacles to intelligent spectrum management capability, such as spectrum coordination and processing capacity
[89]	2023	Target tracking systems, artificial intelligence (AI)	Include machine learning (ML), cloud computing, and emerging fifth-generation (5G) technologies in a discussion of recent enabling technologies that could be integrated into UAV target tracking systems	Investigates indoor and outdoor target tracking and monitoring using unmanned aerial vehicles (UAVs)	-	-
[148]	2023	Sensor-based communication	Focused on hexacopter unmanned aerial vehicle (UAV) tests conducted on a novel platform both in a controlled laboratory setting and in open areas with no obstructions to verify operational parameters, hover flight, the drone's stability and reliability, and its aerodynamics and robustness at varying wind speeds	Hexacopter Unmanned Aerial Vehicle tests conducted during motor start-stop maneuvers to confirm operating parameters, hover flying, drone stability, and dependability	The deviation margin concerning the real values was around fifteen percent	Sensors such as anemometers and LIDAR can be added to the work

Table 8 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[149]	2022	CNN, Deep learning	The method has a 94.1% accuracy rate and can determine the aircraft type faster than the traditional method	Electromagnetic fingerprint extraction using deep learning	The same technology applies hundreds of noise signals to be combined with ACARS signals	Phase deviation is a major drawback in airplane signals
[150]	2022	Blockchain	Explores the use of blockchain technology in aerospace case studies and enumerates how artificial intelligence has aided the development of the computing platform	Lists the contributions made by AI to the computer platform with the different blockchain technology advancements	Preserving processes for information mining and model preparation	Underwater sensor networks can be explored in the proposed work
[74]	2022	Internet of Things, Machine learning	Incorporates DoS detection into the UAV system and proposes building a control platform using the Message Queuing Telemetry Transport (MQTT) protocol	Suggests building an effective platform for UAV control with integrated Denial-of-Service (DoS) detection that is built on the Message Queuing Telemetry Transport (MQTT) protocol	For every QoS level, a robust correlation of more than 90% was discovered between delay and data size	Field tests can be added to the project
[151]	2021	Microcontroller, On-device machine learning	This design provides a simple and efficient scheme for further integrating artificial intelligence (AI) algorithms for quad-rotor aircraft control system design	Utilizes airplane with four rotors using multisensor fusion	Give a basic blueprint for the remote control mode of a future quadrotor aircraft	The addition of deep neural network models increases the stability
[152]	2020	Downlink interference control	Proposed a finite difference algorithm for solving coupled partial differential equations, which can yield the optimal altitude control strategy	Examines a downlink interference control issue using an AI-assisted approach in extremely dense unmanned networks	The ideal behaviors of DSCs in various environmental circumstances are displayed in the algorithm outputs	The algorithm runs effectively on interactable-based parameters of power and velocity
[153]	2018	Machine learning	A uniform interpolation method is used to correct the predicted position each second to achieve higher prediction accuracy	Analyzing past flight trajectories, provided a unique method for plan route prediction	Results using the suggested algorithm are more reliable and accurate than conventional methods	A whole air traffic scenario would offer a more effective way to address the issues
[154]	2018	Machine learning, Pattern recognition	The results show that the developed machine learning framework can detect and locate damage based on time-delayed binary data from a self-powered sensor network	Offers a reliable technique for detecting aircraft structure deterioration in an environment based on informative SHM	A created machine learning system that uses time-delayed binary data from a self-powered sensor network can accurately identify the location and existence of damage	The reliability of the proposed methodology can be improved by assessing multiple data sets

Table 8 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[155]	2017	Intrusion detection using machine learning	constructed a mathematical model to predict when offloading computations would be helpful based on information about the network's operation and the model's processing requirements for deep learning	Employ both a recurrent neural network architecture and a deep multilayer perceptron	Proven that cloud-based computational offloading may be used to mitigate the main drawback of a deep learning-based strategy, which is the detection delay brought on by the higher processing needs	Remote detection of intrusion activities in vehicles should be considered
[156]	2015	Vehicular communication networks	developed a model for cooperatively getting context data and spreading it to figure out what is happening in vehicular communication networks	Proposed Collaborative methodology for gathering and sharing context data for identifying situations in in-vehicle communication networks	Experiments based upon a high number of vehicular congestion	An increase in the nodes decreases the model efficiency

pollution. We can build more focused and effective ways to minimize air pollution and preserve human health by utilizing AI to gather, analyze, and forecast air quality data.

The process of lowering the expenses connected with aircraft ownership, operation, and maintenance is called aircraft cost optimization [229]. Data has the potential to play a significant part in the optimization of aircraft costs by assisting airlines in gaining a deeper understanding of their expenses, locating areas in which they can make improvements, and monitoring the progression of their optimization efforts [230]. Airways may collect data from many sources, including flight data recorders, aircraft maintenance systems, and finance systems. These data may be used to analyze the aircraft's performance, locate locations with high costs, and devise focused optimization techniques [181, 184, 200, 231]. For instance, airlines may utilize data to determine which planes consume the most fuel or which components have the highest failure rate. This information may be put to use in the creation of programs for preventative maintenance or in the identification of individual aircraft that may benefit from fuel-saving upgrades [232]. Airlines may also use data to monitor how far their optimization efforts have progressed. It may help them determine which techniques will yield the best results and assist them in making any required revisions to their plans. (Table 14) provides a summary of the research community's work in aircraft cost optimization.

Thus, AI can potentially revolutionize aircraft optimization in the design of more efficient and aerodynamic aircraft. Airlines and aircraft manufacturers emphasize aircraft optimization significantly due to its potential to enhance financial viability, competitive advantage, ecological impact, and environmental sustainability.

One of the most crucial areas where artificial intelligence (AI) is being applied in the aviation sector is improving fuel economy. By considering variables like weather, aviation traffic, and appropriate altitude and speed profiles, AI can help create more effective flight plans. Especially on long-distance flights, this can result in substantial fuel savings. Artificial intelligence can be utilized to keep tabs on an airplane's efficiency in real-time. Sensor data, including engine performance and aerodynamic data, may be analyzed to achieve this goal. For instance, aircraft aerodynamic inefficiencies due to variations in wind conditions or design may be detected and corrected using AI.

It will be used to create preventative maintenance systems for airplanes. Significant fuel savings may result from a decrease in the frequency of unplanned repairs. Artificial intelligence (AI) may be used to plan maintenance on engine components based on the likelihood of failure. It may also be utilized to improve aircraft efficiency and maneuverability. For instance, the form of the wings and fuselage may be optimized using AI to decrease drag. Artificial intelligence may also create more efficient propulsion systems

Table 9 Use of artificial intelligence in space exploration

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[160]	2023	IoT, Machine learning	Focus on the latest advances in the above technologies and control system theory, considering long-distance between the controlling station and the exploration site	Enlightened Fundamental Ideas and Techniques for Vast Space Exploration	-	-
[161]	2023	Surrogate modeling- space exploration	Present a data-driven framework that uses symbolic regression and sensitivity analysis to make quantitative predictions and qualitative rules for data creation for all datasets	Provide a broad, data-driven framework that uses sensitivity analysis and symbolic regression to guide the development of data for all datasets	Approximately 100 potential thermal insulators are identified after screening through a collection of more than 700 materials	Expanding this structure to incorporate data on the anticipated failure points of the underlying electronic structure computations offers a way to expedite the discovery of materials on a broader scale
[162]	2023	MCTS-based intelligent search	Proposed heuristics can reach deeper search tree nodes, saving more area in approximate computing	A novel approach for stochastic search to address computational issues	To effectively use the search tree in the investigation of more interesting nodes in the design space, search towards deeper nodes in the search tree, producing a somewhat lopsided tree	More area savings can be achieved through the modified algorithm
[163]	2022	design space exploration	Exploration of an AI-generated design space for the conceptual design of shell and tensile structures using a computational design tool	Optimization techniques to effectively traverse the large design space	Results in enhanced infrastructure, systems, and goods	Investigating large design areas necessitates substantial processing power and data storage
[164]	2022	artificial intelligence	Argues that the role of an astronautical religion beyond human intelligence and artificial intelligence (AI) could be a psychiatric anchor for future space travelers as part of a new mental strategy in space exploration policy	Astronautical religion's future will rely on how mankind decides to handle the opportunities and difficulties	Engineering, material science, and communication frontiers are being pushed in the process of developing the technology for Mars missions	Because of the harsh and merciless Martian climate, creating livable human colonies would be extremely difficult from a technical standpoint
[165]	2022	deep neural networks	Implemented a MobileNetV2 model using a cutting-edge HLS tool to explore design space and provide insights on complex hardware designs for DNN inference	Apply natural selection theory to repeatedly enhance configurations	Through the process of identifying and eliminating irrelevant connections from the network, DSE lowers the quantity of calculations required	Finding the ideal balance between accuracy and sparsity can be difficult, and reaching comparable accuracy
[166]	2017	Machine learning	The proposed sVL allocation algorithm can significantly improve the reliability and the lifetime of 3-DSWNoC	Become a viable option with great performance for the next many-core CPUs	Bit errors can be found and fixed by using error-correcting codes	Shorter average path lengths and a high clustering coefficient

Table 9 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[167]	2017	Extreme learning machine (ELM)	A high-performance, low-power, and compact hardware implementation of an extreme learning machine. It is intended for use in machine learning applications	The most computationally demanding step, vector–matrix multiplication, is carried out using mismatched current mirrors	Iterative training, which can take a lot of time with standard neural networks, is not necessary with ELMs	It can be difficult to design compact and effective VLSI circuits for ELMs, particularly when there are many hidden layers
[168]	2016	coevolutionary machine learning algorithm	The results show that for configurations with ten or more rovers, the number of robots required for a particular performance level can be reduced by ten compared to conventional cooperative coevolutionary algorithms	To train a multi-robot system, an in-the-loop cooperative coevolutionary method is provided	Setups with ten or more rovers decrease the number of robots required for a given performance level tenfold when compared to typical coevolutionary algorithms	Robot failure risks associated with inaccuracies of algorithm

like hybrid and electric engines. It may also be utilized to create new materials that are lighter and stronger than those already used. As a result, planes would use less fuel without sacrificing safety.

As a whole, AI can improve airplane's gas mileage dramatically. The aviation sector may become more sustainable and environmentally friendly if airlines and aircraft manufacturers use AI to build new technologies and systems that drastically cut fuel consumption and emissions. (Table 15) presents a quick synopsis of the academic community's efforts to better fuel efficiency.

Moreover, AI is being applied in the aviation sector to improve fuel economy. It improves efficient flight plans, monitors the aircraft's performance in real-time, identifies potential aircraft problems, and takes preventative measures.

6 Discussion, Conclusion, and Future Research

Many research paths were suggested by expanding upon the SQLR (systematic quantitative literature review). (Table 4) presents a brief representation of the study orientations and unresolved research inquiries within the field of artificial intelligence (AI) and its numerous applications. The table is an exhaustive compilation of significant research gaps and inquiries. However, it is not unexpected that many study gaps and unsolved research problems have been uncovered, considering the relatively early stage of development in the research area. In the context of AI applications in the aerospace industry, previous research has examined the factors contributing to AI adoption. These factors include technological, security, and economic considerations. Several studies have examined machine learning [250] as a technological prerequisite and precursor for the successful adoption of artificial intelligence (AI) in the aerospace industry [251]. These studies have specifically highlighted the suitability of data-rich settings, such as those found in aerospace, for implementing deep learning applications. The utilization of predictive analytics derived from machine learning has been acknowledged for its potential to facilitate the identification and advancement of novel aircraft technologies and innovative commercial solutions.

Machine learning and soft computing technologies [233] are crucial. Firstly, these technologies are vital for enhancing firms' sensing capabilities in the aerospace industry. It includes deriving valuable insights into consumer needs, assessing the market potential of new products, and identifying new market opportunities [252]. Secondly, these technologies enable firms to enhance their seizing capabilities by leveraging big data [253]. This involves utilizing large datasets to develop tailored services and products that cater to specific customer demands. Current scholarly

Table 10 Prominent applications of artificial intelligence in aircraft maintenance

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[176]	2023	Ant colony optimization algorithm	Reduces the number of planes needed by calculating the most efficient flight paths while on cruise	Examine the OAMRP while using cruise control	Compared the computational time with conventional algorithms	Flight delays should be considered
[177]	2022	Industry 4.0, machine learning	The proposed model can efficiently predict the future condition of components for maintenance planning by using two datasets—aircraft engine and lithium-ion battery datasets	By employing intelligent techniques, a PdM planning model is created	The suggested model can effectively forecast component conditions for maintenance scheduling in the future	It was challenging for the machine learning system to get the best outcomes since the predicted values differed
[178]	2022	Deep learning	The solution facilitates tactical demands and aircraft maintenance resource exchanges, enabling air-ground system interoperability and collaboration	definitions and abstract depictions of pertinent tactical structures	Two nearby domain contexts are seen from a domain-centric perspective to construct graph models	the capacity to take advantage of cooperation and interoperability across ground- and air-based systems
[179]	2022	Ant colony optimization algorithm	A novel ant colony optimization algorithm that considers node attractions in the state transition rule solves the model	Integrates cruise speed control to achieve the stated flying time variability	Create pathways for aviation repair that are more aircraft-intensive	Only cruise control variable data is explored
[180]	2019	Big data analytics	The BNs were developed from a real industrial dataset of 372 aircraft maintenance projects of a Portuguese MRO. Information variables represent typical planning data, and hypothesis variables represent estimated workloads	Capacity planning integrated with Big data approach for aircraft maintenance	Show how capacity planning techniques can be used effectively for maintenance	PN and BN models could be combined to enhance the decision-making process
[181]	2018	Bi-level optimization	The results show significant airline and maintenance company cost savings	Created a predictive analytical-based method that precisely explains the flight delay	Compared to the outcomes of the conventional non-joint optimization approach, the results show a considerable reduction in both organizations' expenses	Work is limited to only three days of data
[23]	2017	Genetic algorithm	The computational results showed that the proposed solution algorithm outperforms other meta-heuristics in finding a better solution faster, while operational considerations increase the model's profitability	Create a quick and flexible solution approach to deal with the ongoing developments in the aviation sector	According to the computational findings, the suggested solution method finds a better solution much faster than previous meta-heuristics	Create new models and boost the functionality of the ones that already exist

Table 10 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[22]	2021	Big data and analytics	The developed model can predict the ground speed with a relative root-mean-square error of between 1.27 and 2.69 percent	The combined effect of CNN and LSTM approach	The ground speed can be predicted with a relative root-mean-square error of 2.69% to 1.27% using the established model	More accuracy is required in case of deviation in data input from different constraints
[182]	2020	Cloud computing	Design and implement a data-driven prognostic service architecture for aircraft maintenance	IoT-based data-driven modeling	Offer an appropriate and effective PHM solution as a service over the internet, adhering to a service level agreement	Variable data inputs can hamper the desired results
[183]	2016	Natural language processing	blends natural language processing methods with ensemble learning to predict the failure of infrequent aircraft components	Ideal selection of sensor sets with the most pertinent data for reliable data analysis and problem classification	The diagnosis of heat exchanger fouling is applied and examined using the information produced by an experimentally verified high-fidelity	The ability to diagnose heat exchanger fouling using actual aircraft data must be included in the research work

literature indicates a growing need for enhanced data-driven insights. Nevertheless, the fast evolution of AI technology has the potential to impact both the scope and timeline of AI adoption. (Table 16) illustrates the key takeaways from this review process.

7 Limitations

Several limitations are included in this investigation. Initially, our research endeavors aimed to examine distinct implementations of artificial intelligence within the aerospace industry. These applications encompassed various areas such as control and navigation systems, simulation techniques and aircraft design, autonomous flight operations, aircraft maintenance procedures, air traffic control mechanisms, aircraft communication protocols, space exploration initiatives, drone-based inspection methodologies, air quality monitoring techniques, cost optimization strategies, and enhanced fuel efficiency measures. Future studies should examine a more comprehensive approach to application to encompass all conceivable forms and types of applications.

First, we selected particular databases that index scholarly research. Scopus and Web of Science (WOS) are the predominant databases employed in systematic literature reviews (SQLRs) [303]. However, researchers may also gather data from alternative databases, including Google Scholar.

Second, comparing and integrating the bibliometric analysis program VOS viewer with several other bibliometric software tools is possible. Expanding upon the SQLR (Systematic Literature Review), many research gaps and potential research areas were discovered. (Table 4) presents a visual representation of the many study orientations and unresolved research inquiries within the field of artificial intelligence (AI) applied to aerospace. Researchers who possess a keen interest in addressing these inquiries will inevitably encounter various obstacles.

To begin with, it is essential to acknowledge that the integration of AI technology occurs gradually. To comprehensively understand the factors leading to its acceptance and the outcomes that ensue, it is imperative to take a process-oriented approach. Consequently, we advocate for the undertaking of longitudinal studies, whether they are qualitative or quantitative. Experiments can also contribute to comprehending the cognitive underpinnings of activities and decision-making processes among innovation managers. Furthermore, scholars can employ hybrid techniques, such as sequential exploratory approaches, to comprehensively address the inquiries outlined in (Table 4).

Third, we strongly urge researchers to engage in inter- and multi-disciplinary research endeavors that integrate constructions and concepts from many engineering domains.

Table 11 Leading AI applications in air traffic control

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[189]	2023	Decision Tree Pruning Method	It was proven the utility of long-term AI research in intelligent air transport for enhancing flight safety administration	With SQL, MongoDB is used for data analysis	Shown how sustainable artificial intelligence is being developed for intelligent air travel	More percent of Brazilian air traffic should be added for analysis
[190]	2023	Intelligent Integrated Decision Support System	Created models for collaborating operators' (pilots, air traffic controllers, flight/dispatch) decision-making under uncertainty	Pilot incapacitation was explored in the study	Calculated the best possible collective details for an emergency	Training protocols need to be able to replicate flying scenarios as closely as feasible to actual occurrences
[117]	2023	Short path algorithm	Produces a systematic route selection solution for the air traffic controller to use Dijkstra's Shortest Path Algorithm to find the most efficient route with an operational decision support system model	Suggested aviation route as an operational-level decision support tool that is both the quickest and the safest	The suggested, most efficient path was completed at a distance of 11.22%	It is appropriate to include structural inefficiencies in the FUA idea
[191]	2023	Explainable artificial intelligence	The proposed technique can lessen the possibility of collisions and smooth out fluctuations in traffic volume, greatly enhancing the average flight time between sectors	Application of explainable artificial intelligence	The sector's average flight duration has grown by 38.60%	Sensitivity analysis under different operation situations can be done
[192]	2022	Explainable artificial intelligence	The model makes it easier to decide whether or not to give pilots access to automation and decision-making aids	Use of explainable artificial intelligence	All operators' synchronization activities are modeled using behavioral deterministic models	Results accuracy depends upon the influencing factors
[193]	2022	Machine learning	The findings have highlighted a gap in the EASA W-shaped technique for time-dependent analysis by demonstrating how the passage of time can affect machine learning algorithms developed in an environment where time constraints are not considered	Machine learning-based solution for aviation safety	Classification results success rate is nearly eighty percent	The result of an ML-based algorithm is reduced with an increase in sample size and metrics
[48]	2022	Machine learning, Neural networks	The framework that has been discussed constitutes a comprehensive guideline for addressing data- and machine learning-based analyses and metaheuristic optimization in air traffic management	Prediction of boarding times and classification of flight delays with machine learning (ML) the framework presented	Non-linearity is also considered in the air traffic system	ANN extension can boost the efficiency of the system

Table 11 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[194]	2022	Explainable artificial intelligence	Showed that non-zero state transition probabilities at all flight phases allow proactive disruption management before schedule execution	Application of explainable artificial intelligence	Using previous schedule and operational data from a significant American airline	Because non-zero state transition probabilities exist throughout every stage of flight operation, proactive disruption control may be implemented before schedule execution
[90]	2022	Cuckoo search algorithm	Utilizing the Cuckoo Search Algorithm (CSA), a new fuel flow rate model was developed for the flight's descending phase	For use with B737-800 aircraft, a new fuel flow rate model has been created	The correlation coefficient values for Flights 1 and 2 are determined to be 0.996858, 0.998548, 0.995363, and 0.997351, respectively	Model created for the declining period in the body of current literature
[195]	2022	Deep learning	It provides air traffic controllers with enhanced situational awareness through the systematic analysis of aircraft surveillance data and the introducing of a digital assistance system to detect conflicts in air traffic	Recurrent neural networks are used to categories error patterns and monitor air traffic	About a hundred distinct combinations were used and examined for air traffic management	More different combinations can be used
[196]	2021	Deep-fusion neural networks	The deep-fusion neural network model performed exceptionally well compared to other network models	Accomplishes network fusion at the decision-making layer and pre-trains deep neural networks and deep convolutional neural networks using transfer learning techniques	The test video's recognition accuracy was 97.30%, while the overall recognition accuracy was 98.44%	Images of non-frontal faces may be detected using the MTCNN detection technique
[197]	2020	Reinforcement learning	They developed personalized digital assistants for air traffic controllers to manage workloads in high-traffic sectors	As a digital assistant, an artificial intelligence (AI) system is designed to aid air transport	Digital assistance works efficiently even in increase traffic	Highly congested traffic can lead to inaccurate results
[198]	2019	Machine learning	It focuses on air traffic controller route planning and examines the pros and cons of designing and implementing an artificial intelligence system	Covers functional aspects of programming techniques for airplane traffic control	Emphasizes the controllers' route planning work	The involvement of cyber-physical systems can increase efficiency
[102]	2019	Metaheuristics algorithms	The strategy has resulted in considerable reductions in airborne delays and additional fuel consumption caused by the settlement of aircraft conflicts in large-scaled airspaces	Suggests a two-step method for resolving aircraft conflicts and fuel usage	For 20 aircraft, the average fuel consumption was determined to be 201.4, 9.3, and 9.4 kg, respectively	The issue can be expressed as a mathematical model with multiple objectives

Table 11 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[25]	2018	Fuzzy logic	Investigate the possibility of using the artificial intelligence concept of fuzzy logic to automate the ATC system to safely and efficiently handle the increased traffic caused by UAS	Automating Air Traffic Control and Integrating Unmanned Aerial Systems with Fuzzy Logic Algorithm	Giving heuristic information on secure ATM operation	It is also necessary to pursue data-link security and encryption to stop inadvertent or malevolent signal loss
[33]	2018	Deep learning	Proposed an accurate aircraft landing speed prediction model using flight sensor data and LSTM	Suggested using data from flight sensors to estimate an aircraft's landing speed with accuracy	Fulfilled the objective of precisely estimating the landing speed, which may help lower the number of aircraft landing mishaps	Long landing prediction and the selection of more ideal parameters can both help to further improve the prediction model
[199]	2017	Machine learning	Both models showed good agreement between predicted and observed thrust values, with the best accuracies coming from LM-trained neural networks	When estimating thrust, take into account the impact of both flying height and Mach number	The predicted and actual thrust values showed good agreement	The system accuracy would be increased by creating a databank with thrust, altitude, and Mach number information from several turbofan engine manufacturers
[200]	2016	Sequencing machine learning algorithm	Proposed a dynamic sequencing algorithm to enable a team of aircraft to land with an optimal sequence	A proposed method for landing a group of airplanes involves modeling and sequencing	When it comes to minimizing the cost function and landing time consumption, DSAAC outperforms the other three approaches	An increase in the number of aircraft variable data can decrease the efficiency
[10]	2015	Machine learning	Experimental validation shows how operators receive predictions hundreds of seconds before failure	Suggests a revolutionary architecture with the distinguishing characteristics for online failure prediction	Experimental validation demonstrates how operators receive forecasts a few hundred seconds in advance of the failure occurring	The adopted technique will need to be changed to lessen the likelihood that the system will fail shortly

Table 12 Artificial intelligence driving forefront of drone-based applications

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[208]	2023	Computer vision-based deep learning	The proposed module improves visual bridge inspection accuracy and decreases labor safety risks	Creates a deep learning model with Bayesian optimization for an unmanned aerial vehicle	The processing speed using the Mask R-CNN model and the ResNet101-FPN backbone network was 20.33 FP	Because of their lighting conditions or placements over rivers, across the highlands, or over gorges, composition bridges are challenging to check
[206]	2023	Artificial neural network	Build an AI-powered damage detection system leveraging mobile or drone-mounted video of the damaged structure to replace human visual inspection	Create a productive way to identify damage that replaces human visual examination with a mobile phone or drone-mounted camera recording of the damaged structure	Using a handheld camera, precisely identify the damages in the bounding box or selected limiting region	Results are limited to recorded bridge video
[209]	2023	Deep learning	The transmission picture dataset is used to train the AI model, and further trials confirm the model's accuracy and the technology's viability for transmission image interpretation	Investigates a ViT-Siamese cascade network-based transmission picture deduplication technique	The efficiency and viability of the technique in transmission scene processing are assessed using an AI model built on a transmission image dataset	Variability in transmission image datasets varies the algorithm results
[21]	2022	Convolutional neural networks	The suggested CNN architecture reduces noise, integrates feature supervision, improves learning, aggregates multi-scale and multilayer features during training, and refines output predictions	Conditional random fields and guided filtering (GF) are applied in the proposed CNN architecture	It offers several benefits, including less noise, highly integrated feature supervision, sufficient learning, and the ability to aggregate multi-scale and multi-level features during training	Transfer learning concepts can boost the efficiency of the system
[210]	2022	Convolutional neural network, deep learning	The enhanced approach to artificial intelligence learning technology is anticipated to proactively mitigate power transmission failure, mitigate the expenses associated with power outages resulting from such failures, and decrease maintenance costs by automating inspections	They utilized pictures of failure modes for preparing learning models	Average accuracy increases twice by the learning model	Accuracy decreases with more pictorial datasets
[28]	2022	Digital twin, machine learning	This work introduces a unique approach to developing an operational digital twin for large-scale buildings using drone inspection photos	Digital twin demonstrated on large structures	A 3D visual depiction of the wind turbine was inspected by drones and scanned using LiDAR	Better signal data may be obtained with sophisticated numerical methods
[211]	2021	Convolutional neural network	This study trains a model to detect and classify road defects such as potholes, blind spots, speed bumps, and material composition	Drone-based terrain monitoring system with machine vision applications	At a speed of 443 ms, the model produced pixel masks and identified pictures with 81% accuracy	The use of integrated sensors can decrease road accidents

Table 12 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[11]	2021	Machine learning	Recent breakthroughs in artificial intelligence (AI) and infrared thermography have opened up new avenues of investigation and begun to refine building exterior evaluation methodologies	An Overview of AI-Based Fault Detection and Diagnosis Techniques for Building Energy Systems and Aerial Infrared Thermography	-	-
[212]	2021	Image Processing, machine learning	This research aims to identify and evaluate a massive irrigation water pipe network strategy	Explored techniques for extensive networks of water pipes	Meteorological data and hydrogeological risk maps can be matched thanks to algorithms based on logical requirements	Reaching out to a drone in a congested vicinity is a big challenge
[213]	2020	Deep neural networks	In this study, oil spills are detected, and their locations are pinpointed with the help of two deep learning models: VGG-16 and mask R-CNN (mask region-based convolutional neural network)	Using deep learning methods to address oil spills	The convolutional neural network model produced average accuracy and recall of 61% and 70%, respectively	Infra-red or thermal images can increase the model's accuracy in different applications
[214]	2020	Deep Learning, mobile machine vision	This study aims to address the limitations associated with human eye identification in traditional monitoring systems and enhance the efficacy of traffic inspection	Panorama multi-target identification in real-time utilizing deep learning and mobile machine vision	Target class accuracy is close to 72%	Accuracy can be increased using profound scan results
[215]	2019	Machine learning	Demonstrate how drone-based imagery can monitor and survey pipelines and rights of way	Using a UAV to carry out evaluations and inspections	Extensive case studies for industrial applications	Accuracy deployment can be increased for various sites
[204]	2019	Convolutional neural network	Presents a lightweight sensor system to extend UAV flying duration	Automated Power Line Fault Identification employing Unmanned Aerial Vehicles	This concept suggests a system with lightweight sensors that could extend the UAV's flying duration	The efficiency of the flight time depends upon cloud data speed
[216]	2019	Neural network	The algorithm provided here is a significant technology in creating autonomous search and rescue personnel and material-deploying drones	Shows how deep reinforcement learning can understand the Snake game's difficulty control strategy by using the original pixel as input	How to improve the snake's habitat so that it may be used to operate the drone and provide some more forms of disaster aid	The algorithm can be extended to a multi-snake environment
[217]	2018	Machine learning algorithm	Built a UAV platform and tested it in real-world circumstances with an obstacle avoidance system	Unmanned Aerial Vehicle Obstacle Avoidance Using Block Matching	The program could locate and steer clear of every obstruction in the UAV's intended flight route	Adding ultrasonic sensors to spatial obstacle avoidance methods might improve obstacle detection's probability and precision

Table 12 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[218]	2018	Image processing, neural network, deep learning	This article reviews vertical structural examination in oil and gas and its current and future tendencies	A study of the vertical structural inspection process in the oil and gas sector	-	-
[202]	2017	Convolutional neural network	Describe a novel framework for automating the evaluation of damage to the surface of structures in engineering	It was suggested that the faster region-based Convolution Neural Network (faster RCNN) be used at various image depths as an artificial intelligence (AI) tool	Quantitative damage assessment was demonstrated in the study	The assessment of structural surface damage has primarily depended on human examination
[201]	2016	Machine learning	Outlines the successful creation of an integrated navigation system for drones that may be used for aerial inspection and surveillance of infrastructure assets	Airborne monitoring and assessment of infrastructure assets	The full path of drone movement covered across the forest	Climatic conditions can decrease drone efficiency

Table 13 Advances in air quality monitoring are being driven by artificial intelligence

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[16]	2022	Artificial neural networks, Deep learning	This study links many machine learning models to a benchmark aircraft monitoring problem	Uses a machine learning model for load monitoring issues	During transonic buffeting maneuvers, strain sensors are employed on an aircraft wing	A more precise data acquisition system should be used for algorithm implementation
[223]	2020	Machine learning	Hydrological and hydrometeorological disaster risk assessment using physical and mathematical modeling, satellite measurements, and geographically dispersed data	Monitoring the ecological and technological conditions of water management process systems by remote sensing of the Earth	Quantitative estimates of the decline in surface water quality	Climatic conditions can hamper the results
[224]	2020	Environmental drones	Environmental drones are used to do spot checks on the air quality without human intervention	Looks into removing contaminants from the air on a massive basis	Measure the CO2, CO, NH3, SO2, PM, O3, and NO2 levels in the air and note when they are excessive	The use of multiple drones can detect air toxins
[225]	2019	Aerosol Robotic Network	The 10 km AOD product gives more accurate estimates than the 3 km MODIS product, as shown by the higher R2 numbers	Ground Level PM2.5 Estimation Using Data from the MODIS Satellite	To evaluate the performances of the 3 km and 10 km AOD products at various pixel sizes, the MODIS AOD product was formalized with the Surface level AOD	Different distance ranges need to be evaluated from the satellite data
[226]	2018	-	The literature on oil leakage was analyzed in depth, and the relevant certification requirements were evaluated	Aircraft cabin clean air for commercial transportation employing bleed air system	Novel aircraft cleaning system demonstrated	Variability in aircraft size can decrease the algorithm efficiency
[227]	2018	Big Data	Intelligent services and applications are made possible by a platform built on top of ocean big data and based on a UAV system	The combined program offers situation analysis, catastrophe alerts, and environmental forecasts	Intelligent data applications result in concise outcomes	Large system boundaries can be explored in the study
[228]	2009	Supervised learning	Explains why a control and automatic data collecting system is essential for air quality monitoring and how to utilize it to evaluate the results	Mobile air quality monitoring by data acquisition systems	Measurement of air pollutants using LabView	Other fine particulates of air pollutants need to be addressed in the study
[219]	2007	Artificial air monitoring	Monitoring of the quality of the ambient air within exploratory	Implementation of ANITA into air quality measurement	SQL Database created for air contaminants	The system's display features are restricted from local usage, but all analytical findings are kept in an onboard SQL database
[222]	2007	Artificial air monitoring	The fundamental principles of the device, as well as its performance in ground and space tests, are depicted	Created and evaluated an electronic nose to track the quality of the air	Experiments conducted in space and on land have demonstrated the functionality of an electronic nose	Electronic noses can be implemented for aerospace applications

Table 14 Optimization of airplanes operations using artificial intelligence: a brief overview

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[233]	2023	Ant colony optimization	The suggested ACO algorithm outperforms the previous metaheuristic algorithms regarding maintenance time and cost	The MRO process planning problem has a mathematical model built for aircraft optimization	Simulation results using various artificial intelligence based for aircraft operations optimization	The use of hybrid algorithms can depict better results
[234]	2023	Explainable reinforcement learning	To optimize the maintenance schedules of an entire fleet of airplanes, this study provides a deep Learning-based approach to this problem	A working system for scheduling fleet-level aircraft repair	Decisions on airplane maintenance can be made in real-time using the suggested drDQN approach	Maintenance costs can be reduced considerably
[17]	2023	Deep learning	The suggested method significantly contributes to the future development of fully automated and dependable autonomous aircraft vehicle agrochemicals application and management zone categorization	High automation evolution of Unmanned Aerial Systems for agricultural applications	The adopted technology limits the outflow of agrochemicals	Precise dispersion of agrochemicals is a difficult task
[235]	2022	Machine learning	The suggested technique has better search performance than the hybrid artificial potential field and ant colony optimization results	Presents the UAV dispersed mission strategy	Contrasted the outcomes of the ant colony optimization and hybrid artificial potential field simulations	Handling multiple image data is a primary constraint
[236]	2022	Industry 4.0	The research is situated within their manufacturing facilities' actual Airbus production system	Adoption of Industry 4.0 tool for intelligent tool wear measurement for aerospace applications	Correlation matrices were created to examine the reliance between variables at the same cutting time	Deep hole drilling tasks may not work efficiently using the suggested method
[29]	2021	Digital twin	The proposed digital twin solution uses data-driven and physics-based models to improve dependability and minimize aircraft-on-ground occurrences	Digital twins powered by AI are being used in aeronautical applications	Reliability improvement by digital twin technology	The scarcity of data points can pose a major challenge
[237]	2021	Particle swarm optimization	The solution quality is more excellent than mixed integer programming and Egypt-air assignment, which reduced daily costs by 14.6% and 19.3%, respectively	Tool cost optimization is used to solve the fleet assignment issue	Particle swarm optimization produces better results than other techniques	The inclusion of binary representation can be explored in the study
[238]	2020	Ant colony algorithm	The algorithm effectively avoids terrain barriers, has the lowest cost, and fulfills maneuverability and spatial accessibility requirements	When the conventional approach is used for flight path planning, it resolves the issues of premature stagnation and local optimization	The algorithm can successfully avoid terrain barriers, according to simulation data	Constraints integration into terrain information can be a challenge

Table 14 (continued)

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[239]	2019	Deep learning	This study proposes an aircraft adaptive fault diagnostic system framework	The adaptive fault diagnosis system framework may fill up the gaps in the data gathering	Automatic updation of fault diagnosis	The concept of self-learning can be introduced in the current study
[240]	2018	Stochastic aircraft routing	A case study of a prominent Middle Eastern airline and maintenance supplier shows the model's practicality and promise	Relationships between maintenance staffing and airlines' stochastic aircraft routing	The methods used demonstrate considerable cost savings	Scattered data points may reduce the efficiency of the algorithm
[241]	2018	Artificial neural network	Artificial intelligence maximizes goal function while developing morphing UAVs	Redesign of a neural network-powered morphing unmanned aerial vehicle (UAV)	The optimization approach notion that incorporates neural networks is advantageous in terms of time and cost savings	Weight adjustments in neural networks will require modification in the algorithm
[232]	2017	Ant colony optimization	The ant colony method found a four-dimensional trajectory similar to the flight plan trajectory with a 0.91% optimization average	Optimization of Aircraft Reference Trajectories in Four and Three Dimensions	The most affordable trajectory and the cost of the flight was 6.82% less than that of the geodesic reference trajectory	A change in the Mach number may result in less optimization
[31]	2016	Evolutionary computing and genetic algorithms	Shows that AI can help make cost-effective aircraft fleet decisions	Fatigue minimization in aircraft structures	It focuses on optimizing airplane utilization	The aircraft's fatigue may increase with repeated flight cycles
[242]	2015	Ant colony optimization	Reduce operating expenses and flexibly plan and reschedule flights with the proposed algorithm	Dynamic scheduling of airplanes using ant colony optimization	Automated method for resolving the aircraft assignment and recovery issue	Results can be extended to more number of flights
[243]	2014	Big Data	Proposes a strategy that, by utilizing Big Data Structures, generates knowledge that DSS can use in real-time	Cost optimization with data mining techniques on large-scale datasets	Case study on more than six lacs flights	Using big data, more flights can be studied
[244]	2013	Fuzzy systems	The proposed algorithm obtains the maximum benefit at a low cost	Artificial intelligence technique for collaborative decision-making among many aircraft	Cost reduction for battlefield allocation	Study limited to visual range air combat

Table 15 Artificial intelligence in aircraft fuel efficiency

References	Year	Technology used	Inferences	Characteristics	Advantages	Limitations
[117]	2023	Machine learning algorithms	Using the shortest path method helps airlines save money on fuel, time, and seat capacity	A methodical approach to tackle the issues of human-induced route inefficiencies	Considerable eduction in carbon dioxide emission	More flight routes can be added to the study
[112]	2022	Big Data	Deeply examine how big data-based services affect domestic aviation sector growth, company image, and repurchase intention	Outline the effect of big data on the aviation industry	Demographic and reliability analyses were conducted for various applications	It's possible to add foreign airlines for analysis
[245]	2021	Recurrent Neural Network	LSTM prediction of turboprop engine exhaust emissions index and combustion efficiency	The Long-short-term memory approach is used to model the single-shaft T56-A-15 engine's combustion efficiency and exhaust contamination index	The accuracy is close to ninety-five percent while calculating the emission index and combustion efficiency	More input parameters can decrease the efficiency
[246]	2020	Machine learning	In this research, we take a look at how neural networks and decision trees use data to make predictions	A fuel flow model was developed for full-flight operations	Considerable accurate results were obtained by training and validation	Using neural networks to model individual battle stages can lead to increased errors and less generalizability
[247]	2016	Decision support system	Prove the efficacy of the method for predicting ATM trajectories using a real-world dataset complete with relevant meteorological information	An innovative approach to air traffic management using stochastic trajectory prediction	Time series clustering is used to create input observations from an excessive amount of weather parameters to feed into the Viterbi method	Fluctuation of weather data can showcase different results
[248]	2016	Swarm intelligence	Examine the speed profile design problem for aircraft ground movement under the constraints of the surface time-based trajectory	Swarm-based approach for fuel consumption minimization	Aircraft ground movement speed profile design in taxi planning	Control point increments can reduce the efficiency of the system
[249]	2015	Machine learning	Provide an autonomous car solution to the issue of hauling planes at congested airports	Demonstrated the ability to use towing vehicles for autonomous engine-off taxiing	Created a novel concept for fully automatic taxis at crowded airports	-

Table 16 Key Takeaways from this review process

Research questions		Answers
(ReQ1)	*To what extent do aerospace workers and firms differ in their acceptance of different AI technologies, including machine learning, deep learning, and big data?*	The aircraft sector is substantially transforming due to the integration of artificial intelligence (AI) technology. Artificial intelligence (AI) is revolutionizing several aspects of aerospace firms' operations and service delivery, including enhancements in aircraft maintenance, air traffic control, aircraft operations, and customer experience [40, 184, 233, 254, 255]. Despite some initial worries, the adoption of artificial intelligence (AI) is gradually increasing among aerospace workers and organizations. This shift in attitude can be attributed to the rising recognition of the evident benefits of AI implementation. Aerospace industry employees may harbor apprehensions about potential job displacement resulting from automation, limited comprehension of artificial intelligence (AI) technology, and the safety implications of AI implementation in aerospace contexts. However, aerospace companies may resist allocating resources toward adopting artificial intelligence (AI) technology. This hesitancy may be attributed to the considerable expenses associated with implementing AI systems, the challenges posed by regulatory requirements [256], and the potential consequences of unsuccessful AI integration Furthermore, aerospace industry professionals may be reluctant to embrace machine learning technologies due to their inherent complexity and the challenges associated with comprehending and elucidating their underlying principles. Similarly, deep learning technologies may present even more significant comprehension difficulties than conventional machine learning techniques [257]. Moreover, concerns may arise regarding adopting big data technologies, as they can enable tracking and surveillance of workers' actions and behaviors. Nevertheless, there exist specific measures that aircraft companies might take to mitigate the concerns raised by aerospace workers and enterprises effectively. Aerospace companies can foster a more conducive atmosphere for the adoption of artificial intelligence (AI) by offering educational programs and training initiatives on AI technologies, ensuring transparency and accountability about the safety and dependability of AI systems, and engaging in collaborative efforts with workers and unions to establish policies and procedures for the integration of AI technologies. Aerospace firms may expedite the integration of AI technology and harness their numerous advantages by using the following measures

Table 16 (continued)

Research questions		Answers
(ReQ2)	*What impact can the automation of AI systems have on their overall acceptance?*	The automation of artificial intelligence (AI) systems is identified as a prominent development within the field. This indicates that artificial intelligence (AI) systems are progressively acquiring enhanced proficiency in executing jobs that were once undertaken by human beings. The potential consequences of this phenomenon can significantly influence the general reception of artificial intelligence systems. Implementing artificial intelligence (AI) technologies in automated processes can yield several advantages. One potential benefit of automation is its ability to enhance the efficiency and productivity of artificial intelligence (AI) [14, 34, 258] systems through the automation of operations that are repetitive and consume significant amounts of time. This has the potential to allocate human resources towards more strategic and innovative endeavors Furthermore, it is worth noting that automated artificial intelligence (AI) systems have the potential to exhibit superior accuracy and reliability compared to systems managed by humans. This advantage arises from their reduced susceptibility to mistakes and biases. This phenomenon can potentially result in enhanced decision-making processes and more favorable results. Ultimately, automation has the potential to mitigate the expenses associated with the development and operation of artificial intelligence (AI) systems. This has the potential to enhance the accessibility of artificial intelligence to a broader spectrum of enterprises and individuals Conversely, using automated AI systems might give rise to other apprehensions. One of the primary issues revolves around job displacement [259–261]. With the increasing capabilities of AI systems, there exists a potential danger of job displacement for some professions. This phenomenon can potentially result in elevated unemployment levels and societal upheaval. Another issue is the diminished level of openness and accountability exhibited by automated artificial intelligence systems. Comprehending automated artificial intelligence (AI) systems can provide challenges, even for those with expertise in the field, due to their inherent complexity. The presence of some challenges, such as prejudice and discrimination, might complicate the process of recognizing and resolving them. Furthermore, ensuring accountability for the judgments made by automated AI systems might pose significant challenges Automating artificial intelligence (AI) systems gives rise to several ethical considerations. One potential concern is the possibility of employing automated artificial intelligence (AI) systems to create and implement autonomous weaponry, enabling the capability to inflict lethal harm without human involvement [262–264]. Moreover, it is imperative to acknowledge the potential hazard associated with using automated artificial intelligence (AI) systems in developing surveillance mechanisms capable of clandestinely monitoring and tracking individuals' behaviors without explicit agreement. To foster the widespread use of automated artificial intelligence (AI) systems, it is imperative to prioritize the dissemination of knowledge and provision of training programs to enhance individuals' understanding of AI. This initiative aims to enhance individuals' comprehension of the advantages and drawbacks associated with automation and foster confidence in artificial intelligence (AI) technologies. Education and training may be acquired through both official and informal programs. Official programs encompass university courses and professional development programs, while informal programs encompass internet tutorials and public outreach activities Furthermore, ensuring transparency and accountability in AI systems is of utmost importance. The achievement of this objective can be facilitated by implementing AI systems that are designed with a focus on comprehensibility, as well as establishing procedures that enable individuals to contest and seek redress for the choices made by AI systems. Furthermore, establishing ethical rules and laws is crucial in developing and implementing AI systems. Ultimately, the utilization of artificial intelligence (AI) in an ethical manner has significant importance. This entails employing artificial intelligence to uphold and safeguard human rights and fundamental values Furthermore, it entails the utilization of artificial intelligence in a manner that is advantageous to society. Governments may significantly facilitate the promotion of acceptability for automated AI systems by formulating ethical norms and legislation, allocating resources towards research and development, and providing support for education and training initiatives. The broad acceptance and utilization of automated AI systems relies heavily on establishing public trust. Public trust may be fostered by governments and corporations through the establishment of transparency regarding the utilization of AI systems, alongside the demonstration of responsible and advantageous deployment of such systems [265]. As the automation of AI systems progresses, it is crucial to prioritize establishing a reasonable and equitable transition towards a more automated workforce. This entails offering aid to workers who may face displacement due to automation, including initiatives for retraining and facilitating job placement

Table 16 (continued)

Research questions		Answers
(ReQ3)	*How do aerospace companies evaluate the benefits and hazards associated with the use of AI?*	As elucidated in previous scholarly investigations, AI-driven solutions are now employed to enhance several aspects of aviation, including aircraft maintenance, air traffic control, aircraft operations, and the overall client experience. The ongoing advancement of artificial intelligence (AI) holds significant potential to bring about transformative changes within the aerospace sector. The aerospace sector stands to gain considerable advantages from the implementation of artificial intelligence (AI), particularly in terms of enhancing efficiency [246] [266] and production. Artificial intelligence (AI) can automate repetitive processes and consume a significant amount of time, allowing human workers to allocate their efforts toward work that requires strategic thinking and creativity. Artificial intelligence (AI) systems may be effectively employed in the automation of various operations, including but not limited to aircraft inspection, maintenance scheduling, and flight planning. Artificial intelligence (AI) significantly influences the aircraft sector in terms of safety. AI-powered systems can detect possible issues and enhance decision-making processes in real-time, hence contributing to mitigating accident risks [267–269]. AI systems can facilitate the creation of predictive maintenance systems, which may effectively detect and diagnose prospective aircraft malfunctions before their actual occurrence. Artificial intelligence (AI) can be utilized in the development of air traffic control systems, enhancing operational efficiency and mitigating the likelihood of crashes. An additional obstacle lies in guaranteeing AI systems' safe and appropriate utilization. Artificial intelligence (AI) systems possess a high degree of intricacy and provide challenges in terms of comprehension [270] [271], hence impeding the identification and resolution of possible issues, including prejudice and discrimination. Furthermore, it is crucial to establish mechanisms that hold AI systems responsible for their decision-making processes. A range of measures are being used by aerospace enterprises to tackle the complexities related with the utilization of artificial intelligence. Aerospace firms are now allocating resources towards the implementation of training and development initiatives aimed at facilitating the acquisition of novel skills by their workforce, so enabling them to effectively navigate the dynamic nature of the contemporary workplace. Furthermore, aerospace corporations are actively formulating ethical frameworks to govern the utilization of artificial intelligence (AI) in order to guarantee its application aligns with societal welfare. In general, the advantages of artificial intelligence (AI) in the aerospace sector significantly surpass the associated difficulties. Artificial intelligence (AI) is exerting a profound and constructive influence on the aerospace sector, with the potential to assume an even more significant position in the forthcoming years

Table 16 (continued)

Research questions		Answers
(ReQ4)	*What are the most efficacious strategies for mitigating vulnerabilities and threats?*	There are huge advantages and formidable difficulties that come with incorporating AI into aircraft systems. Aviation, aerospace manufacturing, and space exploration might all benefit significantly from AI, but the field also faces new risks and dangers that must be addressed appropriately. An all-encompassing strategy, including every stage of the AI lifecycle from data collection and model creation to deployment and operation, is necessary to successfully reduce these risks and guarantee AI's safe and responsible use in aerospace [207]. Proper data governance and data quality are essential to guarantee the dependability and trustworthiness of AI systems. To guarantee the reliability of the data needed to train and run AI systems, solid data governance standards need to be put in place. Because of the potential for bias and inaccuracy in artificial intelligence (AI) models trained on contaminated data, it is essential to employ data-cleaning techniques to detect and eliminate sources of error in the training set [272] For people to feel comfortable with AI, it must be open and easy to understand. The decision-making processes of some AI models might be difficult to decipher because of their complexity and lack of transparency. Model explain ability and visualization are two methods that may be used to make AI models more open and comprehensible to stakeholders. This transparency is vital for recognizing potential biases and guaranteeing accountability. It is necessary to conduct adversarial testing and robustness evaluation to determine how susceptible AI systems are to manipulation or poisoning. Adversarial testing includes purposely generating inputs meant to deceive or exploit AI models emulating hypothetical attacks by malevolent actors. By putting AI models through adversarial testing, engineers may find where their creations are vulnerable and fix them to make the models more secure. Anomalies in AI system behavior may be detected and dealt with with the help of constant monitoring and auditing [271]. To discover anomalies in AI systems' behavior in real-time, it is essential to set up reliable monitoring methods to gather data on their performance and outputs. Auditing measures should be in place to monitor and record any changes made to AI models and data Person-in-the-loop design concepts should be integrated into AI systems to guarantee that human monitoring and intervention may be made when appropriate. The need for human intervention, when AI systems make crucial judgments or confront unforeseen events, calls for establishing clear standards and processes. This human check is essential for avoiding danger and unwanted outcomes. Security and cybersecurity measures must be implemented to prevent cyberattacks on AI systems [159]. Safeguarding sensitive data and preventing unwanted access to AI systems requires firewalls, intrusion detection systems, and data encryption techniques. Potential security flaws can be found and fixed by routine security audits and vulnerability assessments [273]. Understanding and confidence in the application of AI in aircraft require widespread public engagement and education. Education on the hazards and advantages of AI, as well as the necessity of ethical AI development and responsible usage, should be provided to all relevant stakeholders, including the general public, members of the industry, and legislators. For the success of AI in the real world, this comprehension is essential [274] Regulatory frameworks and standards might benefit space AI research, development, and implementation. To ensure that AI systems are created and utilized ethically, these frameworks should address concerns including data privacy, transparency, responsibility, and safety. Clear and uniform guidelines for using AI in aerospace should be developed through a collaborative effort between regulatory organizations and industry stakeholders. When dealing with global AI security issues, working with other countries and sharing information and expertise is crucial. Building centralized forums where experts can discuss and share solutions to shared problems is essential. To ensure the advantages of AI are achieved safely and responsibly on a global scale, international cooperation can speed up development in AI safety and security. Improvements in AI systems' robustness, security, and transparency can only be achieved by ongoing study and development. Improve the explain ability and interpretability of AI models, and work to build new AI strategies that are intrinsically more resistant to weaknesses and threats. Consistent spending on AI research and development is necessary for the technology to mature to the point where it can satisfy the stringent safety and security standards of the aerospace sector [275]. The aerospace sector can successfully protect itself from the risks and dangers posed by AI while also taking advantage of how AI might revolutionize transportation, production, and exploration

Table 16 (continued)

Research questions		Answers
(ReQ5)	*In what manner do the economic ramifications of implementing AI in the aerospace sector differ across industry segments (e.g., space, aviation, defense)?*	The economic ramifications of integrating artificial intelligence (AI) into the aerospace sector exhibit notable disparities in several areas, including space exploration, aviation, and the military. In space exploration, artificial intelligence (AI) is anticipated to facilitate enhanced efficiency and cost savings through streamlined satellite operations, decreased fuel consumption, and enhanced mission planning [276]. Integrating AI-powered analytics in conjunction with this approach will result in substantial cost reductions and improved allocation of resources. Furthermore, the integration of artificial intelligence (AI) will catalyze the emergence of novel sources of revenue. This will be achieved by facilitating space-based services, such as providing high-resolution satellite images, establishing sophisticated communication networks, and deploying autonomous vehicles for space exploration [277]. Nevertheless, implementing AI automation might potentially result in the displacement of jobs in specific domains, such as satellite ground operations and data processing. Consequently, it becomes imperative to establish upskilling and retraining initiatives that facilitate the smooth transfer of individuals into AI-related positions The aviation industry is expected to see improved air traffic management by applying artificial intelligence (AI) to optimize aircraft routes, decrease delays, and boost airspace utilization. These advancements are anticipated to result in more efficient air travel, cost savings, decreased passenger journey time, and a minimized environmental footprint. Moreover, using artificial intelligence (AI) to analyze sensor data will lead to predictive maintenance and decreased downtime. This will prevent expensive failures and enhance the aircraft's dependability, safety, and maintenance expenses. Artificial intelligence (AI) will further facilitate customized travel experiences by providing tailored suggestions for in-flight entertainment and real-time travel information and streamlining check-in and baggage management procedures [278]. Nevertheless, the possibility of job displacement in air traffic control and aircraft maintenance underscores the need for upskilling and retraining initiatives to respond to these transformations effectively The defense industry stands to gain advantages from implementing advanced surveillance and reconnaissance techniques facilitated by using artificial intelligence (AI) to analyze sensor data obtained from satellites, drones, and radar systems. This integration enables the acquisition of real-time situational awareness, identification of potential threats, and provision of support for military operations. The utilization of AI-enabled autonomous weapons systems, such as unmanned aerial vehicles (UAVs) and guided missiles, can augment military capabilities and mitigate the dangers associated with human mistakes [279]. Furthermore, using artificial intelligence (AI) in cybersecurity will enable network traffic analysis to detect and mitigate cyber threats targeting susceptible military systems. This approach will also facilitate the development of enhanced methods for safeguarding against cyberattacks [280] Nevertheless, the possibility of job displacement in intelligence analysis and cyber defense underscores the need for upskilling and retraining initiatives to bolster AI-driven military systems. The economic ramifications of integrating artificial intelligence (AI) into the aerospace sector are intricate and diverse, presenting a range of favorable and potentially adverse consequences. Artificial intelligence (AI) can enhance operational effectiveness, diminish expenditures, and generate novel money sources [281]. However, it also engenders apprehensions regarding employment displacement and the imperative for acquiring additional skills and undergoing retraining. The economic consequences will differ among industrial groups, as they are shaped by the distinct attributes and difficulties inherent in each sector

Table 16 (continued)

Research questions		Answers
(ReQ6)	*What are the most effective strategies for aerospace companies to integrate artificial intelligence to attain process innovation?*	The integration of artificial intelligence (AI) in aircraft operations can enhance process innovation and commercial performance. A comprehensive strategy is required for aerospace enterprises to attain this objective. The successful integration of AI necessitates the establishment of a clear vision and specific goals. It ensures that AI activities align with the company's business strategy and industry trends. AI use cases will be prioritized based on their potential to have a significant impact in various areas, including but not limited to streamlining design processes, predictive maintenance, and supply chain management. A robust AI infrastructure is necessary to facilitate the integration of AI. This necessitates investments in hardware, software, and data. A data governance framework ensures data quality, security, and privacy compliance, facilitating reliable and ethical AI implementation. The adoption of aerospace AI necessitates the establishment of a culture that fosters creativity and cooperation [92]. To promote innovation and facilitate the exchange of information, it is vital to encourage the exploration, communication, and collaboration between artificial intelligence (AI) systems and domain experts. This collaborative approach will accelerate AI research and ensure the development of AI solutions tailored to specific companies. To ensure the effectiveness of AI integration, it is crucial to identify and prioritize use cases. The potential of AI lies in its ability to address challenges, enhance operational effectiveness, and facilitate novel functionalities. When evaluating use cases, it is important to consider business objectives, feasibility, and return on investment. Every use case necessitates the appropriate utilization of AI tools and methodologies. Select AI algorithms and tools based on data availability, computational requirements, and desired outcomes [282]. Using open-source tools and libraries is recommended to reduce expenses and enhance adaptability. However, complex scenarios may necessitate the use of specialized tools and expertise. Responsible development and deployment of AI models are of utmost importance. Ensure the implementation of fair, transparent, and accountable artificial intelligence (AI) processes during development. It is essential to employ data selection and bias mitigation techniques to mitigate biases in AI models. Implement robust monitoring and auditing measures to detect and rectify bias, fairness, and performance degradation issues. To minimize disruption and ensure a seamless transition, it is imperative to integrate AI solutions into existing processes effectively. AI solutions can be matched with workflows and processes, integration points can be identified, and migration strategies can be developed. Assist staff in adapting to AI-powered workflows and novel methodologies through training and support. It is essential to assess and enhance AI solutions to optimize their effectiveness. Establish performance parameters and monitor key indicators to evaluate AI models' effectiveness and impact on process innovation and business results. Incorporating user and stakeholder feedback can enhance the effectiveness of AI models and procedures, leading to ongoing improvements [283] Upskilling and reskilling workers are necessary to enable their proficiency in utilizing AI technologies. Develop and enhance staff members' capabilities in designing, implementing, and overseeing artificial intelligence solutions. Promote a culture of ongoing learning and adaptability to ensure that workers remain at the forefront of AI innovation as the AI landscape evolves. Collaboration between industries and universities can potentially enhance the adoption and innovation of artificial intelligence [284]. Exchange information and best practices with industry partners and explore opportunities for collaboration. Keep up-to-date with artificial intelligence (AI) advancements and gain access to specialized resources by collaborating with research institutes and academic experts. Aerospace companies can enhance their global competitiveness by adopting a comprehensive approach integrating artificial intelligence, process innovation, and other crucial factors

Table 16 (continued)

Research questions		Answers
(ReQ7)	*What ethical issues should be considered while utilizing artificial intelligence (AI) in the aerospace industry for national security?*	When integrated into national security applications, AI's ethical ramifications must be carefully considered. Several ethical challenges must be addressed to utilize AI ethically and in conformity with human values. AI-driven national security choices must be transparent and explainable to generate confidence. Complex AI systems lack transparency, making their decision-making and output logic challenging to grasp [279]. This ambiguity can hurt responsibility and trust. Making AI systems accessible and explainable enables ethical criticism and guarantees that they follow the rules. Accountability and responsibility must be established as AI systems make vital national security judgments. Determining who is accountable for AI-driven behaviors from conception to deployment is essential for ethical decision-making and AI misuse prevention. Clear accountability must be developed to hold individuals or institutions accountable for AI system acts. AI development must include bias and fairness, especially in national security applications like surveillance, threat assessment, and decision-making. AI systems can reinforce biases in the data they are trained on, resulting in discrimination [285]. Robust bias prevention must be integrated throughout the development lifecycle to ensure AI system fairness. Human oversight must be maintained over crucial decision-making processes, especially those involving force or injury. AI can enhance human skills but should not replace human judgment in combat or delicate national security problems [279]. AI systems should enhance human decision-making, not replace it, and humans should always have the final say over AI-driven activities. AI autonomy and weaponization pose ethical issues regarding unexpected outcomes and losing human control in battle. For ethical usage, autonomous weapons systems must be developed according to defined ethical norms and international rules. AI systems use massive volumes of sensitive personal data, making data privacy and security crucial. Data governance and cybersecurity must be strengthened to protect sensitive data and retain public confidence. Addressing the global security consequences of AI requires international collaboration and rules [283]. Sharing ethical AI usage guidelines helps avert tensions and guarantees that AI benefits all nations. Public awareness and involvement are essential for trust and responsible AI development and deployment. Open discourse and public forums can help people comprehend AI's capabilities and limits, allowing informed decision-making and responsible AI development

Table 16 (continued)

Research questions		Answers
(ReQ8)	*What ethical issues should be considered while utilizing artificial intelligence (AI) in the aerospace industry for national security?*	The emergence of artificial intelligence (AI) has had a significant impact on several fields, and its capacity to improve the protection of vital infrastructure from aircraft-related risks is particularly remarkable. Artificial intelligence (AI) presents a diverse set of sophisticated functionalities that have the potential to significantly enhance the detection, monitoring, interception, and overall efficacy of defense mechanisms against various threats. AI-driven threat detection systems can assess extensive quantities of data derived from a wide range of sensor sources, such as radar, surveillance cameras, and acoustic sensors [286]. Through real-time data analysis, artificial intelligence (AI) can detect abnormalities and possible dangers that may remain undetected The ability to detect threats early is of utmost importance to promptly implement appropriate actions and deter potential assaults. Artificial intelligence (AI) can forecast the flight paths of identified aircraft, offering significant insights for evaluating potential risks and formulating strategies for appropriate countermeasures. Artificial intelligence (AI) can discern possible threats and provide timely alerts to security personnel by analyzing flight routes, speed, and other pertinent parameters. The capacity to forecast future events enables the implementation of proactive strategies, hence mitigating the likelihood of successful assaults. Thorough evaluation and prioritizing threats are essential components of a robust defensive strategy, whereby artificial intelligence (AI) may assume a substantial role [287]. By carefully considering several parameters, including the kind of aircraft, flight route, speed, and other pertinent information, artificial intelligence (AI) can evaluate the degree of danger presented by each identified aircraft The provided data may be utilized to establish a hierarchy for responding to threats and optimizing resource allocation to handle the most imminent hazards efficiently. Artificial intelligence (AI) can operate and manage autonomous defense systems, including interceptors and countermeasures, to effectively neutralize potential aerial threats posed by hostile aircraft [288]. By examining real-time data and adjusting its techniques in response to changing circumstances, artificial intelligence (AI) can swiftly make judgments and execute suitable measures to intercept and eradicate potential dangers. The integration of autonomous capacity can significantly augment the efficacy of defensive systems. Implementing cybersecurity protocols in critical infrastructure control systems is paramount in safeguarding against potential assaults that may jeopardize the integrity of air defense systems. Artificial intelligence (AI) can augment existing cybersecurity protocols by effectively spotting irregularities in network traffic and promptly recognizing possible cyber-attacks, mitigating their potential impact. The use of a proactive strategy can effectively protect critical infrastructure from cyberattacks and ensure the preservation of the integrity of defensive systems. Artificial intelligence (AI) has the potential to offer decision assistance to security professionals in high-pressure scenarios, enabling them to make well-informed judgments in a timely and efficient manner. Through the examination of data and the provision of valuable insights, artificial intelligence (AI) has the potential to enhance the capacities of human individuals, enabling security professionals to make informed and rational decisions even in high-pressure situations [289]. Data integration and fusion play a crucial role in developing a complete understanding of the threat landscape Artificial intelligence (AI) can integrate data from many sources, such as sensor systems, intelligence reports, and meteorological data, offering a comprehensive perspective on prospective dangers. Using this integrated approach allows for enhanced precision in identifying, monitoring, and evaluating potential threats. Artificial intelligence (AI) systems can acquire knowledge via experience and adjust their behavior in response to evolving threat scenarios, enhancing their overall performance and efficacy. The adaptive power of artificial intelligence enables it to proactively anticipate and respond to emerging threats, ensuring continuous safeguarding of vital infrastructure [290]. The collaboration between humans and artificial intelligence (AI) is of utmost importance to optimize the advantages of AI in the realm of threat defense. Artificial intelligence (AI) has the potential to collaborate with human security workers, offering them the necessary knowledge and assistance to facilitate well-informed decision-making and enable efficient execution of tasks. This collaborative effort guarantees that artificial intelligence enhances human capacities, yet humans maintain ultimate control and authority in decision-making [291] In summary, artificial intelligence (AI) presents a robust array of resources to bolster the protection of vital infrastructure from potential risks posed by airplanes. By using the capabilities of artificial intelligence (AI) in threat detection, tracking, interception, cybersecurity, and decision support, it is possible to enhance the protection of critical infrastructure against potential assaults and disruptions. The ongoing development of artificial intelligence (AI) is anticipated to result in an increased scope for its application in bolstering the defense of critical infrastructure

Table 16 (continued)

Research questions		Answers
(ReQ9)	*What are the growing economic models in the space tourism and space exploration sectors resulting from the use of artificial intelligence (AI)?*	Within the domain of space tourism, artificial intelligence (AI) is playing a pivotal role in facilitating space travel experiences that are both more accessible and economically feasible. Artificial intelligence (AI)-driven technologies are currently utilized to optimize launch trajectories, improve spacecraft health monitoring, and customize individualized experiences for space travelers. The convergence of several factors is leading to the emergence of innovative concepts in space tourism, including suborbital flights and space hotels, therefore facilitating the advancement of human exploration boundaries [65] Space exploration is now undergoing a significant shift, primarily influenced by the advancements in artificial intelligence (AI). Artificial intelligence (AI)-driven systems effectively analyze the massive data obtained from satellites and observatories, facilitating novel scientific findings and advancements. These technologies are enhancing the efficiency of spacecraft mission design and optimization, methodically strategizing and implementing robotic missions, and pushing the frontiers of scientific research. The economic models arising from the AI-powered space revolution have a complex and extensive nature [292]. The utilization of artificial intelligence by enterprises to gather, analyze, and commercialize valuable data obtained from space is a prominent factor contributing to data monetization. The data has significant potential for utilization in several domains, such as weather forecasting, resource exploitation, and climate monitoring, yielding considerable economic benefits. Personalized experiences represent a significant business paradigm driven by artificial intelligence (AI). Artificial intelligence (AI) is now utilized to personalize space travel and exploration encounters by creating tailored itineraries, virtual reality tours, and augmented reality experiences catering to individual interests. A tailored strategy has been found to significantly boost user engagement and happiness, stimulating increased demand and contributing to overall economic growth [293] The utilization of artificial intelligence (AI) in autonomous systems is significantly transforming space operations. The aforementioned intelligent systems can operate autonomously in the expanse of space, exhibiting exceptional accuracy in activities such as repairing satellites and maneuvering through asteroid fields. The advancement and implementation of autonomous systems are optimizing operational processes, diminishing expenses, and broadening the range of space missions. AI-powered training programs are revolutionizing the preparation process for space tourists and explorers, redefining their approach to mission readiness [294]. Utilizing virtual reality simulations and augmented reality training modules has resulted in providing immersive and interactive learning experiences, hence augmenting levels of preparation and safety. AI-driven training solutions facilitate the development of a highly proficient and self-assured workforce involved in space exploration [295]. The ongoing development of artificial intelligence (AI) is expected to have a growing influence on the domains of space tourism and space exploration. The confluence of these factors is giving rise to economic models that have the potential to significantly transform the trajectory of space travel and exploration [296]. These models are anticipated to foster innovation, stimulate development, and facilitate groundbreaking discoveries in ways that have not been witnessed before

Table 16 (continued)

Research questions	Answers
(ReQ10) *How can artificial intelligence be utilized to create new aircraft products and services?*	The aerospace industry is entering a new era of innovative aircraft products and services because of the advent of AI. The ability of AI to sift through mountains of data in search of patterns and generate accurate predictions is positively impacting many areas of the aerospace industry, including development, manufacturing, operation, and maintenance. This innovative technology is improving the effectiveness and security of air transport while also allowing for the developing of novel aircraft capabilities and services [297]. AI is helping engineers develop more aerodynamic planes, more fuel-efficient and more accessible to repair. Using AI-powered systems that can simulate several flying scenarios and anticipate the behavior of aircraft components under diverse circumstances may help optimize structural designs for lightweight, performance, and safety. More fuel-efficient, longer-range, and heavier-payload next-generation aircraft are being developed with this data-driven strategy in mind. Artificial intelligence's impact is not confined to the realm of creativity; instead, AI-enabled robots are bringing a new level of accuracy and productivity to manufacturing lines. These robots can significantly improve productivity and efficiency while reducing costs because of their high intelligence levels and manual dexterity. By enhancing supply chain efficiency, simplifying inventory management, and foreseeing potential production bottlenecks, artificial intelligence (AI) has the potential to enhance many aspects of industrial operations. As a result of these automation and optimization methods, production time, product quality, and manufacturing costs have all been cut [298] Using artificial intelligence (AI) to track an airplane's vitals in real-time means better preventative care and less costly failures. To prevent disruptions, systems powered by AI can analyze sensor data from engines, flight controls, and other systems to predict when issues may arise. Predictive maintenance is a form of preventative maintenance that helps aircraft fly for as long as feasible by reducing unscheduled downtime, increasing the useful life of individual parts, and lowering overall repair costs [299]. The air traffic control (ATC) field is another area where AI has a profound effect. The most effective flight paths, with the fewest delays and least air traffic congestion, may be determined by AI-powered systems using real-time traffic data, weather patterns, and other considerations. With this advanced air traffic control system, flight durations may be shortened, emissions can be lowered, and passengers can relax because of the enhanced comfort. The impact of AI in the aviation industry goes beyond the planes themselves, improving the service provided to passengers. AI-powered chatbots might one day assist clients with queries, bookings, and even check-in procedures. Using AI to analyze customer feedback on service quality and other criteria, vacations may be made unique and pleasurable. There are a variety of ways in which AI might dramatically improve aviation in the future [300]. Artificial intelligence (AI) is expected to play a significant role in developing autonomous aircraft, allowing unmanned flights for freight delivery, remote surveillance, and other purposes. The advancement of artificial intelligence can also help hypersonic aircraft, which can travel enormous distances rapidly and effectively. Future air travel will be significantly enhanced by these innovations, providing more freedom of movement, opportunities for exploration, and channels for cross-cultural connection [301, 302]

This approach will result in the generation of more complete and holistic solutions.

Data Availability Data sharing does not apply to this article as no datasets were generated or analyzed during the current study.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

References

1. Insaurralde CC (2020) Artificial intelligence engineering for aerospace applications. In: AIAA/IEEE digital avionics systems conference - proceedings. Bristol Robotics Laboratory, University of the West of England, Bristol, UK
2. Yao J, Tran SN, Sawyer S, Garg S (2023) Machine learning for leaf disease classification: data, techniques and applications. Springer, Dordrecht
3. Mariani MM, Machado I, Nambisan S (2023) Types of innovation and artificial intelligence: a systematic quantitative literature review and research agenda. J Bus Res 155:113364. https://doi.org/10.1016/j.jbusres.2022.113364
4. Tranfield D, Denyer D, Smart P (2003) Towards a methodology for developing evidence-informed management knowledge by means of systematic review. Br J Manag 14:207–222. https://doi.org/10.1111/1467-8551.00375
5. Shankar A (2023) Efficient data interpretation and artificial intelligence enabled IoT based smart sensing system. Artif Intell Rev 56:15053–15077. https://doi.org/10.1007/s10462-023-10519-y
6. Ezugwu AE, Shukla AK, Nath R, Akinyelu AA, Agushaka JO, Chiroma H, Muhuri PK (2021) Metaheuristics: a comprehensive overview and classification along with bibliometric analysis. Artif Intell Rev 54:4237–4316
7. De la Vega Hernández IM, Urdaneta AS, Carayannis E (2023) Global bibliometric mapping of the frontier of knowledge in the field of artificial intelligence for the period 1990–2019. Springer, Dordrecht
8. Peng X, Dai J (2020) A bibliometric analysis of neutrosophic set: two decades review from 1998 to 2017. Artif Intell Rev 53:199–255. https://doi.org/10.1007/s10462-018-9652-0
9. Zhang G, Hsu L-T (2018) Intelligent GNSS/INS integrated navigation system for a commercial UAV flight control system. Aerosp Sci Technol 80:368–380. https://doi.org/10.1016/j.ast.2018.07.026
10. Baldoni R, Montanari L, Rizzuto M (2015) On-line failure prediction in safety-critical systems. Future Gen Comput Syst 45:123–132. https://doi.org/10.1016/j.future.2014.11.015
11. Gertsvolf D, Berardi U, Horvat M (2021) Aerial infrared thermography and artificial intelligence-based fault detection and diagnosis methods for building energy systems: a review of the state-of-the-art. In: K.A. TA, M.T. S, D.E. A (eds) ZEMCH international conference. ZEMCH Network, Building Science Graduate Program, Department of Architectural Science, Ryerson University, Canada, pp 530–540
12. Ahmed HO (2023) Coarse grained FLS-based processor with prognostic malfunction feature for UAM drones using FPGA. In: Integrated communications, navigation and surveillance conference, ICNS. Institute of Electrical and Electronics Engineers Inc.
13. Nahar P, Wu KH, Mei S, Ghoghari H, Srinivasan P, Lee Y L, Guan X (2017, August) Autonomous UAV forced graffiti detection and removal system based on machine learning. In: 2017 IEEE SmartWorld, Ubiquitous Intelligence & Computing, Advanced & Trusted Computed, Scalable Computing & Communications, Cloud & Big Data Computing, Internet of People and Smart City Innovation (SmartWorld/SCALCOM/UIC/ATC/CBDCom/IOP/SCI), pp 1–8. IEEE.
14. Yang Z, Lee WC, Chan HN, Ge M (2022) A real-time tunnel surface inspection system using edge-AI on drone. In: 2022 IEEE International conference on Mechatronics and Automation, ICMA 2022. Institute of Electrical and Electronics Engineers Inc., Hong Kong Productivity Council, Robotics and Artificial Intelligence Division, 78 Tak Chee Ave, Kowloon Tong, Hong Kong, pp 749–754
15. Chen Y-W, Chen K-Y, Fang Y-L (2021) Aiming point guidance algorithm based on proportional navigation guidance scheme. Control Eng Appl Informatics 23:72–81
16. Candon M, Esposito M, Fayek H, Levinski O, Koschel S, Joseph N, Marzocca P (2022) Advanced multi-input system identification for next generation aircraft loads monitoring using linear regression, neural networks and deep learning. Mech Syst Signal Process 171:108809. https://doi.org/10.1016/j.ymssp.2022.108809
17. Sassu A, Motta J, Deidda A, Ghiani L, Carlevaro A, Garibotto G, Gambella F (2023) Artichoke deep learning detection network for site-specific agrochemicals UAS spraying. Comput Electron Agric 213:108185. https://doi.org/10.1016/j.compag.2023.108185
18. Matuszewski J, Pietrow D (2019) Recognition of electromagnetic sources with the use of deep neural networks. In: P. K (ed) Proceedings of SPIE - The International Society for Optical Engineering. SPIE
19. Maleki KN, Ashenayi K, Hook LR, Fuller JG, Hutchins N (2016, September) A reliable system design for nondeterministic adaptive controllers in small UAV autopilots. In 2016 IEEE/AIAA 35th Digital Avionics Systems Conference (DASC), pp 1–5. IEEE
20. Reddy A, Indragandhi V, Ravi L, Subramaniyaswamy V (2019) Detection of Cracks and damage in wind turbine blades using artificial intelligence-based image analytics. Meas J Int Meas Confed. https://doi.org/10.1016/j.measurement.2019.07.051
21. Munawar HS, Ullah F, Heravi A, Thaheem MJ, Maqsoom A (2021) Inspecting buildings using drones and computer vision: a machine learning approach to detect cracks and damages. Drones 6(1):5. https://doi.org/10.3390/drones6010005
22. Lee H, Puranik TG, Mavris DN (2021) Deep spatio-temporal neural networks for risk prediction and decision support in aviation operations. J Comput Inf Sci Eng. DOI 10(1115/1):4049992
23. Eltoukhy AE, Chan FT, Chung SH, Niu B, Wang XP (2017) Heuristic approaches for operational aircraft maintenance routing problem with maximum flying hours and man-power availability considerations. Ind Manag Data Syst 117(10):2142–2170. https://doi.org/10.1108/IMDS-11-2016-0475
24. Cruciol LLBV, Weigang L, De Barros AG, Koendjbiharie MW (2015) Air holding problem solving with reinforcement learning to reduce airspace congestion. J Adv Transp 49:616–633. https://doi.org/10.1002/atr.1293
25. Jenab K, Pineau J (2018) Automation of air traffic management using fuzzy logic algorithm to integrate unmanned aerial systems into the national airspace. Int J Electr Comput Eng 8:3169–3178. https://doi.org/10.11591/IJECE.V8I5.PP3169-3178
26. Richards RA (2002) Application of multiple artificial intelligence techniques for an aircraft carrier landing decision support tool. IEEE Int Conf Fuzzy Syst 1:7–11. https://doi.org/10.1109/fuzz.2002.1004950
27. Shahpar S (2020) Building digital twins to simulate manufacturing variation. In: Proceedings of the ASME Turbo Expo

28. Benzon HH, Chen X, Belcher L, Castro O, Branner K, Smit J (2022) An operational image-Based digital twin for large-scale structures. Appl Sci 12(7):3216. https://doi.org/10.3390/app12073216
29. Apostolidis A, Stamoulis KP (2021) An AI-based digital twin case study in the MRO sector. In: Transportation research procedia. pp 55–62
30. Apostolidis A, Bouriquet N, Stamoulis KP (2022) AI-based exhaust gas temperature prediction for trustworthy safety-critical applications. Aerospace. https://doi.org/10.3390/aerospace9110722
31. Ruotsalainen M, Jylha J, Visa A (2016) Minimizing fatigue damage in aircraft structures. IEEE Intell Syst 31:22–29. https://doi.org/10.1109/MIS.2016.23
32. Tseranidis S, Brown NC, Mueller CT (2016) Data-driven approximation algorithms for rapid performance evaluation and optimization of civil structures
33. Tong C, Yin X, Wang S, Zheng Z (2018) A novel deep learning method for aircraft landing speed prediction based on cloud-based sensor data. Future Gen Comput Syst 88:552–558. https://doi.org/10.1016/j.future.2018.06.023
34. Martinsen M, Zhou Y, Dahlquist E, Yan J, Kyprianidis K (2023) Positive climate effects when AR customer support simultaneous trains AI experts for the smart industries of the future. Appl Energy 339:120988. https://doi.org/10.1016/j.apenergy.2023.120988
35. Gao J, Guo J, Dai A, Situ G (2023) Optical system design: from iterative optimization to artificial intelligence. Zhongguo Jiguang. https://doi.org/10.3788/CJL230497
36. Waisberg E, Ong J, Kamran SA, Paladugu P, Zaman N, Lee AG, Tavakkoli A (2023) Transfer learning as an AI-based solution to address limited datasets in space medicine. Life Sci Space Res 36:36–38. https://doi.org/10.1016/j.lssr.2022.12.002
37. Panda B, Leite M, Biswal BB, Niu X, Garg A (2018) Experimental and numerical modelling of mechanical properties of 3D printed honeycomb structures. Measurement 116:495–506. https://doi.org/10.1016/j.measurement.2017.11.037
38. Huang H, Hu Z, Lu Z, Wen X (2023) Network-scale traffic signal control via multiagent reinforcement learning with deep spatiotemporal attentive network
39. Buster G, Siratovich P, Taverna N, Rossol M, Weers J, Blair A, Akerley J (2021) A new modeling framework for geothermal operational optimization with machine learning (Gooml). Energies 14(20):6852
40. Siyaev A, Valiev D, Jo G-S (2023) Interaction with industrial digital twin using neuro-symbolic reasoning. Sensors. https://doi.org/10.3390/s23031729
41. Solomon A, Crawford Z (2021) Transitioning from legacy air traffic management to airspace management through secure, cloud-native automation solutions. In: AIAA/IEEE digital avionics systems conference - proceedings. Institute of Electrical and Electronics Engineers Inc.
42. Roscoe S, Cousins PD, Handfield R (2023) Transitioning additive manufacturing from rapid prototyping to high-volume production: a case study of complex final products. J Prod Innov Manag 40:554–576. https://doi.org/10.1111/jpim.12673
43. Natali A, Padalkar MG, Messina V, Salvatore W, Morerio P, Del Bue A, Beltrán-González C (2023) Artificial Intelligence tools to predict the level of defectiveness of existing bridges. Proc Struct Integr 44:2020–2027
44. Roy S, Maji A (2022) Sampling-based modified ant colony optimization method for high-speed rail alignment development. Comput Aid Civ Infrastruct Eng 37(11):1417–1433
45. Li W, Zhang X, Huang B, Chen Y, Zhang R, BalaMurugan S (2022) Research on the control method of unmanned helicopter under the background of artificial intelligence. J Interconnect Netw 22(Supp02):2143019. https://doi.org/10.1142/S0219265921430192
46. Ye L, Lu Y, Su Z, Meng G (2005) Functionalized composite structures for new generation airframes: a review. Compos Sci Technol 65:1436–1446. https://doi.org/10.1016/j.compscitech.2004.12.015
47. Jeppu Y, Raman R (2022) A framework for teaching safety critical artificially intelligent control systems to undergrads. In: SAE technical papers. Honeywell Technology Solutions Lab., India
48. Reitmann S, Schultz M (2022) An adaptive framework for optimization and prediction of air traffic management (sub-)systems with machine learning. Aerospace. https://doi.org/10.3390/aerospace9020077
49. Liu Y (2021) Development of hyperspectral imaging remote sensing technology. Natl Remote Sens Bull 25:439–459. https://doi.org/10.11834/jrs.20210283
50. Li K, Zhang R, Wang H, Yu F (2021) Multi-intelligent connected vehicle longitudinal collision avoidance control and exhaust emission evaluation based on parallel theory. Process Saf Environ Prot 150:259–268. https://doi.org/10.1016/j.psep.2021.04.001
51. Tao F, Zhang M (2017) Digital twin shop-floor: a new shop-floor paradigm towards smart manufacturing. IEEE Access 5:20418–20427. https://doi.org/10.1109/ACCESS.2017.2756069
52. Carou D (2021) Aerospace Transformation through Industry 4.0 Technologies. In: SpringerBriefs in Applied Sciences and Technology. Escola de Enxeñaría Aeronáutica e do Espazo, Universidade de Vigo, Ourense, Spain, pp 17–46
53. Hu M, Cao E, Huang H, Zhang M, Chen X, Chen M (2023) AIoTML: a unified modeling language for aiot-based cyber-physical systems. In: IEEE transactions on computer-aided design of integrated circuits and systems
54. Bilen T, Canberk B, Duong TQ (2023) Digital twin evolution for hard-to-follow aeronautical ad-hoc networks in beyond 5G. IEEE Commun Stand Mag 7:4–12. https://doi.org/10.1109/MCOMSTD.0001.2200040
55. Indragandhi V, Ashok Kumar L (2018) Artificial intelligence based speed control of SRM for hybrid electric vehicles. In: 2018 8th International conference on Power and Energy Systems, ICPES 2018. Electrical Engineering, Vellore Institute of Technology, Vellore, India, pp 65–68
56. Mochalov V, Grigorieva O, Zhukov D, Markov A, Saidov A (2020) Remote sensing image processing based on modified fuzzy algorithm. In: Artificial intelligence and bioinspired computational methods: proceedings of the 9th computer science on-line conference 2020, Vol 2–9, pp 563–572. Springer
57. Suththatip S, Perinpanayagam S, Aslam S (2022) (Explainable) Artificial intelligence in aerospace safety-critical systems. In: IEEE aerospace conference proceedings. Cranfield University, Integrated Vehicle Health Management (IVHM) Centre, United Kingdom
58. Murray M (2003) Future directions in control in an information-rich world. IEEE Control Syst 23:20–33. https://doi.org/10.1109/MCS.2003.1188769
59. Ma Z, Kang S, Ma J, Shao L, Wei A, Liang C, Ji Z (2019) High-performance and rapid-response electrical heaters based on ultraflexible, heat-resistant, and mechanically strong aramid nanofiber/Ag nanowire nanocomposite papers. ACS Nano 13(7):7578–7590. https://doi.org/10.1021/acsnano.9b00434
60. Wilson GF, Russell CA (2003) Real-time assessment of mental workload using psychophysiological measures and artificial neural networks. In: Human factors. U.S. Air Force Research Laboratory, Wright-Patterson Air Force Base, OH, USA, pp 635–643
61. Cao MS, Wang XX, Zhang M, Cao WQ, Fang XY, Yuan J (2020) Variable-temperature electron transport and dipole polarization turning flexible multifunctional microsensor beyond electrical

and optical energy. Adv Mater 32(10):1907156. https://doi.org/10.1002/adma.201907156

62. Reigber A, Scheiber R, Jager M, Prats-Iraola P, Hajnsek I, Jagdhuber T, Moreira A (2012) Very-high-resolution airborne synthetic aperture radar imaging: Signal processing and applications. Proc IEEE 101(3):759–783. https://doi.org/10.1109/JPROC.2012.2220511
63. Tracey B, Duraisamy K, Alonso JJ (2015) A machine learning strategy to assist turbulence model development. In: 53rd AIAA aerospace sciences meeting. Stanford University, USA
64. Curran R, Raghunathan S, Price M (2004) Review of aerospace engineering cost modelling: the genetic causal approach. Prog Aerosp Sci 40:487–534. https://doi.org/10.1016/j.paerosci.2004.10.001
65. Izzo D, Märtens M, Pan B (2019) A survey on artificial intelligence trends in spacecraft guidance dynamics and control. Astrodynamics 3:287–299. https://doi.org/10.1007/s42064-018-0053-6
66. Duraisamy K, Zhang ZJ, Singh AP (2015) New approaches in turbulence and transition modeling using data-driven techniques. In: 53rd AIAA aerospace sciences meeting. Department of Aerospace Engineering, University of Michigan, Ann Arbor, 48109, MI, USA
67. Woodward D, Hobbs M, Gilbertson JA, Cohen N (2021) Uncertainty quantification for trusted machine learning in space system cyber security. Proceedings - 8th IEEE international conference on Space Mission Challenges for Information Technology, SMC-IT 2021. Institute of Electrical and Electronics Engineers Inc., The Aerospace Corporation, Data Science and Artificial Intelligence Department, El Segundo, CA, USA, pp 38–43
68. Pelton JN, Dahlstrom E (2020) Small satellites and governmental role in development of new technology, services, and markets. Springer, Berlin
69. Han B, Wang L, Deng Z, Shi Y, Yu J (2022) Source emission and attribution of a large airport in Central China. Sci Total Environ 829:154519. https://doi.org/10.1016/j.scitotenv.2022.154519
70. Erickson JD, Goode R, Grimm KA, Hess CW, Norsworthy RS, Anderson GD, Phinney DE (1992, March) Technology test results from an intelligent, free-flying robot for crew and equipment retrieval in space. In Cooperative Intelligent Robotics in Space II, Vol 1612, pp 402–413. SPIE
71. Virágh C, Vásárhelyi G, Tarcai N, Szörényi T, Somorjai G, Nepusz T, Vicsek T (2014) Flocking algorithm for autonomous flying robots. Bioinspir Biomim 9(2):025012. https://doi.org/10.1088/1748-3182/9/2/025012
72. Clachar SA (2015) Identifying and analyzing atypical flights by using supervised and unsupervised approaches. Transp Res Rec 2471:10–18. https://doi.org/10.3141/2471-02
73. Abdulrahman Y, Parezanovic V, Svetinovic D (2022) AI-blockchain systems in aerospace engineering and management: review and challenges. In: 2022 30th Telecommunications Forum, TELFOR 2022 - proceedings. Khalifa University, Aerospace Engineering, Abu Dhabi, United Arab Emirates
74. da Silva LM, Menezes HBDB, Luccas MDS, Mailer C, Pinto ASR, Boava A, Branco KRLJC (2022) Development of an efficiency platform based on MQTT for UAV controlling and DoS attack detection. Sensors 22(17):6567. https://doi.org/10.3390/s22176567
75. Maksymov VO, Yurchenko OI (2018) Forecast of demand for aviation maintenance and air navigation specialists for the next 20 years. In: 2018 IEEE 5th international conference on Methods and Systems of Navigation and Motion Control, MSNMC 2018 - proceedings. Institute of Electrical and Electronics Engineers Inc., pp 110–113
76. Deng T, Li Y, Chen J, Liu X, Wang L (2021) Informed machine learning-based machining parameter planning for aircraft structural parts. Int J Adv Manuf Technol 117(11):3563–3575. https://doi.org/10.1007/s00170-021-07861-2
77. Tappe M. Dose D, Oelsch M, Karimi M, Hösch L, Heller L, Bachmeir C (2022, April) UAS-based autonomous visual inspection of airplane surface defects. In: NDE 4.0, predictive maintenance, and communication and energy systems in a globally networked world, Vol 12049, pp 8–21. SPIE
78. He F, Yuan L, Mu H, Ros M, Ding D, Pan Z, Li H (2023) Research and application of artificial intelligence techniques for wire arc additive manufacturing: a state-of-the-art review. Robot Comput Integr Manuf 82:102525. https://doi.org/10.1016/j.rcim.2023.102525
79. Toby T, Gopalakrishnan U, Rao SN (2022) A deeper CNN approach for detection of collapsed buildings in drone images. In: Proceedings - 2022 5th international conference on Computational Intelligence and Communication Technologies, CCICT 2022. pp 404–410
80. Aust J, Shankland S, Pons D, Mukundan R, Mitrovic A (2021) Automated defect detection and decision-support in gas turbine blade inspection. Aerospace 8(2):30. https://doi.org/10.3390/aerospace8020030
81. Breda P, Markova R, Abdin AF, Mantı NP, Carlo A, Jha D (2023) An extended review on cyber vulnerabilities of AI technologies in space applications: technological challenges and international governance of AI. J Space Saf Eng. https://doi.org/10.1016/j.jsse.2023.08.003
82. Liu D, Liao T, Sun H, Ren F (2021) Research progress and development direction of Chinese remote sensing software: taking PIE as an example. J Image Graph 26:1169–1178. https://doi.org/10.11834/jig.200125
83. Hamilton D, Watkins L, Zanlongo S, Leeper C, Sleight R, Silbermann J, Kornegay K (2021, August) Assuring autonomous UAS traffic management systems using explainable, fuzzy logic, black box monitoring. In: 2021 10th International conference on Information and Automation for Sustainability (ICIAfS), pp 470–476. IEEE
84. McCall T, Seyed Alavi K, Rana L, Chudoba B (2018) Artificial intelligent research assistant for aerospace design synthesis—solution logic. In: 22nd AIAA International Space Planes and Hypersonics Systems and Technologies Conference. AVD Laboratory, UT Arlington, Dept. of Mechanical and Aerospace Engineering, Arlington, 76019, TX, USA
85. Yang D, Du P, Zhong M, Mao W (2020) A real-time fusion method of external trajectory measurement data based on variable difference method. China Satellite Maritime Tracking, Control Department, Jiangyin, China, pp 574–577
86. Bavle H, Sanchez-Lopez JL, Cimarelli C, Tourani A, Voos H (2023) From slam to situational awareness: challenges and survey. Sensors 23(10):4849. https://doi.org/10.3390/s23104849
87. Ma W, Lu J (2023) Research progress and challenges of electromagnetic launch technology. Diangong Jishu Xuebao 38:3941–3959. https://doi.org/10.19595/j.cnki.1000-6753.tces.230470
88. Rababaah H, Shirkhodaie A (2008) Human-posture classification for intelligent visual surveillance systems. In: Proceedings of SPIE - The International Society for Optical Engineering. Center of Excellence for Battlefield Sensor Fusion, Dept. of Mechanical and Manufacturing Engineering, Tennessee State University, Nashville, USA
89. Alhafnawi M, Salameh HB, Masadeh AE, Al-Obiedollah H, Ayyash M, El-Khazali R, Elgala H (2023) A survey of indoor and outdoor uav-based target tracking systems: current status, challenges, technologies, and future directions. IEEE Access. https://doi.org/10.1109/ACCESS.2023.3292302
90. Oruc R, Sahin O, Baklacioglu T (2022) Fuel flow rate modeling for descent using cuckoo search algorithm: a case study for point merge system procedure at Istanbul airport. Aircr

Eng Aerosp Technol 94:824–833. https://doi.org/10.1108/AEAT-08-2021-0246
91. Fang S, Ru Y, Liu Y, Hu C, Chen X, Liu B (2021) Route planning of helicopters spraying operations in multiple forest areas. Forests 12(12):1658. https://doi.org/10.3390/f12121658
92. Kalaichelvi P, Akila V, Rani TP (2021) Big data in multi-decision making system of the aerospace industry. In: a Closer Look at Big Data Analytics. Nova Science Publishers, Inc., Department of Information Technology, Sri Sairam Engineering College, Chennai, Tamil Nadu, India, pp 69–109
93. Bijjahalli S, Sabatini R, Gardi A (2020) Advances in intelligent and autonomous navigation systems for small UAS. Prog Aerosp Sci. https://doi.org/10.1016/j.paerosci.2020.100617
94. Sha W, Li Y, Tang S, Tian J, Zhao Y, Guo Y, Cheng S (2021) Machine learning in polymer informatics. InfoMat 3(4):353–361. https://doi.org/10.1002/inf2.12167
95. Cheung HC, De Louche C, Komorowski M (2023) Artificial intelligence applications in space medicine. Aerosp Med Hum Perform 94:610–622. https://doi.org/10.3357/AMHP.6178.2023
96. Fysikopoulos A, Alexopoulos T, Pastras G, Stavropoulos P, Chryssolouris G (2015, November) On the design of a sustainable production line: the MetaCAM tool. In: ASME international mechanical engineering congress and exposition, Vol 57588, p V015T19A015. American Society of Mechanical Engineers
97. Bowman M, Kesawan S, Sivapalan S, Sivaprakasam T (2021) Barriers in implementing the convolutional neural network damage detector. In: C.M. W, S. K, V. D (eds) Lecture Notes in Civil Engineering. Springer Science and Business Media Deutschland GmbH, School of Civil Engineering and Built Environment, Queensland University of Technology, QLD, Australia, pp 1333–1340
98. Anahara D, Ohmori S, Yoshimoto K (2019) Research on flight scheduling considering flight time arrangements. J Japan Ind Manag Assoc 70:147–156. https://doi.org/10.11221/jima.70.147
99. Liu J, Hu C, Zhou J, Ding W (2022) Object detection algorithm based on lightweight YOLOv4 for UAV. In: 2022 7th international conference on Intelligent Computing and Signal Processing, ICSP 2022. Institute of Electrical and Electronics Engineers Inc., Air Force Aviation University, Flight Research Department, Jilin, Changchun, China, pp 425–429
100. Le AV, Parween R, Elara Mohan R, Nhan NHK, Enjikalayil Abdulkader R (2020) Optimization complete area coverage by reconfigurable hTrihex tiling robot. Sensors 20(11):3170
101. Ranasinghe K, Sabatini R, Gardi A, Bijjahalli S, Kapoor R, Fahey T, Thangavel K (2022) Advances in Integrated System Health Management for mission-essential and safety-critical aerospace applications. Prog Aerosp Sci 128:100758. https://doi.org/10.1016/j.paerosci.2021.100758
102. Cecen RK, Cetek C, De Armas J (2019) A two-step approach for airborne delay minimization using pretactical conflict resolution in free-route airspace. J Adv Transp. https://doi.org/10.1155/2019/4805613
103. Tang YM, Ip AWH, Li W (2022) Artificial intelligence approach for aerospace defect detection using single-shot multibox detector network in phased array ultrasonic. In: IoT and Spacecraft Informatics. Department of Industrial and Systems Engineering, The Hong Kong Polytechnic University, Hong Kong SAR, China, pp 1–27
104. Fan B, Zhang R (2017) Unmanned aircraft system and artificial intelligence. 武汉大学学报 (信息科学版) 42:1523–1529
105. Tikhonov AI, Sazonov AA, Kuzmina-Merlino I (2022) Digital production and artificial intelligence in the aircraft industry. Russ Eng Res 42:412–415. https://doi.org/10.3103/S1068798X22040293
106. Brandoli B, de Geus AR, Souza JR, Spadon G, Soares A, Rodrigues JF Jr, Matwin S (2021) Aircraft fuselage corrosion detection using artificial intelligence. Sensors 21(12):4026. https://doi.org/10.3390/s21124026
107. Schirmer S, Torens C, Nikodem F, Dauer J (2018) Considerations of artificial intelligence safety engineering for unmanned aircraft. Lecture Notes in Computer Science (including Subser Lect Notes Artif Intell Lect Notes Bioinformatics) 11094 LNCS:465–472. https://doi.org/10.1007/978-3-319-99229-7_40
108. Tikhonov A, Sazonov A (2021) Digitalization and application of artificial intelligence in aircraft. In: AIP conference proceedings. AIP
109. Garcia AB, Babiceanu RF, Seker R (2021) Artificial intelligence and machine learning approaches for aviation cybersecurity: an overview. In: 2021 Integrated Communications Navigation and Surveillance Conference (ICNS). IEEE, pp 1–8
110. Ukwandu E, Ben-Farah MA, Hindy H, Bures M, Atkinson R, Tachtatzis C, Bellekens X (2022) Cyber-security challenges in aviation industry: a review of current and future trends. Information 13(3):146. https://doi.org/10.3390/info13030146
111. Gura D, Khoroshko A, Sakulyeva T, Krivolapov S (2020) Intelligent data processing for navigating drones. J Adv Res Dyn Control Syst 12:396–401. https://doi.org/10.5373/JARDCS/V12SP2/SP20201086
112. Ju S-W (2022) A study on the influence of big data-based quality on satisfaction and repurchase intention. J Syst Manag Sci 12:286–317. https://doi.org/10.33168/JSMS.2022.0315
113. Ahmed HO (2023) Fault tolerant processing unit using gamma distribution sliding window for autonomous landing guidance system. In: 21st IEEE interregional NEWCAS conference, NEWCAS 2023 - proceedings. Institute of Electrical and Electronics Engineers Inc.
114. Zijian HU, Xiaoguang GAO, Kaifang WAN, Evgeny N, Jinliang LI (2023) Imaginary filtered hindsight experience replay for UAV tracking dynamic targets in large-scale unknown environments. Chin J Aeronaut 36(5):377–391. https://doi.org/10.1016/j.cja.2022.09.008
115. Raja G, Essaky S, Ganapathisubramaniyan A, Baskar Y (2023) Nexus of deep reinforcement learning and leader-follower approach for AIoT enabled aerial networks. IEEE Trans Ind Informatics 19:9165–9172. https://doi.org/10.1109/TII.2022.3226529
116. Kong W-R, Zhou D-Y, Zhou Y, Zhao Y-Y (2023) Hierarchical reinforcement learning from competitive self-play for dual-aircraft formation air combat. J Comput Des Eng 10:830–859. https://doi.org/10.1093/jcde/qwad020
117. Kökhan A, Kökhan S, Gökdalay M (2023) An algorithmic application with flexible airspace approach. Aircr Eng Aerosp Technol 95:1045–1053. https://doi.org/10.1108/AEAT-06-2022-0147
118. Basmaji T, Yaghi M, Alhalabi M, Rashed A, Zia H, Mahmoud M, Ghazal M (2023) AI-powered health monitoring of anode baking furnace pits in aluminum production using autonomous drones. Eng Appl Artif Intell 122:106143. https://doi.org/10.1016/j.engappai.2023.106143
119. Liu Z, Xu Q, Shi Y, Xu K, Tan Q (2022, March) Generation method of control strategy for aircrafts based on hierarchical reinforcement learning. In: Artificial intelligence in China: proceedings of the 3rd international conference on artificial intelligence in China, pp 109–116. Springer, Singapore. https://doi.org/10.1007/978-981-16-9423-3_14
120. Wilson AN, Kumar A, Jha A, Cenkeramaddi LR (2022) Embedded sensors, communication technologies, computing platforms and machine learning for UAVs: a review. IEEE Sens J 22:1807–1826. https://doi.org/10.1109/JSEN.2021.3139124
121. Cetin E, Barrado C, Pastor E (2021) Counter a drone and the performance analysis of deep reinforcement learning method and human pilot. In: AIAA/IEEE digital avionics systems

conference - proceedings. Institute of Electrical and Electronics Engineers Inc.
122. Asadi E, Chen W, Fricke H (2021) Estimating stochastic air transport process times using the Fuzzy Critical Path Method: Determination of the Estimated aircraft Total Turnaround Time (ETTT). In: 14th USA/Europe Air Traffic Management Research and Development Seminar, ATM 2021. EUROCONTROL
123. Zhang Y, Tian H, Huang X, Ma C, Wang L, Liu H, Lan Y (2021) Research progress and prospects of agricultural aerobionic technology in China. Appl Sci 11(21):10435. https://doi.org/10.3390/app112110435
124. Dalmau R, Allard E (2020) Air traffic control using message passing neural networks and multi-agent reinforcement learning. In: SESAR Innovation Days. SESAR Joint Undertaking
125. Li Y, Feng B, Zhang Y (2020) Research on yaw crossing point optimization based on genetic algorithm. In: BX, KM (eds) Proceedings of 2020 IEEE International conference on Information Technology, Big Data and Artificial Intelligence, ICIBA 2020. Institute of Electrical and Electronics Engineers Inc., pp 1173–1178
126. Wang R, Zou D, Pei L, Liu P, Xu C (2016) Velocity prediction for multi-rotor UAVs based on machine learning. In: China Satellite Navigation Conference (CSNC) 2016 proceedings: Volume II, pp 487–500. Springer, Singapore. https://doi.org/10.1007/978-981-10-0937-2_41
127. Widrow B, Aragon JC (2013) Cognitive memory. Neural Netw 41:3–14. https://doi.org/10.1016/j.neunet.2013.01.016
128. Bautista-Hernández J, Martín-Prats MÁ (2023) Monte Carlo simulation applicable for predictive algorithm analysis in aerospace. IFIP Adv Inf Commun Technol 678:243–256. https://doi.org/10.1007/978-3-031-36007-7_18
129. Chen D, Yuan L, Zhang Y, Yan J, Kahaner D (2020) HPC software capability landscape in China. Int J High Perform Comput Appl 34(1):115–153. https://doi.org/10.1177/1094342018760614
130. Luo X, Wan H, Wu C, Zheng Y, Zhou F (2020, October) A comprehensive experiment to enhance multidisciplinary engineering ability via UAVs visual navigation. In: 2020 IEEE Frontiers in Education Conference (FIE), pp 1–5. IEEE.
131. Yetkin S, Abuhanieh S, Yigit S (2024) Investigation on the abilities of different artificial intelligence methods to predict the aerodynamic coefficients. Expert Syst Appl. https://doi.org/10.1016/j.eswa.2023.121324
132. Jwo JS, Hsieh HY, Lee CH, Lin CS, Wang PW, Hong CY, Hsu HC (2022) Simulation and modeling of a data twin service for the autoclave curing process. IEEE Access 10:111879–111887. https://doi.org/10.1109/ACCESS.2022.3216062
133. Shafi A, Latham I (2021) Digitalization challenges in composites. Compos Adv Mater Expo 2021:1207–1220
134. Zhu Z, Lu H, Zhao W, Chang X (2023) Materials, performances and applications of electric heating films. Renew Sustain Energy Rev 184:113540. https://doi.org/10.1016/j.rser.2023.113540
135. Wang Y-J, Ma Z, Tang X-H, Wang Z-P (2019) Autonomous obstacle avoidance algorithm of UAVs for automatic terrain following application. In: 2019 IEEE International conference on Unmanned Systems and Artificial Intelligence, ICUSAI 2019. pp 309 – 314
136. Castro DG, Garcia EV (2021) Safety challenges for integrating U-space in urban environments. In: 2021 International conference on Unmanned Aircraft Systems, ICUAS 2021. pp 1258–1267
137. Li S, van der Horst E, Duernay P, De Wagter C, de Croon GC (2020) Visual model-predictive localization for computationally efficient autonomous racing of a 72-g drone. J Field Robot 37(4):667–692. https://doi.org/10.1002/rob.21956
138. Kersandt K, Muñoz G, Barrado C (2018) Self-training by reinforcement learning for full-autonomous drones of the future. In: AIAA/IEEE Digital Avionics Systems Conference - proceedings
139. Peterson M, Du M, Springle B, Black J (2022) SpaceDrones 2.0—hardware-in-the-loop simulation and validation for orbital and deep space computer vision and machine learning tasking using free-flying drone platforms. Aerospace. https://doi.org/10.3390/aerospace9050254
140. Haley J, Tucker J, Nesper J, Daniel B, Fish T (2023, June) Multi-agent collaboration environment simulation. In: Synthetic data for artificial intelligence and machine learning: tools, techniques, and applications, Vol 12529, pp 197–202. SPIE
141. Chen Y, Zhang J, Yang Q, Zhou Y, Shi G, Wu Y (2020, December) Design and verification of UAV maneuver decision simulation system based on deep q-learning network. In: 2020 16th International conference on Control, Automation, Robotics and Vision (ICARCV), pp 817–823. IEEE
142. Wang J, Ding G, Wang H (2018) HF communications: past, present, and future. China Commun 15:1–9. https://doi.org/10.1109/CC.2018.8456447
143. Ivancevic V, Yue Y (2016) Hamiltonian dynamics and control of a joint autonomous land–air operation. Nonlinear Dyn 84:1853–1865. https://doi.org/10.1007/s11071-016-2610-y
144. Liang Z, Li Q, Fu G (2023) Multi-UAV collaborative search and attack mission decision-making in unknown environments. Sensors. https://doi.org/10.3390/s23177398
145. Bany Salameh H, Alhafnawi M, Masadeh A, Jararweh Y (2023) Federated reinforcement learning approach for detecting uncertain deceptive target using autonomous dual UAV system. Inf Process Manag. https://doi.org/10.1016/j.ipm.2022.103149
146. Hussaini H, Yang T, Bai G, Urrutia-Ortiz M, Bozhko S (2023) Artificial intelligence-based hierarchical control design for current sharing and voltage restoration in dc microgrid of the more electric aircraft. IEEE Trans Transp Electrific. https://doi.org/10.1109/TTE.2023.3289773
147. Knoblock EJ, Apaza RD, Gasper MR, Li H, Han R, Wang Z, Adams N (2023) Intelligent spectrum management for future aeronautical communications. IEEE Aerosp Electron Syst Mag. https://doi.org/10.1109/MAES.2022.3233817
148. Stamate M-A, Pupăză C, Nicolescu F-A, Moldoveanu C-E (2023) Improvement of hexacopter UAVs attitude parameters employing control and decision support systems. Sensors. https://doi.org/10.3390/s23031446
149. Wang G, Zou C, Zhang C, Pan C, Song J, Yang F (2022) Aircarft signal feature extraction and recognition based on deep learning. IEEE Trans Veh Technol 71(9):9625–9634. https://doi.org/10.1109/TVT.2022.3180483
150. Priyanka EB, Thangavel S, Sagayam KM, Elngar AA (2022) Wireless network upgraded with artificial intelligence on the data aggregation towards the smart internet applications. Int J Syst Assur Eng Manag 13:1254–1267. https://doi.org/10.1007/s13198-021-01425-z
151. Guan X, Lou S, Li H, Tang T (2021) Intelligent control of quad-rotor aircrafts with a STM32 microcontroller using deep neural networks. Ind Rob 48:700–709. https://doi.org/10.1108/IR-10-2020-0239
152. Li L, Zhang Z, Xue K, Wang M, Pan M, Han Z (2020) AI-aided downlink interference control in dense interference-aware drone small cells networks. IEEE Access 8:15110–15122. https://doi.org/10.1109/aCCESS.2020.2966740
153. Lin Y, Zhang J-W, Liu H (2018) An algorithm for trajectory prediction of flight plan based on relative motion between positions. Front Inf Technol Electron Eng 19:905–916. https://doi.org/10.1631/FITEE.1700224
154. Salehi H, Das S, Chakrabartty S, Biswas S, Burgueño R (2018) Damage identification in aircraft structures with self-powered

sensing technology: a machine learning approach. Struct Control Health Monit 25(12):e2262. https://doi.org/10.1002/stc.2262
155. Loukas G, Vuong T, Heartfield R, Sakellari G, Yoon Y, Gan D (2017) Cloud-based cyber-physical intrusion detection for vehicles using deep learning. IEEE Access 6:3491–3508. https://doi.org/10.1109/ACCESS.2017.2782159
156. Kurmis M, Andziulis A, Dzemydiene D, Jakovlev S, Voznak M, Gricius G (2015) Cooperative context data acquisition and dissemination for situation identification in vehicular communication networks. Wireless Pers Commun 85:49–62
157. Richards DC, Salmon JL, Dickerson TJ, Mattson CA, Neff WJ (2023) A decision support system for multi-stakeholder exploration of the airship design space. J Defense Model Simul 1:15485129231164416
158. Eroglu O, Yilmaz G (2013) A novel fast and accurate algorithm for Terrain Referenced UAV localization. In: 2013 International conference on Unmanned Aircraft Systems, ICUAS 2013 - conference proceedings. pp 660–667
159. Hassanien AE, Darwish A, Abdelghafar S (2020) Machine learning in telemetry data mining of space mission: basics, challenging and future directions. Artif Intell Rev 53:3201–3230. https://doi.org/10.1007/s10462-019-09760-1
160. Arzo ST, Sikeridis D, Devetsikiotis M, Granelli F, Fierro R, Esmaeili M, Akhavan Z (2022) Essential technologies and concepts for massive space exploration: challenges and opportunities. IEEE Trans Aerosp Electron Syst 59(1):3–29
161. Purcell TAR, Scheffler M, Ghiringhelli LM, Carbogno C (2023) Accelerating materials-space exploration for thermal insulators by mapping materials properties via artificial intelligence
162. Rajput MA, Alyami S, Ahmed QA, Alshahrani H, Asiri Y, Shaikh A (2023) Improved learning-based design space exploration for approximate instance generation. IEEE Access 11:18291–18299
163. Mirra G, Pugnale A (2022) Exploring a design space of shell and tensile structures generated by AI from historical precedents. J Int Assoc Shell Spatial Struct 63(3):172–188
164. Kim DW (2022) Mars space exploration and astronautical religion in human research history: psychological countermeasures of long-term astronauts
165. Tragoudaras A, Stoikos P, Fanaras K, Tziouvaras A, Floros G, Dimitriou G, Stamoulis G (2022) Design space exploration of a sparse mobilenetv2 using high-level synthesis and sparse matrix techniques on FPGAs. Sensors 22(12):4318
166. Das S, Doppa JR, Pande PP, Chakrabarty K (2017) Design-space exploration and optimization of an energy-efficient and reliable 3-D small-world network-on-chip
167. Yao E, Basu A (2017) VLSI extreme learning machine: a design space exploration
168. Colby M, Yliniemi L, Tumer K (2016) Autonomous multiagent space exploration with high-level human feedback
169. Lei D, Zhong S-S (2013) MRO oriented civil aircraft engine removal date prediction system. Jisuanji Jicheng Zhizao Xitong 19:1715–1720
170. Liu Z, Mrad N (2014) Data fusion for the diagnostics, prognostics, and health management of aircraft systems. Adv Intell Syst Comput 215:389–399. https://doi.org/10.1007/978-3-642-37835-5_34
171. Kong C (2014) Review on advanced health monitoring methods for aero gas turbines using model based methods and artificial intelligent methods. Int J Aeronaut Sp Sci 15:123–137. https://doi.org/10.5139/IJASS.2014.15.2.123
172. Chen X, Ren H, Liu J (2013) Intelligent structural rating system based on backpropagation network. J Aircr 50:947–951. https://doi.org/10.2514/1.C032085
173. Dangut MD, Skaf Z, Jennions IK (2021) An integrated machine learning model for aircraft components rare failure prognostics with log-based dataset. ISA Trans 113:127–139. https://doi.org/10.1016/j.isatra.2020.05.001
174. Siraskar R, Kumar S, Patil S, Bongale A, Kotecha K (2023) Reinforcement learning for predictive maintenance: a systematic technical review. Artif Intell Rev 56(11):12885–12947
175. Tamilselvan P, Wang P (2013) Failure diagnosis using deep belief learning based health state classification. Reliab Eng Syst Saf 115:124–135. https://doi.org/10.1016/j.ress.2013.02.022
176. Zhang Q, Chan FTS, Fu X (2023) Improved ant colony optimization for the operational aircraft maintenance routing problem with cruise speed control. J Adv Transp. https://doi.org/10.1155/2023/8390619
177. Abidi MH, Mohammed MK, Alkhalefah H (2022) Predictive Maintenance Planning for Industry 4.0 using machine learning for sustainable manufacturing. Sustain. https://doi.org/10.3390/su14063387
178. Olsson E, Candell O, Funk P, Sohlberg R (2022) Assessment and modelling of joint command and control in aircraft maintenance contexts using enterprise models and knowledge graph representations. Int J COMADEM 25:13–22
179. Zhang Q, Chan FTS, Chung SH, Fu X (2022) Operational aircraft maintenance routing problem incorporating cruise speed control. Eng Optim. https://doi.org/10.1080/0305215X.2022.2146683
180. Dinis D, Barbosa-Póvoa A, Teixeira ÂP (2019) Valuing data in aircraft maintenance through big data analytics: a probabilistic approach for capacity planning using Bayesian networks. Comput Ind Eng 128:920–936. https://doi.org/10.1016/j.cie.2018.10.015
181. Eltoukhy AEE, Wang ZX, Chan FTS, Chung SH (2018) Joint optimization using a leader–follower Stackelberg game for coordinated configuration of stochastic operational aircraft maintenance routing and maintenance staffing. Comput Ind Eng 125:46–68. https://doi.org/10.1016/j.cie.2018.08.012
182. Bouzidi Z, Terrissa LS, Zerhouni N, Ayad S (2020) QoS of cloud prognostic system: application to aircraft engines fleet. Eur J Ind Eng 14:34–57. https://doi.org/10.1504/EJIE.2020.105080
183. Najjar N, Gupta S, Hare J, Kandil S, Walthall R (2016) Optimal sensor selection and fusion for heat exchanger fouling diagnosis in aerospace systems. IEEE Sens J 16(12):4866–4881
184. Murrieta-Mendoza A, Hamy A, Botez RM (2016) Lateral reference trajectory algorithm using ant colony optimization. In: 16th AIAA aviation technology, integration, and operations conference. American Institute of Aeronautics and Astronautics Inc, AIAA, pp 1–10
185. Saïd KM, Abdelouahid L (2021) The ibn battouta air traffic control corpus with real life ads-b and metar data. Adv Intell Syst Comput 1193:371–384. https://doi.org/10.1007/978-3-030-51186-9_26
186. Sui D, Liu K (2023) A framework for optimising flight efficiency of a crossing waypoint by balancing flight conflict frequency and flight-level usage benefits. Aeronaut J. https://doi.org/10.1017/aer.2023.45
187. Xia B, Mantegh I, Xie W (2021) Integrated emergency self-landing method for autonomous UAS in urban aerial mobility. In: International conference on control, automation and systems. IEEE Computer Society, pp 275–282
188. Kanyilmaz A, Tichell PRN, Loiacono D (2022) A genetic algorithm tool for conceptual structural design with cost and embodied carbon optimization
189. Monteiro LB, Ribeiro VF, Garcia CP, Rocha Filho GP, Weigang L (2023) 4D trajectory conflict detection and resolution using decision tree pruning method. IEEE Lat Am Trans 21(2):277–287
190. Shmelova T, Yatsko M, Sierostanov I (2023) Collaborative decision making (CDM) in emergency caused by captain incapacitation: deterministic and stochastic modelling. Int J Decis Support Syst Technol. https://doi.org/10.4018/IJDSST.320477

191. Wan L, Ye W, Xu C, Li J, Huang X, Gong W, Tian Y (2023) An approach for three-dimensional sectorization in the terminal area based on airspace function. In: Wireless communications and mobile computing, 2023
192. Yiu CY, Ng KK, Li X, Zhang X, Li Q, Lam HS, Chong MH (2022) Towards safe and collaborative aerodrome operations: assessing shared situational awareness for adverse weather detection with EEG-enabled Bayesian neural networks. Adv Eng Inform 53:101698
193. Pérez-Castán JA, Pérez Sanz L, Fernández-Castellano M, Radišić T, Samardžić K, Tukarić I (2022) Learning assurance analysis for further certification process of machine learning techniques: case-study air traffic conflict detection predictor. Sensors 22(19):7680
194. Ogunsina K, Papamichalis M, DeLaurentis D (2022) Relational dynamic Bayesian network modeling for uncertainty quantification and propagation in airline disruption management. Eng Appl Artif Intell. https://doi.org/10.1016/j.engappai.2022.104846
195. Ortner P, Steinhöfler R, Leitgeb E, Flühr H (2022) Augmented air traffic control system—artificial intelligence as digital assistance system to predict air traffic conflicts. AI 3:623–644. https://doi.org/10.3390/ai3030036
196. Liang H, Liu C, Chen K, Kong J, Han Q, Zhao T (2021) Controller fatigue state detection based on ES-DFNN. Aerospace 8(12):383
197. Tran PN, Pham DT, Goh SK, Alam S, Duong V (2020) An interactive conflict solver for learning air traffic conflict resolutions. J Aerosp Inf Syst 17(6):271–277
198. Madanan M, Hussain N, Velayudhan NC, Sayed BT (2019) Embedding machine learning in air traffic control systems to generate effective route plans for aircrafts in order to avoid collisions. J Theor Appl Inf Technol 97:605–616
199. Baklacioglu T (2017) Metaheuristic and machine learning models for TFE-731-2, PW4056, and JT8D-9 Cruise thrust. Int J Turbo Jet Engines 34:221–232. https://doi.org/10.1515/tjj-2016-0002
200. Wu Y, Sun L, Qu X (2016) A sequencing model for a team of aircraft landing on the carrier. Aerosp Sci Technol 54:72–87. https://doi.org/10.1016/j.ast.2016.04.007
201. Ogido S, Kyan A, Takazato S, Maesato R, Anezaki T (2016) Proposed integrated drone navigation and autonomous flight system for aerial inspection and surveillance of infrastructure objects. IEEJ Trans Ind Appl 136:753–759. https://doi.org/10.1541/ieejias.136.753
202. Chen Z, Tang S (2017) Level-of-detail assessment of structural surface damage using spatially sequential stereo images and deep learning methods. In: F-KC, FK (eds) Structural health monitoring 2017: real-time material state awareness and data-driven safety assurance - proceedings of the 11th International Workshop on Structural Health Monitoring, IWSHM 2017. DEStech Publications, School of Computing and Engineering, University of Missouri, Kansas City, USA, pp 3210–3216
203. Durdevic P, Ortiz-Arroyo D, Li S, Yang Z (2019) Vision aided navigation of a quad-rotor for autonomous wind-farm inspection. In: BW, ZK, MD (eds) IFAC-PapersOnLine. Elsevier B.V., Aalborg University, Department of Energy Technology, Niels Bohrs Vej 8, Esbjerg, Denmark, pp 200–205
204. Korki M, Shankar ND, Shah RN, Waseem SM, Hodges S (2019, February) Automatic fault detection of power lines using unmanned aerial vehicle (UAV). In: 2019 1st International conference on Unmanned Vehicle Systems-Oman (UVS), pp 1–6. IEEE
205. Yao PF, Geng B, Yang M, Cai YM, Wang T (2020, December) Research on technology of autonomous inspection system for UAV based on improved YOLOv4. In: 2020 5th International conference on Mechanical, Control and Computer Engineering (ICMCCE), pp 664–668. IEEE
206. Beeram SK, Kadarla S, Kalapatapu P, Pasupuleti VDK (2023) Structural damage identification from video footage using artificial intelligence. In: PR, AM (eds) Lecture notes in civil engineering. Springer Science and Business Media Deutschland GmbH, Mahindra University, Ecole Centrale College of Engineering, Hyderabad, India, pp 774–783
207. Bécue A, Praça I, Gama J (2021) Artificial intelligence, cyberthreats and Industry 4.0: challenges and opportunities. Springer, Dodrecht
208. Liu C-Y, Chou J-S (2023) Bayesian-optimized deep learning model to segment deterioration patterns underneath bridge decks photographed by unmanned aerial vehicle. Autom Constr. https://doi.org/10.1016/j.autcon.2022.104666
209. Chen Z, Chen S, Peng X, Bian J, Jiang L, Zhang X (2022, December) ViT-siamese cascade network for transmission image deduplication. In: International forum on digital TV and wireless multimedia communications, pp 391–406. Springer Nature, Singapore
210. Jung N-J, Hwang M-H, Lee D-H, Song U-K (2022) A study on learning methods for power transmission facilities based on deep learning using multi segmentation and tagging. Trans Korean Inst Electr Eng 71:436–442. https://doi.org/10.5370/KIEE.2022.71.2.436
211. Viswanath S, Krishnamurthy RJ, Suresh S (2021) Terrain surveillance system with drone and applied machine vision. In: AAD, MS, FPGM (eds) Journal of Physics: Conference Series. IOP Publishing Ltd, Department of Applied Computing Sciences, Madras Sciencitific Research Foundation, Tamil Nadu, Chennai, India
212. Massaro A, Panarese A, Galiano A (2021) Technological platform for hydrogeological risk computation and water leakage detection based on a convolutional neural network. In: 2021 IEEE International Workshop on Metrology for Industry 4.0 and IoT, MetroInd 4.0 and IoT 2021 - Proceedings. Institute of Electrical and Electronics Engineers Inc., MIUR Research Institute, Dyrecta Lab Srl, BA, Conversano, Italy, pp 225–230
213. Ghorbani Z, Behzadan AH (2020) Identification and instance segmentation of oil spills using deep neural networks. In: HEN, JB (eds) World Congress on Civil, Structural, and Environmental Engineering. Avestia Publishing, Texas A&M University, College Station, TX, USA, pp 140–141
214. Wen A (2020) Real-time panoramic multi-target detection based on mobile machine vision and deep learning. In: Journal of Physics: Conference Series. IOP Publishing Ltd, Changchun University of Science and Technology, China
215. Marathe S (2019) Leveraging drone based imaging technology for pipeline and RoU monitoring survey. In: Society of Petroleum Engineers - SPE Symposium: Asia Pacific Health, Safety, Security, Environment and Social Responsibility 2019. Society of Petroleum Engineers, Cairn Oil and Gas, Vertical of Vedanta Ltd, India
216. Wu C, Ju B, Wu Y, Lin X, Xiong N, Xu G, Liang X (2019) UAV autonomous target search based on deep reinforcement learning in complex disaster scene. IEEE Access 7:117227–117245
217. Ivanovas A, Ostreika A, Maskeliūnas R, Damaševičius R, Połap D, Woźniak M (2018) Block matching based obstacle avoidance for unmanned aerial vehicle. In: Artificial intelligence and soft computing: 17th international conference, ICAISC 2018, Zakopane, Poland, June 3–7, 2018, proceedings, Part I 17, pp 58–69. Springer
218. Sudevan V, Shukla A, Karki H (2018) Inspection of vertical structures in oil and gas industry: a review of current scenario and future trends. In: SEG/AAPG/EAGE/SPE Research and Development Petroleum Conference and Exhibition 2018, RDP

2018. Society of Exploration Geophysicists, Department of Mechanical Engineering, Petroleum Institute, A part of Khalifa University of Science and Technology, United Arab Emirates, pp 65–68
219. Stuffler T, Mosebach H, Kampf D, Honne A, Odegard H, Schumann-Olsen H, Tan G (2007) The air quality monitor ANITA-going into operation on the international space station (No. 2007-01-3148). SAE technical paper
220. Mc Farland MJ, Nelson TM, Palmer GR (2004) Development of a hazardous air pollutants monitoring program using the data quality objectives process. J Air Waste Manag Assoc 54:614–622. https://doi.org/10.1080/10473289.2004.10470932
221. Belsma LO (2004) Satellite aerosol detection in the NPOESS era. In: Regional and global perspectives on haze. Aerospace Corporation, Los Angeles, CA, USA, pp 991–1010
222. Martinelli E, Zampetti E, Pantalei S, Lo Castro F, Santonico M, Pennazza G, Cotronei V (2007) Design and test of an electronic nose for monitoring the air quality in the international space station. Microgravity Sci Technol 19:60–64
223. Mashkov O, Kosenko V, Savina N, Rozov Y, Radetska S, Voronenko M (2020) Information technologies for environmental monitoring of plankton algae distribution based on satellite image data. In: Lecture notes in computational intelligence and decision making: proceedings of the XV international scientific conference "Intellectual Systems of Decision Making and Problems of Computational Intelligence" (ISDMCI'2019), Ukraine, May 21–25, 2019, pp 434–446. Springer
224. Rohi G, Ejofodomi O, Ofualagba G (2020) Autonomous monitoring, analysis, and countering of air pollution using environmental drones. Heliyon. https://doi.org/10.1016/j.heliyon.2020.e03252
225. Basit A, Ghauri BM, Qureshi MA (2019) Estimation of ground level pm2.5 by using modis satellite data. In: 6th International conference on Aerospace Science and Engineering, ICASE 2019. Institute of Electrical and Electronics Engineers Inc., National Center for Remote Sensing Geo-Informatics, Institute of Space Technology, Karachi, Pakistan
226. Berlowitz I (2018) Commercial transport aircraft cabin clean air using bleed air system. In: 58th Israel Annual Conference on Aerospace Sciences, IACAS 2018. Israel Annual Conference on Aerospace Sciences, Israel Aerospace Industries, BEDEK Aviation Group, Aircraft and Programs Division, Israel, pp 149–196
227. Yan D, Wang C, Zhou N, You X (2018) Construction and application of ocean big data platform based on UAV system. In: LW, HY, ZZ et al (eds) Proceedings of SPIE - The International Society for Optical Engineering. SPIE, CH UAV Technology Co., Ltd, China
228. Ionel I, Popescu F (2009) Data acquisition system in a mobile air quality monitoring station. In: Proceedings - 2009 5th international Symposium on Applied Computational Intelligence and Informatics, SACI 2009. University Politehnica of Timisoara, Faculty of Mechanical Engineering, MMUT Department, Timisoara, Romania, pp 557–562
229. Schwabacher M, Gelsey A (1998) Multilevel simulation and numerical optimization of complex engineering designs. J Aircr 35:387–397. https://doi.org/10.2514/2.2336
230. Giannakoglou KC (1999) Designing turbomachinery blades using evolutionary methods. In: Proceedings of the ASME Turbo Expo
231. Tüű-Szabó B, Földesi P, Kóczy LT (2017) Improved discrete bacterial memetic evolutionary algorithm for the traveling salesman problem. In: Advances in intelligent systems and computing. pp 27–38
232. Murrieta-Mendoza A, Hamy A, Botez RM (2017) Four- and three-Dimensional aircraft reference trajectory optimization inspired by ant colony optimization. J Aerosp Inf Syst 14:597–616. https://doi.org/10.2514/1.I010540
233. Guraksin AM, Ozcan A (2023) ACO-based approach for integrating product lifecycle management with MRO services in aviation industry. Soft Comput 27:337–361. https://doi.org/10.1007/s00500-022-07560-4
234. Dang HN, Chang K, Chen G, Chen HM, Khan S, Franco M, Blasch E (2023, June) Scheduling condition-based maintenance: an explainable deep reinforcement learning approach via reward decomposition. In: 2023 26th International conference on Information Fusion (FUSION), pp 1–8. IEEE
235. Yang W, Wu M, Wen X, Wang S, Heng Y, Zhang Z (2022, November) Distributed task architecture of UAV swarm based on potential field direction. In: International conference on Frontiers of Traffic and Transportation Engineering (FTTE 2022), Vol 12340, pp 412–416. SPIE
236. Domínguez-Monferrer C, Fernández-Pérez J, De Santos R, Miguélez MH, Cantero JL (2022) CFRP drilling process control based on spindle power consumption from real production data in the aircraft industry. Proc CIRP 107:1533–1538
237. Abouzeid AA, Eldin MM, Razek MA (2021) Particle swarm optimization for airlines fleet assignment. Indones J Electr Eng Comput Sci 22:427–434. https://doi.org/10.11591/ijeecs.v22.i1.pp427-434
238. Li S, Ma C, Li Q, Zeng J, Wang L (2020, November) Application of improved ant colony algorithm in flight path planning. In: 2020 IEEE international conference on Information Technology, Big Data and Artificial Intelligence (ICIBA), Vol 1, pp 763–771. IEEE.
239. Yang L, Wang J, Zhang G, Li X, Fu H (2019, June) An adaptive fault diagnosis system framework for aircraft based on man-in-loop. In: 2019 IEEE International conference on Prognostics and Health Management (ICPHM), pp 1–4. IEEE
240. Chan FTS, Eltoukhy AEE (2018) Investigating the interrelationship between stochastic aircraft routing of airlines and maintenance staffing of maintenance providers. In: 2018 5th International conference on Industrial Engineering and Applications, ICIEA 2018. pp 254–261
241. Oktay T, Arik S, Turkmen I, Uzun M, Celik H (2018) Neural network based redesign of morphing UAV for simultaneous improvement of roll stability and maximum lift/drag ratio. Aircr Eng Aerosp Technol 90(8):1203–1212
242. Sousa H, Teixeira R, Cardoso HL, Oliveira E (2015) Airline disruption management: dynamic aircraft scheduling with ant colony optimization. In: ICAART 2015 - 7th International Conference on Agents and Artificial Intelligence, proceedings. pp 398–405
243. Cruciol LLBV, Weigang L, Li L, Clarke J-P (2014) In-flight cost optimization for air traffic flow management using data mining method on big data. In: OPT-i 2014 - 1st international conference on engineering and applied sciences optimization, proceedings. pp 1491–1498
244. Fu L, Liu J, Meng G, Xie F (2013) Research on beyond visual range target allocation and multi-aircraft collaborative decision-making. In: 2013 25th Chinese Control and Decision Conference, CCDC 2013. pp 586–590
245. Kayaalp K, Metlek S, Ekici S, Şöhret Y (2021) Developing a model for prediction of the combustion performance and emissions of a turboprop engine using the long short-term memory method. Fuel. https://doi.org/10.1016/j.fuel.2021.121202
246. Baumann S, Klingauf U (2020) Modeling of aircraft fuel consumption using machine learning algorithms. CEAS Aeronaut J 11:277–287. https://doi.org/10.1007/s13272-019-00422-0
247. Ayhan S, Samet H (2016) Aircraft trajectory prediction made easy with predictive analytics. In: Proceedings of the ACM

SIGKDD international conference on knowledge discovery and data mining. pp 21–30
248. Zhang T, Ding M, Zuo H, Zeng L, Sun Z (2016, June) A two-stage speed profile design methodology for smooth and fuel efficient aircraft ground movement. In: 2016 12th IEEE International Conference on Control and Automation (ICCA), pp 479–484. IEEE
249. Morris R, Chang ML, Archer R, Cross EV, Thompson S, Franke J, Hemann G (2015, April) Self-driving aircraft towing vehicles: a preliminary report. In: Workshops at the twenty-ninth AAAI conference on artificial intelligence
250. Yairi T, Takeishi N, Oda T, Nakajima Y, Nishimura N, Takata N (2017) A data-driven health monitoring method for satellite housekeeping data based on probabilistic clustering and dimensionality reduction. IEEE Trans Aerosp Electron Syst 53(3):1384–1401
251. Aksit E, Haapala KR, Tabei A (2023) Digital multiphase material microstructures for image-based AI methods. In: Lecture notes in mechanical engineering. School of Mechanical, Industrial, and Manufacturing Engineering, Oregon State University, Corvallis, OR, USA, pp 723–734
252. Ahmad A (2019) Reliable and fault tolerant systems on chip through design for testability. In: Proceedings - 2019 Amity International conference on Artificial Intelligence, AICAI 2019. Department of Electrical Computer Engineering, College of Engineering, Sultan Qaboos University, Oman, Oman, pp 50–53
253. Wang M, Shi D, Guan N, Zhang T, Wang L, Li R (2019, November) Unsupervised pedestrian trajectory prediction with graph neural networks. In: 2019 IEEE 31st International conference on Tools with Artificial Intelligence (ICTAI). pp 832–839. IEEE
254. Ye B, Sherry L, Chen C-H, Tian Y (2016) Comparison of alternative route selection strategies based on simulation optimization. Chin J Aeronaut 29:1749–1761. https://doi.org/10.1016/j.cja.2016.09.012
255. Hu Q, Shao X, Yang H, Duan C (2022) Spacecraft attitude planning and control under multiple constraints: review and prospects. Hangkong Xuebao. https://doi.org/10.7527/S1000-6893.2022.27351
256. Suh YA, Kim JH, Yim M-S (2019) An investigation into the feasibility of monitoring a worker's psychological distress. In: Advances in intelligent systems and computing. Nuclear Environment and Nuclear Security Laboratory, Department of Nuclear and Quantum Engineering, Korea Advanced Institute of Science and Technology (KAIST), Daejeon, South Korea, pp 476–487
257. Thukaram P, Mohan S (2019) Digital twins for prognostic profiling. SAE Tech Pap. https://doi.org/10.4271/2019-28-2456
258. Aslan D, Çetin BB, Özbilgin İG (2019) An innovative technology: augmented reality based information systems. In: SS (ed) Procedia Computer Science. Elsevier B.V., HAVELSAN Inc., Ankara, Turkey, pp 407–414
259. Khan A (2023) Implementation of industry 4.0 in the development of the space industry
260. Iqbal BA, Yadav A (2021) Fourth industrial revolution: its role and contribution in employment, generation and skills development. J Glob Econ Trade Int Bus 1:85–96
261. Van Roy V, Vertesy D, Damioli G (2020) AI and robotics innovation Handb labor. Hum Resour Popul Econ 1:1–35
262. Emanuilov I, Dheu O (2021) Flying high for AI? Perspectives on EASA's roadmap for AI in aviation. Air Sp Law 46:1
263. Mandrake L, Doran G, Goel A, Ono H, Amini R, Feather MS, Kaufman J (2022, March) Space applications of a trusted ai framework: experiences and lessons learned. In: 2022 IEEE Aerospace Conference (AERO), pp 1–20. IEEE
264. Hallows R, Glazier L, Katz MS, Aznar M, Williams M (2022) Safe and ethical artificial intelligence in radiotherapy–lessons learned from the aviation industry. Clin Oncol 34(2):99–101
265. Koch W (2023) AI for aerospace and electronic systems: technical dimensions of responsible design. IEEE Aerosp Electron Syst Mag 38:106–111. https://doi.org/10.1109/MAES.2022.3228300
266. Aggour KS, Gupta VK, Ruscitto D, Ajdelsztajn L, Bian X, Brosnan KH, Vinciquerra J (2019) Artificial intelligence/machine learning in manufacturing and inspection: a GE perspective. MRS Bull 44(7):545–558
267. Savić D (2022) Digital water developments and lessons learned from automation in the car and aircraft industries. Engineering 9:35–41
268. Yin Y, He J, Zhao L, Pei J, Yang X, Sun Y, Chen Q (2022) Identification of key volatile organic compounds in aircraft cabins and associated inhalation health risks. Environ Int 158:106999
269. Dong Y, Tao J, Zhang Y, Lin W, Ai J (2021) Deep learning in aircraft design, dynamics, and control: review and prospects. IEEE Trans Aerosp Electron Syst 57(4):2346–2368
270. Oche PA, Ewa GA, Ibekwe N (2021) Applications and challenges of artificial intelligence in space missions. IEEE Access
271. Furano G, Meoni G, Dunne A, Moloney D, Ferlet-Cavrois V, Tavoularis A, Fanucci L (2020) Towards the use of artificial intelligence on the edge in space systems: challenges and opportunities. IEEE Aerosp Electron Syst Mag 35(12):44–56
272. Mirchandani S, Adhikari S (2020) Aerospace cybersecurity threat vector assessment. In: ASCEND 2020. p 4116
273. Kharchenko V, Illiashenko O, Fesenko H, Babeshko I (2022) AI cybersecurity assurance for autonomous transport systems: scenario, model, and IMECA-based analysis. International conference on multimedia communications, services and security. Springer, Berlin, pp 66–79
274. Breda P, Markova R, Abdin A, Jha D, Carlo A, Mantı NP (2022, September) Cyber vulnerabilities and risks of AI technologies in space applications. In: 73rd International Astronautical Congress (IAC), Paris, France
275. Ali M, Hu YF, Luong DK, Oguntala G, Li JP, Abdo K (2020, October) Adversarial attacks on ai based intrusion detection system for heterogeneous wireless communications networks. In: 2020 AIAA/IEEE 39th Digital Avionics Systems Conference (DASC), pp 1–6. IEEE
276. Cockburn IM, Henderson R, Stern S (2018) The impact of artificial intelligence on innovation: an exploratory analysis. The economics of artificial intelligence: an agenda. University of Chicago Press, Chicago, pp 115–146
277. Ezhilarasu CM, Skaf Z, Jennions IK (2019) The application of reasoning to aerospace Integrated Vehicle Health Management (IVHM): challenges and opportunities. Prog Aerosp Sci 105:60–73. https://doi.org/10.1016/j.paerosci.2019.01.001
278. Martin A-S, Freeland S (2021) The advent of artificial intelligence in space activities: new legal challenges. Space Policy 55:101408
279. Johnson J (2019) Artificial intelligence & future warfare: implications for international security. Def Secur Anal 35:147–169
280. Tang Y-C (2009) An approach to budget allocation for an aerospace company-Fuzzy analytic hierarchy process and artificial neural network. Neurocomputing 72:3477–3489. https://doi.org/10.1016/j.neucom.2009.03.020
281. Battina DS (2018) The future of artificial intelligence at work: a review on effects of decision automation and augmentation on workers targeted by algorithms and third-party observers. Int J Innov Eng Res Technol 5:1
282. Dou X (2020) Big data and smart aviation information management system. Cogent Bus Manag 7:1766736
283. Kania EB (2019) Chinese military innovation in artificial intelligence. Testimony to US-China Econ Secur Rev Comm

284. Dhanabalan T, Sathish A (2018) Transforming Indian industries through artificial intelligence and robotics in industry 4.a0. Int J Mech Eng Technol 9:835–845
285. Gill AS (2019) Artificial intelligence and international security: the long view. Ethics Int Aff 33:169–179
286. De Spiegeleire S, Maas M, Sweijs T (2017) Artificial intelligence and the future of defense: strategic implications for small-and medium-sized force providers. The Hague Centre for Strategic Studies
287. Morgan FE, Boudreaux B, Lohn AJ, Ashby M, Curriden C, Klima K, Grossman D (2020) Military applications of artificial intelligence. RAND Corporation, Santa Monica
288. Babuta A, Oswald M, Janjeva A (2020) Artificial intelligence and UK national security: policy considerations
289. Schmidt E, Work RO, Bajraktari Y, Catz S, Horvitz EJ, Chien S, Moore AW (2021) National Security Commission on artificial intelligence
290. Allen GC (2019) Understanding China's AI strategy: clues to Chinese strategic thinking on artificial intelligence and national security
291. Hoadley DS, Lucas NJ (2018) Artificial intelligence and national security
292. Mudgal S, Li H, Rekatsinas T, Doan A, Park Y, Krishnan G, Raghavendra V (2018, May) Deep learning for entity matching: a design space exploration. In: Proceedings of the 2018 international conference on management of data, pp 19–34
293. Lamperti F, Roventini A, Sani A (2018) Agent-based model calibration using machine learning surrogates. J Econ Dyn Control 90:366–389
294. Afshinnekoo E, Scott RT, MacKay MJ, Pariset E, Cekanaviciute E, Barker R, Beheshti A (2020) Fundamental biological features of spaceflight: advancing the field to enable deep-space exploration. Cell 183(5):1162–1184
295. Gunning D, Aha D (2019) DARPA's explainable artificial intelligence (XAI) program. AI Mag 40:44–58
296. Lu Y (2019) Artificial intelligence: a survey on evolution, models, applications and future trends. J Manag Anal 6:1–29
297. Li BH, Hou BC, Yu WT, Lu XB, Yang CW (2017) Applications of artificial intelligence in intelligent manufacturing: a review. Frontiers of Information Technology & Electronic Engineering 18(1):86–96
298. Bughin J, Hazan E, Sree Ramaswamy P, Dc, W, Chu M (2017) Artificial intelligence the next digital frontier
299. McGrew T, Sysoeva V, Cheng CH, Miller C, Scofield J, Scott MJ (2022) Condition monitoring of DC-link capacitors using time–frequency analysis and machine learning classification of conducted EMI. IEEE Trans Power Electron 37(10):12606–12618
300. Varian H (2018) Artificial intelligence, economics, and industrial organization. the economics of artificial intelligence: an agenda. University of Chicago Press, Chicago, pp 399–419
301. Soni N, Sharma EK, Singh N, Kapoor A (2020) Artificial intelligence in business: from research and innovation to market deployment. Proc Comput Sci 167:2200–2210
302. Makridakis S (2017) The forthcoming Artificial Intelligence (AI) revolution: its impact on society and firms. Futures 90:46–60
303. Irwan D, Ali M, Ahmed AN, Jacky G, Nurhakim A, Ping Han MC, El-Shafie A (2023) Predicting water quality with artificial intelligence: a review of methods and applications. Arch Comput Methods Eng 30(8):4633–4652