



Review

Challenges and prospects of artificial intelligence in aviation: a bibliometric study



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ABSTRACT

The primary motivation for this study is the recent growth and increased interest in artificial intelligence (AI). Despite the widespread recognition of its critical importance, a discernible scientific gap persists within the extant scholarly discourse, particularly concerning exhaustive systematic reviews of AI in the aviation industry. This gap spurred a meticulous analysis of 1,213 articles from the Web of Science (WoS) core database for bibliometric knowledge mapping. This analysis highlights China as the primary contributor to publications, with the Nanjing University of Finance and Economics as the leading institution in paper contributions. *Lecture Notes in Artificial Intelligence* and the *IEEE AIAA Digital Avionics System Conference* are the leading journals within this domain. This bibliometric research underscores the key focus on air traffic management, human factors, environmental initiatives, training, logistics, flight operations, and safety through co-occurrence and co-citation analyses. A chronological examination of keywords reveals a central research trajectory centered on machine learning, models, deep learning, and the impact of automation on human performance in aviation. Burst keyword analysis identifies the leading-edge research on AI within predictive models, unmanned aerial vehicles, object detection, and convolutional neural networks. The primary objective is to bridge this knowledge gap and gain comprehensive insights into AI in the aviation sector. This study delineates the scholarly terrain of AI in aviation using a bibliometric methodology to facilitate this exploration. The results illuminate the current state of research, thereby enhancing academic understanding of developments within this critical domain. Finally, a new conceptual framework was constructed based on the primary elements identified in the literature. This framework can assist emerging researchers in identifying the fundamental dimensions of AI in the aviation industry.

1. Introduction

Artificial Intelligence (AI) is rapidly evolving and being integrated across various sectors, including medicine, banking, and transportation (Wamba-Taguimdje et al., 2020). This increasing trend has entered the aviation industry, although its adoption remains in its early stages (Ivanov et al., 2021). Discussions surrounding AI have been prevalent since the 1950s; however, within the last decade, its development has accelerated significantly across various domains (Haenlein and Kaplan, 2019). In the contemporary era, which is characterized by an exponential increase in data volume across numerous sectors, there has been simultaneous algorithm advancement and a notable enhancement in computational hardware capabilities (Zaoui et al., 2024). AI has been recognized to significantly enhance flight journey management. It contributes to various technological aspects, including machine learning,

and extends its utility to software/hardware development and applications, such as intelligent maintenance and flight route optimization (Abduljabbar et al., 2019). Salvador et al. (2022) highlighted the potential of machine learning and pattern generation in enhancing reliability and safety in the aerospace industry. It discusses the use of logical analysis of data (LAD) and machine learning techniques to improve the reliability, safety, and cost reduction of the aerospace industry, particularly in evolving technologies such as autonomous aircraft. Budalakoti et al. (2008) demonstrated the reliability of employing an unsupervised machine learning algorithm to enhance safety measures during the landing phase of an aeroplane. Weather planning is another application of AI within the aviation industry. Khattak et al. (2024) introduced the Bayesian-optimized TabNet (BO-TabNet) system to improve the accuracy of predicting wind shear severity near airport runways, emphasizing its potential application in enhancing aviation safety. Currently, machine

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learning approaches are used to analyze the sentiment of airline passenger tweets (Wu and Gao, 2024). Furthermore, Stefani et al. (2023) showed an approach for applying the Assessment List for Trustworthy AI (ALTAI) to develop an AI-based digital air traffic control operator, emphasizing the importance of deriving specific system requirements and showcasing the necessity of ALTAI for trustworthy AI development.

AI has precipitated significant transformations within the aviation industry, manifesting in a broad spectrum of applications that span flight operations, aircraft maintenance, and air accident analysis. Integrating AI technologies into these domains substantially enhances operational safety, efficiency, and passenger comfort (Yetkin et al., 2024). The deployment of AI-driven solutions in aviation optimizes real-time decision-making processes and augments predictive maintenance capabilities, thereby minimizing downtime and operational costs. Moreover, the role of AI in analyzing and interpreting data from air accidents is pivotal for identifying underlying issues and preventing future incidents. The potential of AI in revolutionizing the aviation sector is vast, promising a future in which air travel is safer, more efficient, and more comfortable for all stakeholders involved (Youseftorkaman et al., 2023).

Moreover, the aviation sector is confronted with a range of complex and multifaceted challenges, including escalating fuel costs, increasing customer demand, regulatory issues, technological constraints, safety concerns, ethical considerations, and the integration of advanced autonomous systems to reduce production time and costs (Pierrat et al., 2021; Zaoui et al., 2024). These challenges require innovative strategies and solutions to sustain industrial growth and operational efficiency. For instance, Degas et al. (2022) argued the growing complexity of air traffic management presents significant challenges, underscoring the potential of explainable artificial intelligence (XAI) in enhancing safety and increasing user acceptance of AI systems within the aviation industry. Lee et al. (2020) presented a safety analysis of flight events (SAFE) methodology, a machine learning-based approach designed to enhance the understanding of risk factors during flight operations. The methodology integrates data cleaning, correlation analysis, supervised learning techniques, and advanced visualization to comprehensively assess safety-related events. Furthermore, in aviation maintenance, Gao and Mavris (2022) reviewed the application of statistical and machine learning methods to facilitate more efficient, accurate, and data-driven analyses of aircraft environmental impacts, including fuel consumption, emissions, and noise. It provides an overview of key research themes and representative studies and explores opportunities for further integrating these techniques to advance the sustainability of aviation operations. Several leading civil aviation organizations have published official documents emphasizing the expanding role of AI in the industry in several dimensions, including ethics. These documents provide strategic recommendations for the effective implementation of AI, underscoring its potential to drive innovation and enhance operational efficiency within the aviation sector (EASA, 2023; FAA, 2022).

Recent studies have explored the application of deep learning across various domains. Deep learning models have shown promising results in stock market prediction, with researchers investigating different data sources, neural network structures, and evaluation metrics (Jiang, 2021). Graph-based deep learning has achieved state-of-the-art performance in communication networks for modelling network topologies in wired and wireless scenarios (Jiang, 2022). Similarly, graph neural networks have been successfully applied to traffic forecasting to model spatial and temporal dependencies in transportation systems, including road traffic flow, passenger flow in urban rail transit, and demand forecasting on ride-hailing platforms (Chon and Hao, 2024; Jiang et al., 2022). In addition, Alam et al. (2024) presented the development and evaluation of an artificial neural network (ANN) model for predicting domestic air passenger demand in emerging economies, specifically Bangladesh, using nine socioeconomic input variables, highlighting the growing importance of deep learning, particularly graph-based approaches, in solving complex problems across different fields. They also provide comprehensive reviews of recent studies, open data sources, and potential future research directions in their respective domains.

This study was driven by the recent growth and increased interest in AI, particularly within the aviation industry. Despite the widespread recognition of the critical importance of AI, this study identifies a discernible gap in the existing scholarly discourse, specifically regarding a comprehensive systematic review of the role of AI in the aviation industry. This gap in knowledge and understanding spurred us to conduct a meticulous bibliometric analysis to bridge this gap and provide a detailed exploration of the current research landscape, trends, and emerging areas of AI in aviation.

This study presents a bibliometric analysis of AI in aviation, leveraging analytical tools such as CiteSpace, Scimago Graphica, and VOSviewer, and a robust methodological framework integrating literature review techniques. This study quantitatively deconstructs the corpus of knowledge in this field through bibliometric analytics, thereby identifying key research trends and hotspots.

The objectives of this investigation were as follows: (1) to delineate the knowledge architecture that underpins the nexus between AI and aviation, thereby elucidating the structural dimensions of this interdisciplinary field; (2) to pinpoint lacunae within the existing body of research, highlighting areas ripe for further inquiry; (3) to encapsulate the current trajectory of ongoing scholarly endeavors, offering a snapshot of contemporary research dynamics; and (4) to predict future directions and emergent trends, furnishing insights into the prospective evolution of the domain.

The contributions of this research are significant and threefold. First, it furnishes a comprehensive schema of AI within the aviation sector, thereby laying a foundational knowledge base for future scholarly work. This endeavor elucidates the principal dimensions of AI in aviation, facilitating a structured platform for subsequent research. Second, identifying research frontiers within the field reveals existing knowledge deficits, catalyzing further exploration of AI within the aviation industry. Thirdly, articulating a conceptual framework offers an expedited conduit for novices to assimilate the core principles and prevailing discourses within the study area, streamlining the academic induction process. The unique contributions of this study lie in its comprehensive and systematic approach to mapping AI research in aviation, identifying emerging trends, developing a new conceptual framework, and focusing on practical safety and human-factor applications. These contributions are marginal because they fill a gap in the literature and provide a foundation for future research and development in this critical area.

The remainder of this paper is organized as follows. In the subsequent section, we present a methodological approach to this topic. Sections 2 and 3 show a bibliometric study. Section 4 presents the proposed conceptual framework. Section 5 presents future study options using a new roadmap for AI. Section 5 expounds on the conclusions, limitations, and future work.

2. Records collection and methodology

The Web of Science (WoS) core database was selected for this study because of its prominent role in bibliometric analysis (Ji et al., 2023; Li et al., 2021). A comprehensive research query ALL = (“Aeronautic” OR “Aviation”) AND (“Artificial Intelligence” OR “AI” OR “Machine Learning” OR “Deep Learning” OR “Genetic Algorithm” OR “Big Data”) was employed to collect bibliometric references within the WoS core database. The search spanned 1900–2024, yielding 2,878 documents. These data were gathered in EndNote X9, which served as a reference and citation management tool. Records by type distribution are shown in Table 1, which includes 1,645 articles, the most significant document type, accounting for 57.4% of all literature. Proceeding paper is the second most common document type with 36.5% of the literature totaling 1,167 documents. It also includes review articles (2.3%), early access (1.7%), and others (1.56%).

Considering the comprehensive literature gathered via research inquiries, sophisticated software tools have been utilized to generate quantitative data and visual representations that elucidate the AI domain within the aviation literature. This study employed VOSviewer,

Table 1
Documents by type distribution.

Number	Type	Documents	Percentage (%)
1	Article	1,645	57.40
2	Proceeding paper	1,167	36.50
3	Review article	67	2.30
4	Early access	50	1.70
5	Editorial	12	0.40
6	Data paper	4	0.14
7	Others	12	1.56

CiteSpace, and Scimago Graphica as pivotal tools for knowledge mapping and bibliometric analysis. Notably, VOSviewer emerges as a significant tool for literature visualization, that can perform collaborative network analysis, citation and co-citation analysis, co-authorship, and co-occurrence analysis. The VOSviewer software facilitated the mapping of collaborative networks in academia, countries, universities, institutions, and journals. Scimago Graphica is a new visualization image-drawing tool that, combined with VOSviewer, allows for geographic visualization and literature image drawing. CiteSpace provides various features, including bibliometric analysis, a keyword timeline view, and burst detection. Utilizing CiteSpace, we conducted an evolutionary analysis of keyword trajectories and discerned emerging frontiers in research. By integrating these sophisticated software tools, insights into academic collaborations, citation patterns, co-citations, keyword co-occurrences, and geographical distribution of research hotspots in AI and aviation were uncovered. Fig. 1 shows the graphical illustration of the research methodology.

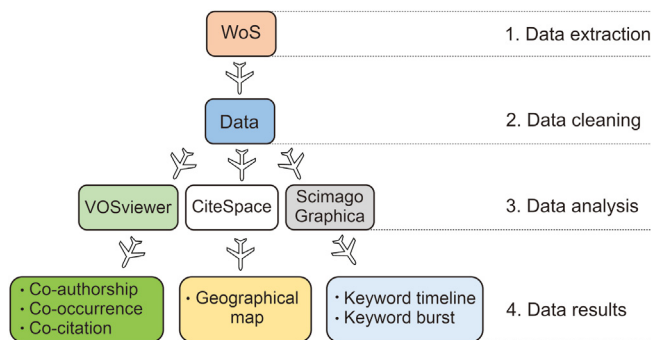


Fig. 1. Research methodology steps.

3. Bibliometric outcome and analysis

3.1. Academic work over the years

Monitoring the temporal progression of article publication is an essential metric for assessing trends in the evolution of research fields. The temporal pattern of publications mirrors the shifting focus and burgeoning interest in a particular domain. The chronological distribution of publications from 1968 to 2024 is shown in Fig. 2. These publications were segmented into four distinct phases delineated by their respective years of publication and frequency of citations to facilitate a structured analysis of the field's development over time.

The initial phase (1900–1990) shows the start of the publication of articles and initial citations. This era witnessed the initial steps in this research domain, with a few relevant documents signaling the field's inception. Between 1940 and 1970, the field of AI was primarily engaged in examining algorithms and investigating various research challenges, especially in the fields of knowledge-based systems (KBS) and ANN systems (Youseftorkaman et al., 2023). KBS are computational frameworks that offer advisory outputs derived from knowledge explicitly provided by human experts by utilizing predefined rules. These systems can mimic human decision-making processes within specific domains by applying logical reasoning to the available data and knowledge bases.

In contrast, ANNs represent a distinct class of computational models inspired by the neurological structure of the human brain. ANNs consist of interconnected nodes or “neurons” arranged in multiple layers, enabling them to learn and make decisions by adjusting the connections based on input data. This architecture facilitates their application across diverse fields, including medicine, biology, engineering, language translation, law, and construction (Youseftorkaman et al., 2023). The versatility of ANNs stems from their ability to process complex patterns and nonlinear relationships within large datasets, thereby offering solutions to problems that are difficult to solve using traditional computational approaches. In 1955, McCarthy et al. (2006) convened a seminal research conference focusing on AI. The primary objective of this gathering was to explore methodologies for enabling machines to interpret and utilize language and to investigate the potential for automating tasks traditionally performed by humans using computational devices (Zaoui et al., 2024). This initiative marked a pivotal moment in the history of AI, laying the groundwork for subsequent developments in machine learning, computer vision, and natural language processing (NLP). The conference catalyzed interdisciplinary collaboration and innovation, aiming to replicate or augment human cognitive functions through technological means. This foundational period set the stages for

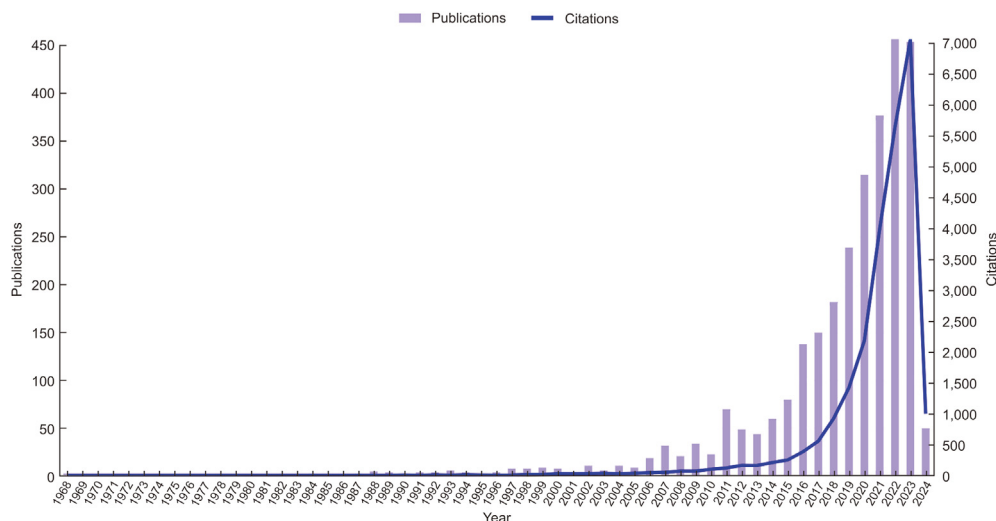


Fig. 2. Temporal dissemination of publications and citations.

subsequent advancements. From the 1970 to the 1990s, the era witnessed several pivotal technologies, such as multimedia, computer vision, statistical machine learning, and natural language processing. These developments have marked significant field diversification, expanding application domains and methodological approaches.

Following the 1990s, a notable shift occurred as engineers and researchers began integrating and applying diverse AI methodologies to address complex issues across various disciplines. This period of integration and application was characterized by a multidisciplinary approach that leveraged AI to solve multifaceted problems in multiple fields of the aviation industry. Some of these challenges, such as fuel consumption (Lin et al., 2024; Lopes et al., 2022; Oh et al., 2024), flight delays (Mamdouh et al., 2023; Shen et al., 2024), environmental impacts (Andrade and Walsh, 2024), growing traveling demand (Anupam and Lawal, 2024; Chu et al., 2024), maintenance (Kwakye et al., 2024; Lopes et al., 2024a, 2024b), and safety (Khattak et al., 2022; Khattak et al., 2024; Khattak et al., 2024a; Lopes et al., 2024b; Lopes et al., 2024a, 2024b) are some of the areas of crucial importance that will support the future of the aviation industry. Table 2 lists some of the critical points in the AI evolution, according to Zaoui et al. (2024) and Grzybowski et al. (2024). Fig. 3 shows the timeline of the main historic events in AI.

3.2. Literature distribution research by country analysis

Examining scholarly output and citation metrics within AI and aviation delineates the leading contributors in terms of research volume and impact. This analysis focuses on quantifying the dissemination and scholarly influence of countries in this interdisciplinary field and systematically evaluates publication and citation volumes at the national level. As presented in Table 2, the study ranks the top ten countries based on the total number of documents, correlating these findings with geographical regions, total citations received, and the average citation per document (ACPD) metric.

This systematic approach provides an understanding of the global landscape of research activities and their influence on AI and aviation. By highlighting countries that demonstrate a higher propensity to produce and disseminate influential research, this analysis offers insights into the geographic distribution of academic contributions and their relative

Table 2
Leading research countries.

Rank	Country	World zone	Records	Citations	ACPD
1	China	Asia	1,401	10,842	8.59
2	USA	North America	540	6,274	12.51
3	UK	Europe	151	1,975	13.68
4	Germany	Europe	113	1,282	11.65
5	Russia	Oceania	102	405	4.08
6	France	Europe	92	1,126	12.60
7	India	Asia	90	660	7.42
8	Canada	North America	86	1,123	14.21
9	Italy	Europe	65	1,037	16.75
10	Netherlands	Europe	55	589	10.96

Note: ACPD: average citations per document.

impact on the global knowledge economy within this specialized area of study.

China, the USA, and the UK emerged as the foremost contributors, substantiating their prominence in paper production in the research domain. Nevertheless, China's ACPD is 8.59, placing it at a lower level of literature citations. This shows that, despite the number of documents published by Chinese researchers (1,401), China's large number of publications on AI and aviation have not been matched by an equally high level of average citation impact per paper. However, Italy has the highest average citation among the ten countries with an ACPD of 16.75, despite being the ninth most prolific country in documents. Table 2 also shows that Asia, North America and Europe are the main continents for AI and aviation.

From 2012 to 2024, there is a noticeable increase in moderate-level publication activities across the spectrum of analyzed countries. The US, China, and the UK are distinguished by their relatively earlier emergence in the publication timeline than India, Canada, Italy, and the Netherlands, indicating a more prolonged history of research contributions. By contrast, the remaining nations exhibited comparable average publication rates, suggesting parity in their research outputs over time.

The data revealed a pervasive trend of solid collaborative ties among the countries studied, with the US standing out for its exceptional engagement in international research collaborations. An analysis of publication volume data, presented in Table 3 and visualized in Fig. 4,

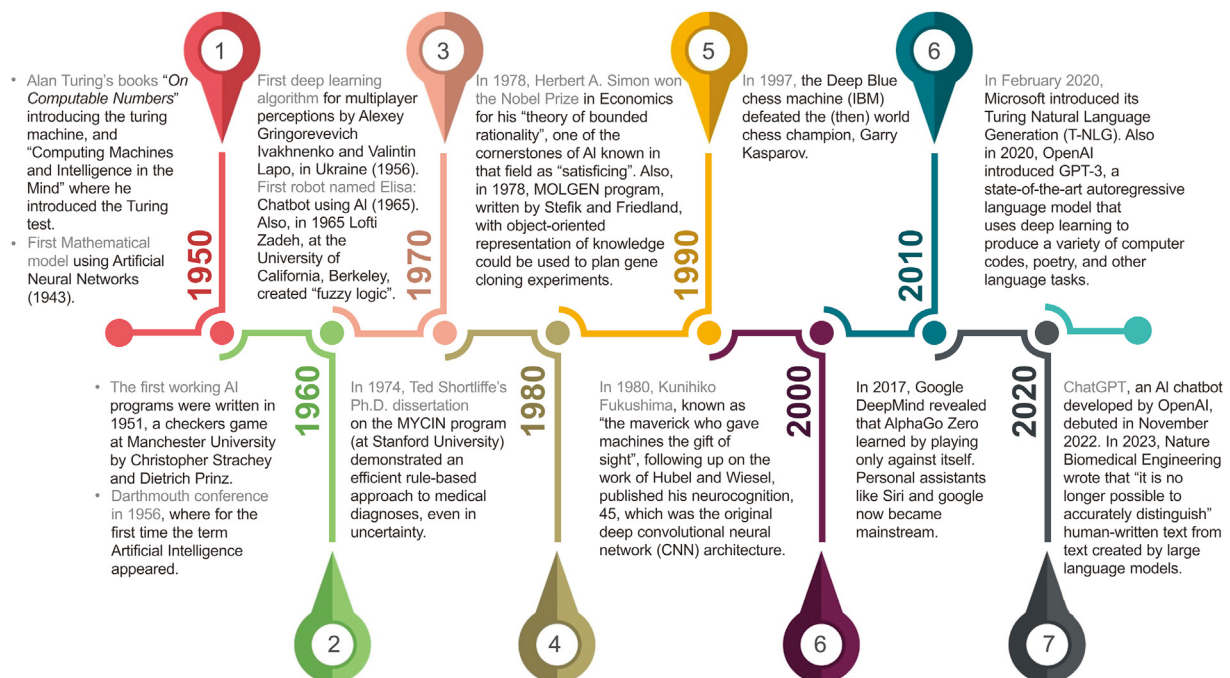


Fig. 3. Timeline of historical events in artificial intelligence (AI).

Table 3
Leading authors based on publications.

Rank	Author	Affiliation	Country	Records	Citations	ACPD
1	Yang Liu	Nanjing University of Finance & Economics	China	28	1,118	39.93
2	Yue Zhang	China Academy of Civil Aviation	China	26	338	13
3	Jing Zhang	Changsha Aeronautical Vocational and Technical College	China	25	231	9.24
4	Zhe Wang	Shanghai University of Engineering Science	China	23	59	2.57
5	Li Yu	Nanjing University of Aeronautics and Astronautics	China	22	274	12.45
6	Jia Liu	Auburn University	US	22	424	19.27
7	Yu Wang	The Civil Aviation Flight University of China	China	22	81	3.68
8	Gianluca Borghini	Sapienza University of Rome	Italy	18	316	17.56
9	Gianluca Di Flumeri	Sapienza University of Rome	Italy	18	316	17.56
10	Juan Wang	Nanjing University of Posts and Telecommunications	China	18	400	22.22

Note: ACPD: average citations per document.

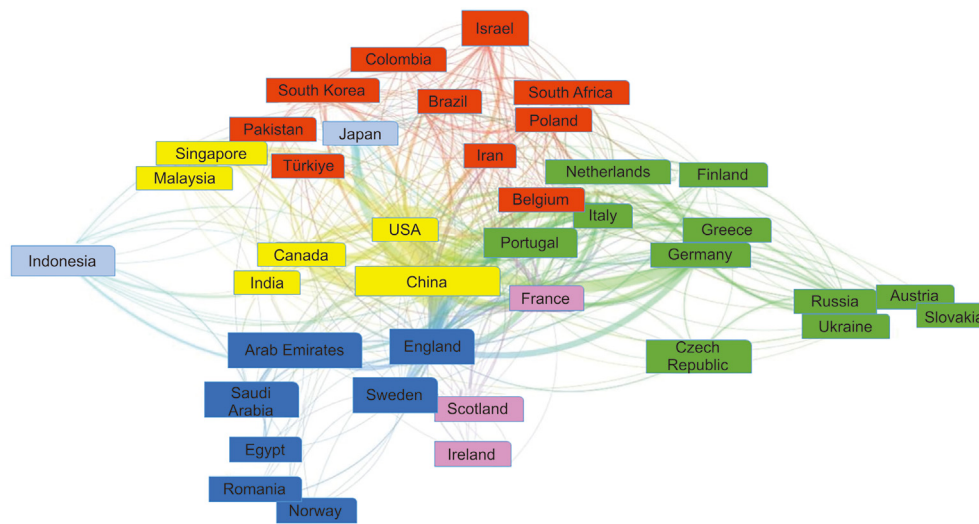


Fig. 4. Collaboration network of Countries/regions.

positions the US and the UK as the second- and third-most prolific countries, respectively, in terms of publication count. However, China demonstrates a relatively lower degree of collaboration with other nations, which may be one of the factors affecting the citation counts of its own scholarly works.

3.3. Intellectual collaboration and significant research

Table 3 presents the top ten AI and aviation researchers, showing an estimable spread across geographies, half of which are affiliated with China, evidencing their leadership in the domain.

The most prolific publications are by Yang Liu, Yue Zhang, Jing Zhang, Zhe Wang, and Yu Li. These authors are at the vanguards of scholarly productivity in their respective fields. Moreover, two authors from Italy, Gianluca Borghini and Gianluca Di Flumeri, have emerged as significant collaborators and engaged in joint research endeavors since 2004. Their collective work is centered on advancing Artificial Intelligence within aviation and medicine, specifically by developing new systems that study mental workloads and human-computer interactions. Their seminal works (Aricò et al., 2016; Aricò et al., 2019; Borghini et al., 2022; Di Flumeri et al., 2022) contribute significantly to this niche of aviation safety and human-machine interface technology, forming a distinctly collaborative cluster.

Yang Liu from Nanjing University of Finance and Economics in China had the highest ACPD of 39.93. His work relies on using deep learning algorithms (Yang et al., 2019; Zhang et al., 2017) and genetic algorithms (Deng et al., 2022; Ma et al., 2019) in several facets of the aviation industry, particularly traffic automation detection (Liu et al., 2023; Yang et al., 2019; Zhang et al., 2022), human factors (Qin et al., 2021),

planning (Liu et al., 2020; Wang et al., 2023a, 2023b; Zheng et al., 2021), and knowledge management (Cao et al., 2022; Liu et al., 2011).

3.4. Key universities/institutions and collaboration analysis

In the analysis conducted using the WoS Core Collection database, 799 universities, and institutions were identified as contributors to scholarly literature on artificial intelligence (AI) within the aviation sector. The ten leading universities and institutions are listed in Table 4. An examination of this table reveals a significant geographic distribution of research output, with half of the top ten institutions located within China, indicating that China is the principal region for AI research in aviation, characterized by robust research intensity. The US host two institutions within this top echelon. Notably, despite the ninth position of NASA Ames Research Center, as shown in Table 4, it boasts a singular institution with the second ACPD, underscoring its impactful contributions to the field.

As listed in Table 4, the premier institution is the Civil Aviation University of China, which reflects its prolific output in aviation and aerospace AI research.

3.5. Journal publication and collaborative endeavors

The systematic evaluation of journal volumes through the lens of document publications yields critical insights into content distribution across the research landscape. Table 5 presents the ten leading journals, characterized by their respective citation indices, impact factors, and ACPD. Among these, *IEEE Access*, *Aerospace*, and *Sensors* have emerged as the foremost journals in terms of document publication. The impact factors were 3.9, 2.6, and 3.9.

Table 4
Leading academic institutions based on publications.

Rank	University/institution	Country	Records	Citations	Links	ACPD
1	Civil Aviation University of China	China	161	1,834	34	11.39
2	Nanjing University of Aeronautics Astronautics	China	19	742	36	6.24
3	Beihang University	China	13	1,121	27	9.58
4	Chinese Academy of Sciences	China	13	610	27	8.36
5	Civil Aviation Flight University of China	China	11	298	18	4.26
6	NASA	USA	11	636	18	9.09
7	Northwestern Polytechnical University	China	10	302	17	4.44
8	Shanghai Jiao Tong University	China	10	353	18	7.06
9	NASA Ames Research Center	USA	9	416	3	10.67
10	Shenyang Aerospace University	China	9	252	12	6.63

Table 5
Leading publications based on article count.

Rank	Publication	Records	Abstracting and indexing	Impact factor (2023)	Links	ACPD
1	<i>Lecture Notes in Artificial Intelligence</i>	112	SCIE	0.90	210	2.16
2	<i>IEEE AIAA Digital Avionics System Conference</i>	74	SCIE	0.96	263	2.09
3	<i>IEEE Access</i>	68	SCIE	3.90	259	16.71
4	<i>Chinese Control and Decision Conference</i>	54	SCIE	0.40	134	2.94
5	<i>Proceedings of SPIE</i>	52	SCR	0.20	125	2.94
6	<i>Lecture Notes in Computer Science</i>	48	CPCI	1.27	110	6.90
7	<i>Aerospace</i>	45	SCIE	2.60	245	8.42
8	<i>Proceedings of 2020 IEEE 2nd International Conference on Civil Aviation Safety and Information Technology ICCASIT Sensors</i>	44	CPCI	2.40	178	1.82
9	<i>Applied Sciences - Basel</i>	38	SCIE	3.90	207	9.84
10		32	SCIE	2.70	213	4.72

It may initially seem counterintuitive that lecture notes in AI exhibit a relatively modest impact factor and low ACPD, despite their prominence by document count. This phenomenon can be attributed to the journal's broad thematic focus, which extends to AI and aviation, and affects its overall citation metrics. Conversely, *IEEE Access* boasts the highest ACPD among the top ten journals, significantly contributing to its robust impact factor.

The analysis highlights journals like *Lecture Notes in Artificial Intelligence*, the *IEEE AIAA Digital Avionics System Conference*, and *IEEE Access* for their notable publications. These figures underscore the substantial of the journal's influence within the research domain, reflecting their pivotal role in shaping scholarly discourse and informing practices within AI.

The prominence of a journal within the academic community is frequently associated with its publication volume, a metric that signifies both the breadth and depth of the research it encompasses. Through a comprehensive analysis that integrates publication metrics with collaboration patterns, it is possible to discern journals that occupy leading positions in situational AI and aviation. This approach helps identify articles that have sparked significant research interest, becoming focal points for scholarly discourse in these fields. By examining these dual aspects, scholars and practitioners can better understand prolific journals in terms of output and are central to the collaborative networks that drive innovation and knowledge dissemination in AI and aviation research.

3.6. Contemporary research and knowledge assessment

The concept of co-citation, initially proposed by Marshakova-Shaikovich (2005), has emerged as a fundamental tool in bibliometric analyses, evaluating the degree of similarity between references simultaneously cited within a scholarly work. This methodological approach, which identifies instances in which a single article cites two or more prior studies in tandem, has become instrumental in discerning the relational dynamics and thematic congruence among cited literature.

According to Small (1973), co-citation frequency is a quantitative indicator of the relevance and influence of specific concepts and theories in a given academic discipline. Frequently co-cited literature forms the cornerstone of the research domain, with journals that accumulate high

co-citation counts being recognized as leading voices and authoritative sources in their respective fields.

By meticulously examining these highly co-cited works and journals, scholars can map the foundational research base that underpins their field of study. Complementarily, the most cited literature within a contemporary timeframe offers a window into the prevailing research trends and focal areas of investigation, as noted by Liang et al. (2023). Thus, this analytical lens provides invaluable insights into the historical and current research landscape, facilitating a comprehensive understanding of the evolution of scholarly discourse and the emergence of new knowledge frontiers.

Table 6 presents the ten leading journals with significant co-citations ranked by co-citation frequency. This ranking provides 2023 impact factors and links. The top three highly co-cited journals are *Proceedings on Computer Vision and Pattern Recognition*, *Lecture Notes in Artificial Intelligence*, and *IEEE Access*.

Expert Systems with Applications is a prominent high quality journal with the highest ACPD, as shown in Table 6. This journal focuses on exchanging information on expert and intelligent systems applied in industries, governments, and universities worldwide.

Beyond *Expert Systems with Applications*, the top ten highly-cited journals encompass diverse subjects, such as transport, operational research, decision-making, and computer science. *Proceedings of Computer Vision and Pattern Recognition* and *IEEE Transactions on Pattern Analysis and Machine Intelligence* were among the top journals with the highest impact factors, as shown in Table 6.

To ensure methodological rigor in the visualization of our cocitation analysis, we employed VOSviewer with a predetermined threshold for inclusion set at a minimum cocitation frequency of 20. This criterion facilitated the delineation of seven distinct nodes. Subsequently, the visual representation (as depicted in Fig. 5) was constructed using Scimago Graphica software. In this visualization, the dimensionality of each node is directly proportional to the frequency of co-citations among journals, where larger nodes denote higher frequencies of co-citations. Furthermore, the visual map features interconnecting lines of varying thicknesses, which indicate the strength of collaboration between entities. Notably, thicker lines signify more robust collaborative ties, thereby highlighting the degree of interconnectivity within the network.

The analysis of journal co-citation dynamics, as illustrated in Fig. 5, reveals the formation of four distinct clusters within the dataset. Central to these findings is the identification of a principal cluster, depicted in green, comprising seven nodes. This cluster predominantly focuses on human-computer interactions. In contrast, the remaining journals were represented as individual nodes within the network. Journals such as *Aerospace Science Technology*, *Nature*, and *Sensors* are distinguished by their high co-citation frequencies, thereby underscoring their critical role as seminal sources of literature in AI and aviation safety. Furthermore, an examination of the network revealed significant cross-cluster collaboration, with particular emphasis on the interactions among the ten journals, highlighting a noteworthy level of interdisciplinary cooperation within the field.

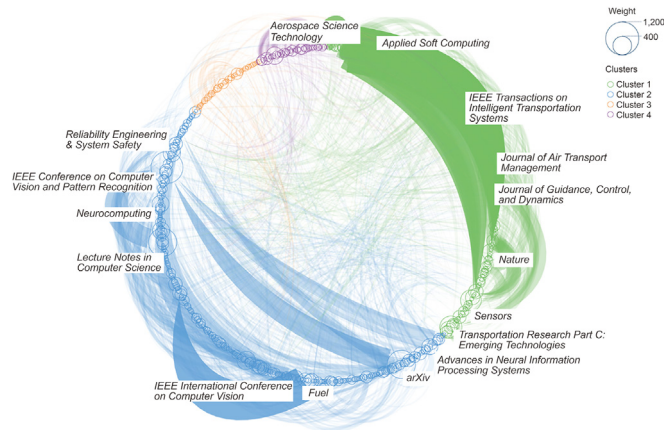


Fig. 5. Highly co-cited publications collaboration mapping.

Table 6
Top ten publications with high co-citation frequency.

Rank	Journal/conference proceedings	Co-citation	Impact factor (2023)	Links	ACPD
1	<i>Proceedings on Computer Vision and Pattern Recognition</i>	1,136	23.46	513	23.46
2	<i>Lecture Notes in Computer Science</i>	891	1.27	557	6.90
3	<i>IEEE Access</i>	686	3.9	592	16.71
4	<i>Journal of Air Transport Management</i>	620	6	456	19.58
5	<i>Transportation Research Part C Emerging Technologies</i>	563	8.3	477	12.62
6	<i>Sensors Basel</i>	496	3.73	581	9.84
7	<i>Expert Systems with Applications</i>	420	8.5	536	29.47
8	<i>IEEE Transactions on Pattern Analysis and Machine Intelligence</i>	390	23.6	468	23.60
9	<i>European Journal of Operational Research</i>	386	6.4	404	6.40
10	<i>IEEE Transactions on Intelligent Transportation Systems</i>	366	8.5	480	12.46

Table 7
Top ten cited articles and journals.

Reference	Title	Journal/conference proceedings	Citations
Zhang et al. (2017)	Automated pixel-level pavement crack detection on 3D asphalt surfaces using a deep-learning network	<i>Computer-Aided Civil and Infrastructure Engineering</i>	580
Jing et al. (2017)	A convolutional neural network-based feature learning and fault diagnosis method for the condition monitoring of gearbox	<i>Measurement</i>	450
Barricelli et al. (2019)	A survey on digital twin: definitions, characteristics, applications, and design implications	<i>IEEE Access</i>	401
Sheridan (2016)	Human-robot interaction: status and challenges	<i>Human factors</i>	307
Deng et al. (2022)	An enhanced, fast, non-dominated solution sorting genetic algorithm for multi-objective problems	<i>Information Sciences</i>	240
Yuan et al. (2021)	Deep learning with spatiotemporal attention-based LSTM for industrial soft sensor model development	<i>IEEE Transactions on Industrial Electronics</i>	239
McGovern et al. (2017)	Using artificial intelligence to improve real-time decision-making for high-impact weather	<i>Bulletin of the American Meteorological Society</i>	203
(Mintz and Brodie, 2019)	Introduction to artificial intelligence in medicine	<i>Minimally Invasive Therapy & Allied Technologies</i>	195
Trahey et al. (2020)	Energy storage emerging: a perspective from the Joint Center for Energy Storage Research	<i>Proceedings of the National Academy of Sciences</i>	194
Gui et al. (2020)	Flight delay prediction based on aviation big data and machine learning	<i>IEEE Transactions on Vehicular Technology</i>	158

An investigation of extensively referenced scholarly works revealed the fundamental elements constituting a research domain, as identified by Li and Liu (2020). To comprehend the predominant literature in the spheres of AI and Aviation, Table 7 was meticulously constructed using RStudio in conjunction with the Bibliometrix: Biblioshiny package (Aria and Cuccurullo, 2017), which was further enhanced by the citation analysis capabilities provided by the WoS. Table 7 delineates the top ten articles that garnered the most citations, detailing their titles, authors, years of publication, journals in which they were published, and the number of citations received. This table is organized based on the number of citations that these articles accumulated from 1900 to 2024.

The most cited work, “Automated pixel-level pavement crack detection on 3D asphalt surfaces using a deep-learning network”, by Zhang et al. (2017), was published in the *Computer-Aided Civil and Infrastructure Engineering* Journal. Its broad application encompasses CrackNet, an efficient architecture based on a convolutional neural network (CNN) for automated pavement crack detection on 3D asphalt surfaces, with a focus on achieving pixel-perfect accuracy. CrackNet comprises five layers and more than one million parameters. It was trained on 1,800 3D pavement images and tested successfully on 200 images, achieving high precision, recall, and F-measure. The architecture of CrackNet can maintain pixel-level accuracy by ensuring invariant data width and height through all layers without using pooling layers that downsize the outputs. This study highlights the limitations of traditional crack detection methods and emphasizes the potential of deep learning techniques, specifically CrackNet, to achieve superior performance in detecting pavement cracks.

The second entry is “A CNN-based feature learning and fault diagnosis method for gearbox condition monitoring”. Jing et al. (2017), featured in the journal *Measurement*, outlined and identified a CNN-based method for the fault diagnosis of gearboxes, demonstrating superior performance in adaptively learning features from frequency data and high diagnostic accuracy compared to traditional methods. This article delves into the

Junghyun Kim. His research includes air traffic management (Kim and Kim, 2023; Ramée et al., 2020) and flight planning (Kim et al., 2021; Kim et al., 2021a, 2021b).

Mica Endsley is the leading highly co-cited author in the cyan cluster with 19 nodes. This is predominantly influenced by Endsley's scholarship, which manifests as connections with all other clusters. The network graph underscores Endsley's pivotal role in Situation Awareness (SA). The graph shows the importance of Endsley's work on SA, specifically with the SA model in dynamic decision-making (Endsley, 1988, 1995a, 1995b), published in *Human Factors*, which significantly impacted future literature. This model has been foundational in shaping the academic discourse surrounding SA, indicating Endsley's significant impact in this domain. Parasuraman et al. (2008) investigated cognitive processes that enhance the comprehension of human performance within complex systems, thereby facilitating advancements in automated design. Their research illustrated the efficacy of computational modelling in quantifying these constructs through behavioral, physiological, and subjective assessments, as established in their earlier work (Parasuraman et al., 2000). This approach underscores the potential of integrating diverse measurement techniques to comprehensively understand the cognitive dynamics in human-automation interactions. These 19 nodes are centered on methods and procedures for enhancing SA theory, mainly through cognitive measures within the field of ergonomics. The distributed cognition concept encompasses various agents, including both humans and technological systems that work collaboratively to achieve common goals that require significant communication and coordination, as noted by Stanton (2016). As transportation systems evolve, cognitive processes adapt to changes in tasks, environment, and interactions. Further advancing this area of study, Stanton et al. (2019) proposed that the event analysis of systemic teamwork (EAST) offers a robust framework for capturing the complexities of distributed cognition using a network-of-networks approach. This methodology allows a detailed examination of the interdependent dynamics within teams, highlighting the intricate interactions and cognitive exchanges that drive collective performance. Gianluca Borghini emerged as a highly co-cited author in this cluster. Particularly with his research in air traffic management (Aricò et al., 2019; Borghini et al., 2020; Hurter et al., 2022), human factors (Borghini et al., 2022; Giorgi et al., 2021; Moura Lopes et al. 2024; Ronca et al., 2023) human-machine interface (Ronca et al., 2020), and neurophysiological research (Sciaraffa et al., 2019, 2022).

The remaining blue cluster with 29 nodes indicates an ongoing effort to evaluate the performance of alternative aviation fuels, which has renewed interest in the effects of jet fuel composition changes on gas turbine operability and performance (Edwards, 2017). Additionally, in this cluster, Wu Deng from the Civil Aviation University of China studied AI applications for the aviation industry (Deng et al., 2019; Gao et al., 2013).

3.7. Keywords, hot spots, and citation keywords burst analysis

An analysis of keyword co-occurrence delineates the focal areas of current interest, whereas a study of high-frequency keywords identifies the dominant themes in ongoing research. Table 8 presents the three

Table 8
Prominent co-occurring keywords.

Rank	Keywords	Co-occurrences	Total strength
1	Machine learning	344	1,080
2	Deep learning	235	663
3	Performance	170	383
4	Artificial Intelligence	168	332
5	Model	149	196
6	Genetic algorithm	142	340
7	Optimization	138	455
8	Aviation	135	435
9	Prediction	100	375
10	Design	85	278

most frequently cited keywords: machine learning with 344 occurrences, deep learning with 235 occurrences, and genetic performance with 170 occurrences. The connectivity strength among the top ten keywords was proportional to the frequency of their co-occurrence, emphasizing the importance of machine learning and deep learning in modern research on AI within the aviation industry.

A comprehensive analysis of 465 keywords was conducted to explore the research trends in AI and aviation. This analytical process identified 465 nodes distributed across seven distinct clusters.

The first cluster comprises 108 nodes, with the “genetic algorithm” keyword showcasing 167 links and a total link strength of 340. In the first cluster, publications revolve around models, particularly emphasizing prediction and simulation algorithms. Most studies employing genetic algorithms have attempted to optimize and predict operational facets within the aviation industry (Bala Bisandu and Moulitsas, 2024; Guedan-Pecker and Ramirez-Atencia, 2024; Sun and Ieee, 2023; Zhu et al., 2024). Operational safety is also a concern for researchers (Midtjord et al., 2022; Xiong et al., 2023). Genetic programming has become a reality in many facets of the aviation industry, including maintenance (Kowalski et al., 2021; Li et al., 2016; Peng and Mohammadinia, 2020; Shang, 2022), fuel consumption (Singh, 2018; Singh et al., 2020), airport capacity (Liu et al., 2020), air traffic management (Guedan-Pecker and Ramirez-Atencia, 2024; Taylor et al., 2015), and training (Wang et al., 2023a, 2023b). Overall, this cluster pertains to the internal aspects of prediction. We have designed this cluster with the term “prediction” to encompass all these aspects.

The second cluster comprises 92 nodes with the “artificial intelligence” keyword showcasing 88 links and a total link strength of 332. Within this cluster, publications revolve around big data, emphasizing the challenges of AI in the identification and management of information systems. Yousefotorkaman et al. (2023) explored the capabilities of AI in the aviation industry and its impact on air accidents. Johnson (2023) explained the potential of AI to revolutionize the aviation industry. Machine learning and artificial intelligence applications have been extensively used to address safety problems and enhance efficiency across various transport modes (Tselentis et al., 2023, Zhang and Mahadevan, 2021). Khafizov et al. (2021) provide a general overview of big data and its applications in the aviation sector. They analyzed scientific papers and conducted interviews with industry professionals to understand the relevance and potential applications of big data in the aviation sector. Their work emphasizes the growing importance of data management and strategic decision-making in the aviation industry. As data volumes increase exponentially, adopting big data solutions becomes crucial for airlines to remain competitive and optimize their business processes. This conclusion underscores the significance of leveraging big data technologies to enhance operational efficiency, customer service, and overall performance in the aviation sector. Overall, this cluster pertained to data management in the aviation industry. We designed this cluster using the term “big data” to encompass all these aspects.

The third cluster comprises 92 nodes, with the “performance” keyword showcasing 170 links and a total link strength of 383. Within the Cyan cluster, publications revolve around human factors, particularly emphasizing the challenges of AI in human workload, SA, automation, and performance. Endsley's (1995b) research titled “Toward a theory of situation awareness in dynamic systems” and published in the journal *Human Factors* introduced a groundbreaking model for SA in dynamic decision-making environments. This model articulates SA using a hierarchical structure spanning three levels. The first concerns the perception of elements present in the immediate environment. The second level focused on comprehending these elements of the current situation. The third and final levels involve the projection of future states based on the current situational analysis Endsley (1995b). Developing an EEG-based workload prediction model for aviation to assess real-time mental workload in noisy operational environments to reduce accidents caused by human errors is essential for safety performance (Giorgi et al., 2021;

Gorji et al., 2023; Jiang et al., 2022; Salvan et al., 2023); also explainable AI (XAI) in the aviation industry emphasizes the importance of understandable explanations for decision-making and building trust between users and intelligent systems (Sutthithatip et al., 2021). Overall, this cluster pertains to human factors in the aviation industry. We designed this cluster using the term “human factors” to encompass all these aspects.

The fourth cluster comprised 92 nodes, with the “machine learning” keywords showing 344 links and a total link strength of 1,080. Machine-learning algorithms are used in the aviation industry. They can be used to support air traffic management (Bogad et al., 2022; De Petris et al., 2022; Kim et al., 2021), emissions prediction (Kumar et al., 2022; Verma et al., 2021), aircraft maintenance (Effertz et al., 2022; Freed et al., 2022), safety (Huang et al., 2021; Kaewunruen et al., 2021; Liu et al., 2021; Omrani et al., 2024), and human factors (Gorji et al., 2023). Overall, this cluster pertains to the machine learning facet in the aviation industry. We have designed this cluster with the term “machine learning” to encompass all these aspects.

The fifth cluster comprises 235 nodes, with the “deep learning” keyword showing 88 links and a total link strength of 663. Deep learning, a specialized domain within machine learning, employs hierarchical neural networks, called deep neural networks, to approximate the intricate cognitive processes associated with human decision-making (Shrivastava et al., 2023). Deep learning has been implemented in several areas of the aviation industry including weather predictability (Kumar and Kumar, 2024; Leinonen et al., 2023; Ait Ouadil et al., 2023; Saha and Valles, 2023), risk assessment (Chen et al., 2023; Chu et al., 2024; Han et al., 2023; Tsai and Lai, 2023), safety (Wang et al., 2023a, 2023b; Wei, 2020; Zhou et al., 2020), and air traffic management (Ghosh et al., 2023; Ouf, 2023; Qu et al., 2023). Overall, this cluster pertains to the deep learning facet in the aviation industry. We have designed this cluster with the term “deep learning” to encompass all these aspects.

The sixth cluster included 42 nodes, which was the smallest in the clustering set. The top three keywords were impact, COVID-19, and air transportation, suggesting a strong emphasis on AI-related research among the external factors impacting the aviation industry. COVID-19 has had a massive impact on the aviation industry, especially on air transportation (Pereira et al., 2023; Yang and Chen, 2022). Sun et al. (2020) provided a comprehensive analysis of the impact of COVID-19 on global aviation from a complex system perspective, highlighting changes

in connectivity patterns, differential effects on international and domestic air transportation, and delayed reactions of the aviation industry to the pandemic. Overall, this cluster pertains to the external factors in the aviation industry. We have designed this cluster with the term “impact” to encompass all these aspects.

3.8. The evolution of keywords in the literature

This study performed temporal analysis using the CiteSpace tool, as illustrated in Fig. 7. This figure presents a keyword timeline, where the horizontal axis indicates chronological progression and the vertical axis categorizes the keyword clusters. Each node on the timeline corresponds to a specific keyword, and the node size denotes the frequency of the keyword's appearance in the literature. The node color reflects the keyword's evolution rate, with darker shades indicating more rapid evolution. Fig. 7 shows the most prominent keywords on the left side of the diagram.

The bubble size represents the frequency of the terms. Larger bubbles indicated a higher frequency. Terms like “model”, “performance”, “optimization”, “design”, and “networks” have more giant bubbles, indicating they are frequently mentioned in the literature. The horizontal axis represents the years, ranging from 1994 to 2024. Several terms show an increasing trend, indicating a rise in interest and research in areas such as, “model”, “performance”, and “optimization”, particularly from around 2010 onwards, also, some terms such as “genetic algorithms” and “networks”, have been mentioned consistently over a more extended period but showed increased frequency in recent years. Genetic programming approaches for complex problems in the aviation industry have evolved since 1999. Toratani et al., (2022) emphasized the importance of route design in civil aviation, introduced an optimization method for the RNP AR approach (airport instrument approach procedure), and set the objective of developing a more efficient route design. Aircraft maintenance is a significant part of the supply chain that ensures the airworthiness of airplanes. Shang (2022) discussed the importance of aviation material scheduling, introduced an NSGA-II with an adaptive design for optimization, and provided a solution superior to traditional methods. It also discusses the applications of genetic algorithms in various fields.

Newer terms like “industry 4.0”, “particle swarm optimization”, and “virtual reality” appear to have emerged more recently, with activity starting in the past decade. “Industry 4.0” and “particle swarm optimization” show an apparent increase in frequency, suggesting these are

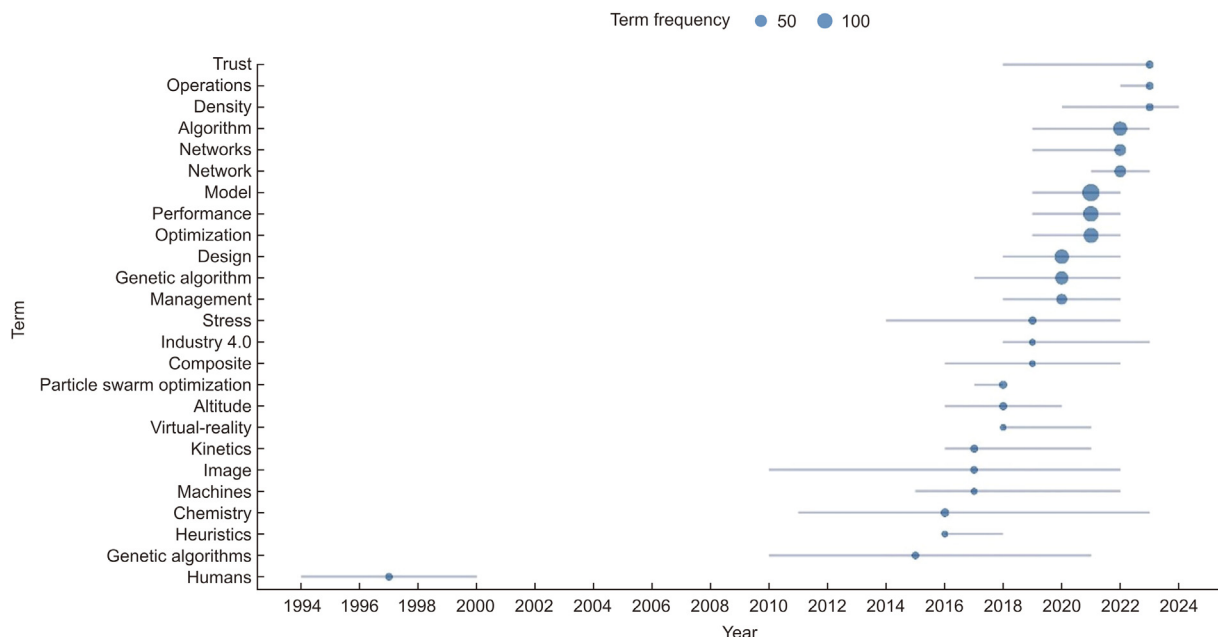


Fig. 7. Most prominent keywords.

emerging areas of interest in applying AI to aviation. Other terms, like “humans” and “genetic algorithms”, have data points or measurable observations dating back to the late 1990s, suggesting longstanding interest in these areas, though they may not appear as frequently in recent years compared to newer terms.

The term “model” is one of the most frequently mentioned and has shown consistent growth, reflecting its central role in AI applications within aviation. The increasing size of bubbles over time for several terms indicates that AI application in aviation is a growing field, with more research being published in recent years.

Fig. 7 provides a clear visual representation of the evolution of the frequency of various AI-related terms in aviation over time, highlighting both long-standing areas of interest and emerging trends.

Fig. 8 shows the distribution of keywords related to AI in aviation extracted from the WoS. The size of each block represents the frequency of the keywords, with larger blocks indicating more frequent mentions. Key areas of focus include “model” (144 instances, 8%), “performance” (101 instances, 6%), and “optimization” (90 instances, 5%). Emerging topics such as “genetic algorithms” and “neural networks” highlight the ongoing innovation in AI applications within the aviation sector. The diversity of the keywords reflects the multifaceted nature of AI research in aviation, ranging from design and classification to safety and management.

The three more dominant keywords are "model", with the most significant block, indicating that AI modeling is a critical area in aviation research; "performance", the second-largest block suggesting that performance optimization using AI is a significant focus. The key word "optimization" highlights the importance of optimizing various aspects of aviation through AI.

Significant research areas include design and classification. These areas also hold considerable importance with 83 (5%) and 66 (4%) instances, respectively, suggesting a focus on AI-driven design and classification systems for aviation. System and prediction: Both keywords frequently appear, with “system” having 80 cases (5%) and “prediction” having 79 instances (5%), indicating their relevance in the application of AI.

Emerging topics are genetic algorithms, networks, and neural networks. These keywords, appearing with 60 (3%), 39 (2%), and 36 (2%) instances, respectively, suggest ongoing research and application of these AI techniques in aviation. Simulation, identification, and management: Keywords such as simulation (30 instances, 2%), identification (24 instances, 1%), and management (28 instances, 2%) indicate the specific applications of AI in simulating aviation scenarios, identifying issues, and managing systems.

Other notable keywords: behavior, framework, safety, and Internet: These keywords reflect various applications and considerations such as behavioral modeling (33 instances, 2%), AI frameworks (32 instances,

2%), safety (20 instances, 1%), and Internet-related aspects (17 cases, 1%). Combustion, dynamics, diagnosis, and temperature: These keywords (each with 1% or 17–22 cases) highlight the specific technical applications of AI in aviation, such as combustion processes, dynamic systems, diagnostics, and temperature control.

Less frequent but relevant topics: big data, emissions, fatigue, prognostics: Keywords like big data (13 instances, 1%), emissions (13 cases, 1%), fatigue (12 instances, 1%), and prognostics (11 cases, 1%) indicate niche but important areas where AI is being applied in aviation.

3.9. Keyword burst frontline classification

The CiteSpace's Burst Detection tool was employed to analyze the literature within the AI domain in the aviation industry. The top ten keywords with the highest burst intensity were combined with a previous analysis of the publication timeline in AI research. This facilitates the visualization of the evolution of keyword trends over time, as depicted in Fig. 9.

For the analysis, we considered five years starting in 1994. The top five keywords in mutation intensity between 2018 and 2024, by keyword and strength, are: “atmospheric modeling” (4.90), “convolutional neural networks” (3.80), “object detection” (3.53), “unmanned aerial vehicles” (3.39), and “predictive models” (3.39). The “atmospheric modeling” keyword has the highest value, with 4.9. These keywords will remain popular in future research because they will appear in 2024. Between 1999 and 2008, the top keywords were “situation awareness” (3.63), “human factors”(3.48), “data mining”(5.50), and “genetic algorithms” (23.68). Between 2009 and 2014, there were only four keyword bursts, with the highest-strength keyword being “big data” (8.23). From 2015 to 2020, the keyword “classification” had the highest score, with a strength of 4.75. Between 2021 and 2024, keywords such as “atmospheric modeling”, “convolutional neural networks”, “object detection”, “parameters”, “unmanned aerial vehicles”, and “predictive models” still burst in 2024. This phase had more mutations in keywords, with an increase in AI research literature. Therefore, we may consider that the research frontier in AI in the aviation industry focuses on the keywords with the most robust links, such as “predictive models”, “unmanned aerial vehicles”, “convolutional neural networks”, and “object detection”.

4. Proposed conceptual framework

A conceptual framework is a network of linked concepts built using a qualitative method based on grounded theory (Jabareen, 2009). In our exploration of AI within the aviation industry domain, we developed an extensive framework by conducting meticulous co-citation, keyword, and



Fig. 8. Distribution of keywords by Web of Science (WoS).

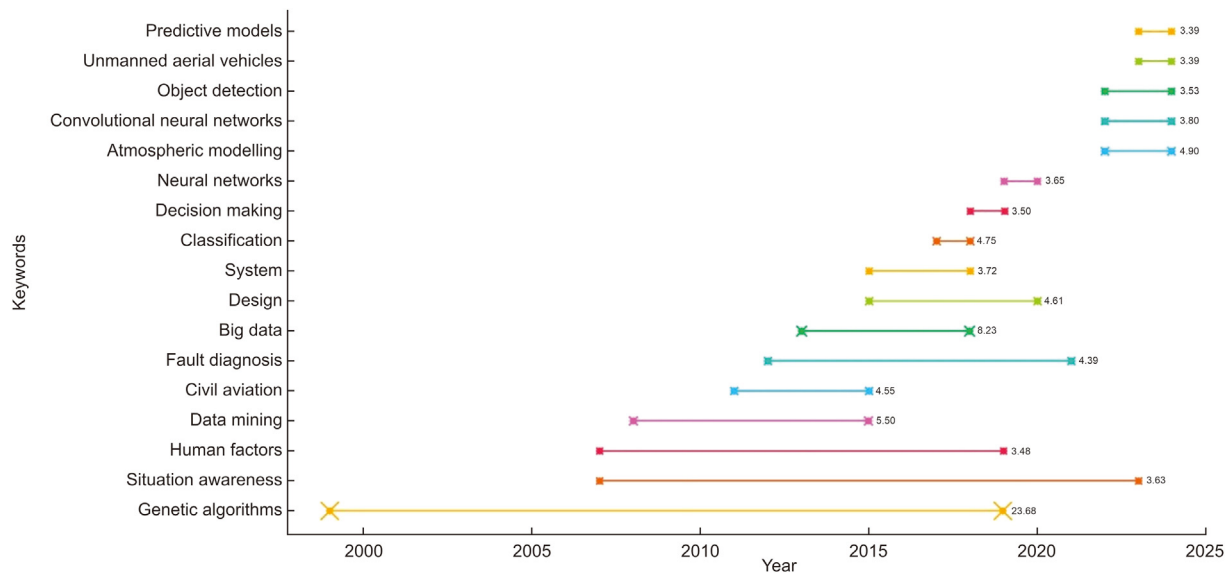


Fig. 9. Top 17 keywords with strongest citation bursts.

co-occurrence analyses of existing literature. This systematic review highlights several pivotal themes integral to AI based on keyword strength: genetic algorithms, prediction, AI, big data, performance, human factors, machine learning, deep learning, and impact. To develop our conceptual map, we used the following steps: bibliometric analysis with co-citation, keyword link strength, and the co-occurrence of existing literature, revealing the main keyword strength topics. Subsequently, we identify the specific concepts that are intricately associated with these broader themes. Finally, we established connections between the overarching concepts by integrating relevant specific concepts and aligning them with our study's objectives, reinforcing the coherence and depth of our research framework and identifying the eight dimensions in our study.

AI is recognized as a potential determinant in managing human behavior across complex and dynamic operational settings. Technological design, ergonomics, and predictive models have emerged as crucial factors for enhancing AI understanding and decision-making efficacy in aviation environments.

Disruptive technologies such as AI and ML can revolutionize our understanding by augmenting human cognitive processes and redefining products, services, and value propositions. These advancements can significantly influence the aviation industry by enhancing decision-making capabilities and operational efficiency.

Fig. 10 illustrates the conceptual framework established through a rigorous bibliometric analysis. This framework currently does not include various information system theories as explicit dimensions; however, we recognize their fundamental importance in research on AI. To substantiate and refine our proposed model, an in-depth examination of theories such as cognitive fit theory, self-efficacy, task-technology fit (TTF), and the Unified Theory of Acceptance and Use of Technology is critical for model validation. Integrating cognitive fit, self-efficacy, TTF Theory, and the unified theory of acceptance and use of technology (UTAUT) into the framework enhances its depth by addressing the technological and human-centric aspects of AI implementation in aviation. Cognitive fit theory is linked to the design of AI-driven data visualizations and predictive models, ensuring alignment with user cognitive processes for improved decision-making. Self-efficacy theory connects human factors and training components, emphasizing the importance of building user confidence in interacting with AI systems and enhancing performance and adoption. The TTF theory supports the alignment of AI tools with specific aviation tasks. This ensures that technologies such as neural networks and object detection systems are well-matched to their respective applications, leading to more operational efficiency. Finally,

UTAUT provides a comprehensive framework for understanding and promoting the acceptance of AI technologies, linking them to the decision-making and human factor domains by addressing key factors such as performance expectancy and effort expectancy, ultimately driving user adoption and effective utilization across the industry.

Fig. 10 presents the eight dimensions of literature. We show the most common facets of the aviation industry and how AI can help reorganize and evolve the industry. One of the facets of AI mentioned in this study is the impact on human factors, namely, in the new studies of SA and cognitive processes. AI can enhance SA and cognitive processes during aviation (Kabashkin et al., 2023; Tang et al., 2022). AI-based systems can improve pilot decision-making, reduce workload, and increase safety (Ramos et al., 2023; Shmelova et al., 2019). These systems assist in various aspects of flight operations, including weather updates, system management, and information retrieval (Ziakkas et al., 2022). AI can also mitigate aviation safety factors, such as pilot fatigue and adverse weather conditions (Pillai et al., 2020). Augmented cognition systems integrated with flight management systems improve pilot performance and SA (Naranji, 2015). However, the implementation of AI in aviation faces challenges such as user resistance and the need for careful consideration of human factors (Okkonen et al., 2022; Ziakkas et al., 2022). As AI technology advances, it is expected to become crucial to transition toward extended minimum crew operations (eMCO) and single pilot operations (SiPO) (Sanchez et al., 2023; Ziakkas et al., 2023). AI-driven strategies are increasingly employed to reduce emissions and noise pollution in aviation. Machine learning techniques enhance environmental impact analysis and improve fuel burns, emissions, and noise modeling accuracy (Gao and Mavris, 2022). Advanced deep learning models such as AIoT-enhanced EEMD-CEEMDAN-GCN have demonstrated superior performance in predicting air quality trends and carbon emissions (Bhatti et al., 2024). AI-powered frameworks enable noise impact estimation for novel aircraft and operations, thereby facilitating holistic environmental mitigation strategies (Synodinos, 2017). Real-time vessel routing optimization using machine learning can significantly reduce emissions in maritime operations (Molloy et al., 2023). In the aviation sector, AI and large language models have shown the potential to reduce CO₂ emissions by up to 18% per flight, while decreasing overall costs by 24% (Thatcher et al., 2024). However, it is crucial to consider the carbon footprints of AI models when evaluating their effectiveness in reducing emissions (Delanoë et al., 2023).

Airport management can be enhanced by AI-driven facial recognition, luggage scanning, and suspicious passenger behaviors. Passenger flow

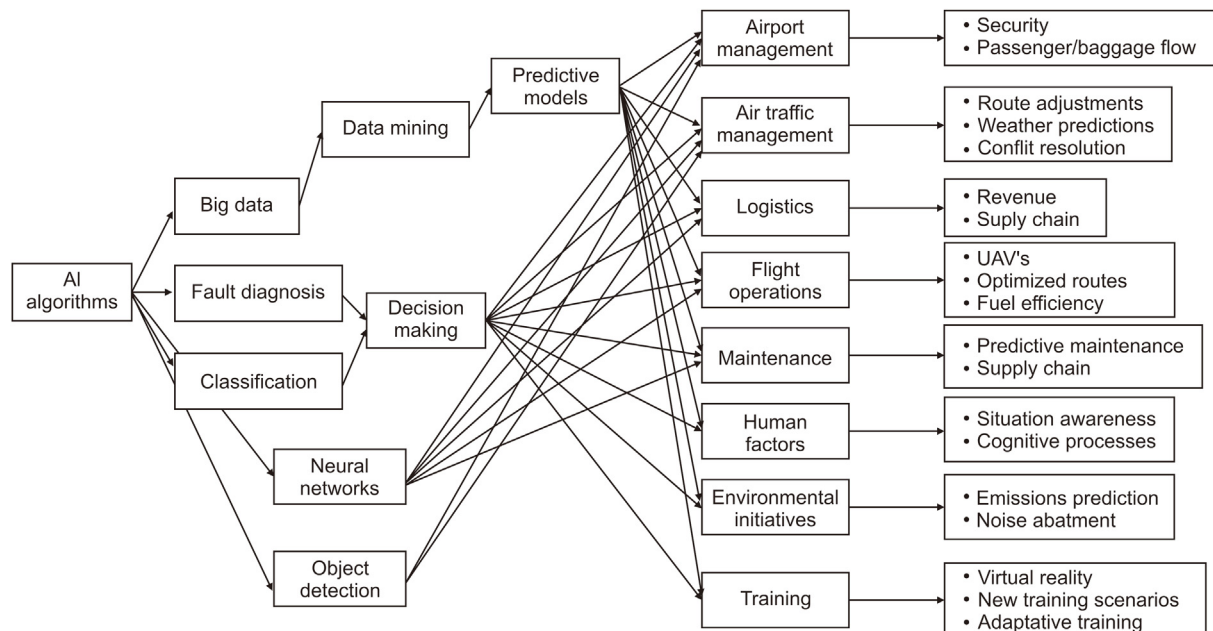


Fig. 10. Conceptual framework with eight dimensions involving artificial intelligence (AI).

analysis can improve passenger boarding and deboarding using AI-driven crowd management and prediction. Pilot training can be adapted for performance with real-time feedback and new dynamic scenarios with immersive virtual reality simulations for pilots and crew. In addition, augmented reality can help technicians enhance their hands-on experience training, thereby improving their performance and error management. Because the aviation industry relies on several supply chains, AI can analyze and predict failures and urgent needs. Flight operations can enhance unmanned aerial vehicles using AI-driven drones, virtual copilots, and fully autonomous passenger and goods transportation systems. Finally, logistics can boost dynamic price strategies by planning new passenger AI-driven seat allocation.

5. Conclusions, limitations, and future work

This study aims to delineate the research terrain of artificial intelligence (AI) in the aviation field. We used advanced bibliometric tools, namely VOSviewer, Scimago Graphica, and CiteSpace, to analyze scholarly publications from the Web of Science core database from 1990 to 2023. This analysis explores the spatiotemporal patterns, collaborative networks, foundational research, focus areas, and developing trends within this domain. We intend to ascertain the principal research themes, identify the leading nations contributing to this field, and highlight the most frequently cited studies. The results demonstrated a predominant concentration of literature on safety, training, planning, human factors, maintenance, automation, machine learning, deep learning, and genetic programming. The principal findings are summarized as follows.

The evolution of the AI and aviation literature has progressed through three phases: the initial phase (1900–2005), followed by the second phase (2006–2018), and culminating in the third phase (2018–2023). Regarding geographical distribution, China led in publications, as illustrated in Table 2, among the top ten research countries. The primary contributors to the academic landscape were the Civil Aviation University of China and the Nanjing University of Aeronautics, as shown in Table 4. Liu Yang is a prolific academic researcher at the Nanjing University of Finance and Economics in China, with 28 published articles, 1,118 citations, and an average citation index of 39.93. Key journals in the AI and aviation domains include *Lecture Notes in Artificial Intelligence*, *IEEE AIAA Digital Avionics System Conference*, and *IEEE Access*, as listed in Table 5.

Research on AI and aviation primarily focuses on conceptualizing and defining safety, training, planning, human factors, maintenance, automation, machine learning, deep learning, genetic programming, and advancing artificial intelligence frameworks. These domains represent the core areas of application highlighted in the scholarly literature. Notably, several journals were distinguished based on their significant co-citation frequencies, underscoring their prominence within this field. These include *Lecture Notes in Artificial Intelligence*, *IEEE AIAA Digital Avionics System Conference*, *IEEE Access*, *Chinese Control and Decision Conference*, and *Lecture Notes in Computer Science*. A comprehensive analysis of article counts, citation metrics, and co-citation data reveals that *Lecture Notes in Artificial Intelligence*, *IEEE AIAA Digital Avionics System Conference*, and *IEEE Access* are the leading journals in advancing the discourse on AI and aviation research.

Several pivotal areas, including information systems, machine learning, deep learning, modeling techniques, genetic programming, and the exploration of human-computer interfaces, have driven research into AI in the aviation industry. Progress in this field is characterized by two primary trajectories: investigations into big data and the design of new predictive systems. Leading-edge studies that focus on performance in terms of management strategies, model design, and system architecture are at the forefront of this evolution. The results of these studies highlight the current developmental focal points and provide insights into emerging trends. These insights can guide scholars, foster the exploration of various research themes, and promote the development of innovative concepts in the field.

The insights derived from this analysis underscore the transformative potential of AI in aviation, particularly in enhancing operational efficiency and safety. Policymakers and industry stakeholders should focus on creating collaborative frameworks to accelerate AI adoption, while ensuring that ethical considerations and human factors remain at the forefront of future developments.

Finally, we introduced a novel conceptual framework that encapsulates the eight dimensions identified in our bibliometric study. These dimensions, discerned within the analyzed papers, were systematically categorized to visualize critical aspects concerning AI within the aviation research domain. Additionally, we delineated the principal concepts and research frontiers associated with this topic through a timeline keyword analysis. This analytical approach enables new empirical studies to refine the theoretical framework of AI, particularly when considering the

ethical implications of artificial intelligence and machine learning within the aviation sector.

Our bibliometric analysis provides crucial insights into the present state and central concerns of AI in the aviation sector, highlighting key journals, scholars, and institutions. These insights, along with their theoretical implications, are instrumental in helping newcomers immediately understand the core aspects of the field. In addition, this study is crucial for advancing the discipline by identifying new research trends and directions, thereby contributing to the comprehensive evolution of AI in aviation.

The scope of the literature reviewed in this study is explicitly confined to articles focused on AI, with the analysis adopting a macroscopic approach that integrates various disciplinary perspectives. However, it is essential to acknowledge that despite attempts to maintain objectivity, the process of scientific knowledge mapping can be susceptible to reviewer biases in selecting, interpreting, and analyzing the literature.

Although this analysis centers solely on AI and aviation across multiple disciplines, it is a foundational resource. Future research could utilize meta-analytical methods that adhere to the PRISMA guidelines to systematically review AI and aviation on specific topics. Furthermore, examining human performance in the dynamically complex context of aircraft piloting requires additional research, particularly with the emergence of new trends in AI. Expanding the databases can also enhance our understanding of a discipline's knowledge structure.

CRedit authorship contribution statement

Nuno Moura Lopes: Writing – review & editing, Writing – original draft, Visualization, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Manuela Aparicio:** Validation, Supervision. **Fátima Trindade Neves:** Validation, Supervision.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

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