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Bibliometric Analysis of Studies on Artificial Intelligence in the Air Transportation Sector

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Abstract

The use of artificial intelligence is becoming widespread in almost all sectors. The air transportation sector is naturally where artificial intelligence studies are frequently carried out. In both the application process and academic studies, studies on artificial intelligence have increased significantly in recent years. It is thought that examining the studies conducted in this context will contribute to the understanding of the existing literature on artificial intelligence and help predict the trends that will emerge in the future. For these reasons, this study aims to conduct a bibliometric analysis of studies on artificial intelligence in the air transportation sector. The analysis of 1712 academic studies obtained from the Scopus database was conducted with R Bibliometix and VOSViewer software. In the study, analyses such as the authors and countries with the highest number of publications, the most influential authors and countries, the institutions that contribute the most to the studies, the most influential journals, thematic analysis, co-occurrence, co-citation, and bibliographic coupling analysis were performed. As a result of the analysis, it was determined that most of the studies are from the Asian region, and the rate of cooperation in the studies is high, but the rate of international cooperation is relatively low. On the other hand, it was revealed that the motor themes in studies on artificial intelligence are air traffic control, Unmanned Aerial Vehicle, optimization, eye tracking, and automation, while the basic themes are machine learning, deep learning, aviation safety, neural network, and situation awareness.

1. Introduction

Academic studies on artificial intelligence (AI) date back to the 1960s. The article “Bibliography on Simulation, Gaming, Artificial Intelligence, and Allied Topics” written by Shubik in 1960 and published in the Journal of the American Statistical Association provides a bibliography of topics such as simulation, gaming, and AI (Shubik, 1960). Following this study, it is seen that many studies on AI have been carried out in the literature. When the keyword “Artificial Intelligence” is searched in the Scopus database, it is seen that approximately 580,000 articles have been published. When the distribution of the published articles by year is analyzed, it can be mentioned that the number of studies on AI in 1984-1985 doubled compared to the previous years. This situation is not surprising. Indeed, the 1980s can be seen as the year when internet technology started to become widespread (Leiner et al., 1997). The fact that data silos on the Internet contain the data necessary for the processing of AI and algorithms (O'Neill et al., 2023) has led to an increase in the number of studies on AI.

In literature, it is possible to encounter very different definitions of what AI is. This is because AI has a definition specific to each field where it is used. This makes it difficult to answer the question of what AI is. If a general definition is desired; AI can be defined not as a technology or a set of technologies, but as an ever-evolving limit of emerging computing capabilities (Berente et al., 2021). In another definition, AI refers to the ability of a machine to communicate, reason, and operate independently in a human-like manner when faced with both familiar and novel situations (Du-Harpur et al., 2020). Although AI is doing great things today, humanity's expectations for AI are much higher. In the future, it seems inevitable that AI will become one of the routines of our daily lives.

AI has different applications in many sectors. However, it is very important to show them in a certain typology to understand where AI has come from. In this context, AI has become frequently used in object recognition and perception, predictive maintenance, gesture and speech recognition, robotic surgery, medical applications, military robotics, agriculture, service robotics, autonomous driving, and robotic manufacturing (Soori et al., 2023).

When the literature on AI is examined, it is seen that research has been carried out in many fields of science. Among these fields of science, it is seen that most studies are carried out in the fields of computer science, engineering, mathematics, and medical sciences, respectively (Scopus, 2024). However, in addition to these fields of science, social sciences, physics and astronomy, decision sciences, material sciences, biochemistry, genetics and molecular biology, business, management and accounting, energy, environmental sciences, arts and humanities, earth and planetary sciences, chemical engineering, economics and finance, chemistry, neuroscience, agricultural and biological sciences, health professions, psychology, pharmacy, pharmacology and toxicology, immunology and microbiology, nursing, veterinary medicine and dentistry (Scopus, 2024).

The studies carried out in the mentioned fields of science are carried out in a widespread framework that concerns human life, from measuring the academic performance of students in the field of education (Haron et al., 2025) to the use of AI for the diagnosis of cancer disease in the field of medicine (Nivedhitha et al., 2024). However, it is almost impossible not to get lost in literature since the field of study on AI is so wide and it is one of the most popular topics of the last period. In this context, it would be useful for researchers to draw a framework of how the literature has been shaped in the past, how it has developed, and where it will evolve in the future. While it is impossible to draw such a framework for all studies on AI, it is also unnecessary. Instead, drawing sector or subject-based frameworks will contribute more to the relevant research field. With this in mind, this study aims to draw a framework for studies on AI in the air transportation sector.

The air transportation sector is seen as a sector that has serious impacts on the economic and social development of countries (Raihan et al., 2024). According to the Air Transport Action Group (ATAG), the contribution of the air transportation sector to the global economy amounted to $3.5 trillion in 2019 (ATAG, 2020). That year, the air transport sector contributed to creating 11.3 million direct, 18.1 million indirect, and 13.5 million induced jobs worldwide (ATAG, 2020). On the other hand, the air transportation sector also has significant impacts on the development of other sectors. For example, the air transportation sector is closely linked to the tourism sector. Both sectors feed each other and coexist together (Bieger & Wittmer, 2006; Forsyth, 2016). While the presence of tourism destinations increases the number of airline passengers, the opening of new destinations through air transportation increases the number of tourists. According to (Putrik et al., 2022), more than half of international tourism activities are realized through air transportation. According to ATAG data, the air transportation sector has a catalytic effect on the creation of around 45 million new jobs in the tourism sector (ATAG, 2020). The fact that the air transportation sector both transports more tourists and contributes to the creation of new business areas in the field of tourism is quite remarkable in terms of economic and social development. It would be wrong to talk only about the impact of the sector on the tourism sector. The development and sustainability of international trade is also one of the positive externalities of the air transport sector. For example, although 1% of global cargo transportation is carried by air cargo, approximately 6.5 trillion dollars' worth of cargo was transported by air cargo in 2019 (ATAG, 2020). This value is equal to approximately one-third of total cargo transportation activities. The reason why the cargo volume is low, but the revenue generated is high is due to the high unit value of the products transported by air cargo. The speed benefit of air cargo also contributes to the smooth continuation of daily production (such as fast delivery of machinery and equipment). On the other hand, it is of course possible for products that can spoil quickly (flowers, food, vaccines, etc.) to take place in world markets by air cargo. As can be seen, the air transportation sector has serious social and economic impacts both globally and on the development of countries. In this context, it is thought that studies on the air transportation sector should be carefully examined.

In the air transportation sector, which is one of the leading sectors in terms of technological advances, it is not surprising that AI applications are rapidly adapted to the processes. However, the air transportation sector involves many different disciplines. While the sector is in the field of science in terms of technical issues such as aircraft production, aircraft maintenance, and air traffic management, it is in the field of social sciences in terms of airport management, airline management, and ground handling management. On the technical side, topics such as aerodynamics (Cao et al., 2014; Lynch & Khodadoust, 2001), fuel (Daggett et al., 2006), engine technology (Bewlay et al., 2016; Pollock, 2016), and materials science (Kumar & Padture, 2018; Parveez et al., 2022) are frequently studied, while on the social science side, topics such as service marketing (Marina et al., 2016; Park et al., 2020), passenger satisfaction (Bakır et al., 2022), culture (Quick, 1992; Yayla-Kullu et al., 2015) are frequently studied. On the other hand, topics such as optimization (Deng et al., 2022; García et al., 2005), ergonomics and human factors (Arcúrio et al., 2018; Brown et al., 2023), safety (Kayhan et al., 2018; Tamasi & Demichela, 2011) and security (Bağan & Gerede, 2019; Stroeve et al., 2022), which need to be studied both technically and socially, are also frequently studied in the air transport sector. In this context, it is considered that studies on AI may have emerged under very different topics. In the light of the aforementioned, the research questions of this study are formulated as follows;

1. What is the level of development of academic AI studies for the air transportation sector?

2. Which countries and researchers focus on which topics for the concept of AI in the air transportation sector?

3. Which topics are trending in AI studies in the air transportation sector?

To answer the research questions, the study is structured as follows. Section 2 reviews previous studies on AI in the air transportation sector. Section 3 provides information on the methodology of the study, and Section 4 presents the results of the study. Finally, Section 5 discusses the findings of the study, makes predictions for future studies, and concludes the study.

2. Literature Review

A literature review was conducted to understand the studies on AI applications in the field of aviation. For a better understanding of the subject, it would be a more accurate approach to consider the studies under two headings: technical sciences and social sciences studies.

It is possible to mention that the number of studies in the field of social sciences in studies on AI in air transportation is less than the number of technical studies. However, there are still many studies in the field of social sciences in literature. For example, some studies utilize deep learning and artificial neural networks in studies carried out to prevent fraudulent practices in airline ticketing (Aras & Guvensan, 2023). In studies within the scope of social sciences, AI is mostly used to investigate passenger demand for airline companies. In the study of Srisaeng et al. (2015), artificial neural networks were used for demand forecasting for low-cost carriers, in the study of Wan et al. (2020), the long-short-term memory technique was used, and in the study of Jin et al. (2020), kernelized extreme learning machine method was used. Demand forecasts were carried out not only for airlines but also for businesses that do not exist but are expected to operate for urban air mobility (Rajendran et al., 2021). On the other hand, airports also emerge as another demand forecasting component. In the study of Koçak (2023), deep learning method was used to investigate airport passenger demand.

Another topic examined in social science studies on the use of AI in air transportation is passenger profiling. Zheng et al.'s (2016) study used deep neural networks to identify disruptive passengers, while Gu et al. (2020) study used back-propagation neural networks to identify the root causes of passengers' disruptive behavior due to airport delays. Similarly, Koshekov et al. (2021) study used deep learning for more successful passenger profiling.

Another area of use of AI is customer loyalty. While Chanpariyavatevong et al. (2021) used Bayesian networks to create customer loyalty in airline companies, Yao et al. (2022) used genetic algorithms to predict the next flights of frequent flyers. On the other hand, some studies used deep learning-supported Gated Recurrent Unit to predict airline ticket prices (Degife & Lin, 2023). Chin et al. (2023) used machine learning methods to predict no-show passengers in airline operations. Ouf (2023) used a deep learning method to improve airline service quality and increase passenger satisfaction.

Chouraqui and Doniat (2003) and Q. Li et al. (2023) used machine learning and AI applications to detect pilot errors, in other words, human factors. In another study on human factors, deep supervised active learning, artificial neural networks, and random forest models were used to determine the effect of human factors on aircraft accidents (Nogueira et al., 2023).

One of the topics addressed in AI studies in aviation is related to situational awareness. In the study of Khazab et al. (2013), multi-agent systems were examined to increase situational awareness, in the study of Kilingaru et al. (2013), a rule-based system was examined, in the study of Ramos et al. (2023), a decision support system was aimed to be developed with the Integrated Flight Advisory System (IFAS) using AI. In the study of Thatcher (2014), the use of AI to determine the situational awareness of student pilots was examined. In the study of Gomolka et al. (2022), a deep neural network approach was used with eye tracking to record and analyze the attention of pilots, and in the study of Taheri Gorji et al. (2023), machine learning was used to distinguish the cognitive workloads of pilots during the flight.

Another topic related to AI in aviation is the reporting of incidents affecting aviation safety. Accurate and unbiased reporting is critical to preventing future unsafe incidents. For example, Oza et al. (2009) developed a decision support system to classify reports of incidents affecting aviation safety and health, Wang et al. (2016) developed a concurrency network-based algorithm to increase the accuracy of classifying reports, and Abedin et al. (2010) investigated learning-based algorithms to improve reporting systems and improve labeling used in reports. Hsiao et al. (2013) used artificial neural networks to analyze safety reporting, Jin et al. (2021) and Zhang et al. (2021) used a sequential deep learning technique to classify safety incidents, and Madeira et al. (2021) used machine learning method to identify human factor categories in aircraft accident reports.

Another group of studies examined in AI studies consists of studies conducted to increase aviation safety. For example, in the study of Bareither and Luxhøj (2007), Bayesian belief networks were used to determine aircraft accident cases and accident antecedents and to increase flight safety by reducing the potential risks of certain types of accidents. In the study of Mohaghegh et al. (2009), a hybrid model was created using Bayesian belief networks and an attempt was made to determine organizational factors in aircraft maintenance activities. In the study of Xiaomei et al. (2019), a deep neural network model was used to estimate the aviation risk index, while in the study of Zhang and Mahadevan (2021), Bayesian network modeling was used to determine the causal relationships of airline accidents.

When studies on AI in air transportation are examined, it is seen that many studies have been conducted in the field of technical sciences. These studies have been carried out in a wide variety of fields. Among these fields, topics such as material production, design, engineering, aircraft maintenance, and air traffic stand out. For example, in the study of Huang et al. (2003), artificial neural networks and genetic algorithms were used in the shaping of sheet metals used in aircraft, and in the study of Qiu et al. (2016), a genetic algorithm that makes compliance estimation was used in the design of a device used to reduce vibrations. In the study of Ernst and Weigold (2021), machine learning and AI approaches were used in the design of compressor blades used in aircraft engines, and in the study of Meister et al. (2021), the use of AI applications to increase the efficiency of the production processes of composite materials used in aircraft was investigated. Similarly, Djavadifar et al. (2022) used a deep convolutional neural network model to detect boundaries and defects in composite materials. Lu et al. (2006) used artificial neural networks in helicopter design, Moon et al. (2014) a deliberate particle swarm optimization approach for the design of aircraft platforms, Morris et al. (2016) used AI to ensure the silence of Unmanned Aerial Vehicles (UAVs), Secco and Mattos (2017) artificial neural networks to predict aircraft aerodynamic coefficients, Yu et al., 2018) a particle swarm optimization algorithm was used for the development of electrohydrostatic actuators. Baklacioglu et al. (2018) used artificial neural networks and hybrid genetic algorithms to calculate the energy sustainability of business jets, Okpoti et al. (2019) a Lagrangian-based algorithm was used to design a universal electric motor for general aviation aircraft. Xu et al. (2019) used deep neural networks and reinforcement learning techniques in the development of UAVs, Jiao et al. (2023) used reinforcement learning to improve the safety and efficiency of anti-skid system, and Ghienne and Limare (2023) used machine learning to measure structural stress during flight.

Another area of use of AI in technical sciences in air transportation is related to aviation security. In the study of Singh et al. (2004), learning algorithms were used to improve x-rays used in airport screening processes, in the studies of Kim et al. (2020) and Su et al. (2023), deep learning and artificial neural networks were used to detect objects that could breach security in screening processes. In the study of Koroniotis et al. (2020), AI-supported cyber defense techniques were examined to ensure the cyber security of smart airport systems.

Another issue addressed in studies on the use of AI in air transportation is the detection of errors in air-ground communication. For example, in the study of Ragnarsdottir et al. (2006), errors in communication between pilots and Air Traffic Control (ATC) were tried to be minimized with language technology. Similarly, in the study of Guimin et al. (2018), errors in air-ground communication were tried to be eliminated with deep learning.

The field of technical sciences where most AI studies are conducted is the air traffic component. Issues such as the complex structure of air traffic, the emergence of conflicts, and the fact that the human factor is very decisive in this area lead to increased academic studies on AI in air traffic. For example, graph-based algorithms were used in the study of Li et al. (2010). In the study of Cruciol et al. (2015), multi-agent systems were used for a more successful air traffic flow. In the study of Ghoneim and Abbass (2016), the minimum separation distances between aircraft were estimated using an optimization algorithm. In the study of Cai et al. (2017), a route and time slot assignment algorithm were used, in the study of Chen et al. (2017), a chance-based model using an integer programming optimization model was used, and in the study of Xiao et al. (2018), a hybrid indirect and direct genetic algorithm was developed. Lin et al. (2019) and Liu et al. (2019) discuss trainable deep-learning methods to improve air traffic flow prediction accuracy and stability. Another topic addressed in studies on air traffic is related to conflicts. In the study of Casado and Bermúdez (2020), artificial neural networks are used to detect and resolve conflicts between aircraft during the final approach, while in the study of Tran et al. (2020), an AI digital assistant solution is proposed to contribute to the resolution of conflicts between airspace users.

AI studies also include studies on air traffic controllers. In the study of Shen and Wei (2021), deep learning methods were used to detect the fatigue of air traffic controllers, while in the study of Pham et al. (2020), machine learning techniques were used to increase the success of air traffic planning controllers. Another topic addressed in AI studies on air traffic is the reduction of air traffic complexity and the detection of anomalies. One of the topics addressed in AI studies on air traffic is the reduction of air traffic complexity and the detection of anomalies. Machine learning was used to reduce complexity in the study of Rehman (2021), and a hyperheuristic framework based on reinforcement learning was used in the study of Juntama et al. (2022). In the study of De Riberolles et al. (2022), industrial control systems based on deep learning were examined for anomaly detection, and an explainable semi-supervised deep learning model was used in the study of Memarzadeh et al. (2022). In Xu et al. (2023), Bayesian ensemble graph attention network is used to predict air traffic density, while in the study of Shijin et al. (2016), an adaptive ant colony algorithm is used to optimize air route networks. Finally, in the study of Kistan et al. (2018), the requirements, certification processes, and acceptance processes for the use of AI in air traffic systems are investigated.

Another topic addressed in studies on AI applications in aviation is the detection of terrain and obstacles on the terrain. Gandhi et al. (2006) developed a learning algorithm for obstacle detection, Zhao et al. (2017) used a mixed integer linear programming method based on hemisphere matching and horizon control, Kang et al. (2008) investigated the use of artificial neural networks for terrain detection of UAVs, and Kamiya (2010) investigated a system that detects and warns about changes in the airport environment with AI.

Another topic addressed in AI-related studies is aircraft trajectories. In the study of Fallast and Messnarz (2017), a random tree algorithm is used to automatically select the trajectory and landing area for a general aviation aircraft in the event of a pilot losing control, while in the study of Hashemi et al. (2020), deep learning techniques are investigated to predict aircraft trajectories. In the studies of Pang et al. (2021) and Zhang and Mahadevan (2020), Bayesian neural networks and Bayesian deep learning models are used for flight trajectory prediction.

One of the topics covered in AI studies in aviation is related to aircraft maintenance processes. These studies mostly focus on predicting failures or failures that have not yet occurred. For example, in the study of Weckman et al. (2006), a decision support system was designed for engine restoration, and in the study of Kong (2014), AI was used to monitor engine performance and health. In the study of Chen et al. (2016), a real-time fault detection algorithm was used to monitor rotating components in aircraft engines. In the studies of Dangut et al. (2021) and Wang et al. (2019), particle swarm optimization and machine learning were investigated for the early detection of rare failures in aircraft engine bearings, while in the study of Matuszczak et al. (2021), machine and deep learning methods were used together to determine the condition of turbofan engine components. Of course, the studies conducted are not only related to aircraft engines. For example, in the study of Brandoli et al. (2021), the use of AI for aircraft fuselage corrosion detection was investigated, and in the study of S. Li et al. (2023) used deep learning algorithms to detect damage to aircraft wings.

Another topic addressed in AI studies concerns the physical characteristics of airports and ground handling facilities. For example, in the study of Ceylan et al. (2008), neural networks were used to determine the performance and damage of airport paved areas. Similarly, in the study of Kaya et al. (2018), neural networks were used for more practical pavement calculations of airport runways. In the study of Ip et al. (2010), a multi-agent-based model was developed for the optimization of maintenance vehicles in ground handling equipment maintenance processes.

Another topic addressed in AI studies is the reduction of flight delays. In the study of Wang and Gao (2013), Bayesian networks were used to reduce the safety risks arising from flight delays. In the studies of Alla et al. (2021) and Qu et al. (2020), artificial neural networks were used to predict flight delays, while machine learning was used in the studies of Hatıpoğlu et al. (2022) and Mamdouh et al. (2023). In the study of Lui et al. (2022), the Bayesian approach was used to investigate the effect of weather conditions on arrival delays.

Among the topics examined in AI studies are studies on the optimization of airports. In the study of Weiszer et al. (2015), it is stated that using a genetic algorithm to optimize all processes at an airport makes operations more efficient. In the study of Zhang et al. (2019), a regression model based on three neural networks was created to investigate the propagation effect of flight delays at airports, and in the study of Felkel et al. (2021), airports using AI were examined to determine the arrival times of aircraft from gate to gate more accurately. In the study of Zhang et al. (2022), the machine learning method was used to prevent vehicle collisions in airport ground operations, and in the study of Chow et al. (2022), an evolutionary algorithm was used to assign gates to aircraft in airport terminal buildings. In the study of Mangortey et al. (2022), the machine learning method was used to analyze and evaluate airport operations, and Du et al. (2022) used a deep learning approach to estimate airport capacity accurately. Öztürk and Kuzucuoğlu (2016) mentioned the development of fully autonomous robots to collect objects that could cause foreign object damage (FOD) at airports. Adi et al. (2022) used convolutional neural networks to detect FODs to increase aviation safety.

Another topic addressed in AI studies is related to weather forecasting. In the study of Boneh et al. (2015), Bayesian networks were used for fog prediction activities at the airport, while in the studies of Bartok et al. (2022) and Shankar and Sahana (2023), a machine learning approach was adopted to predict visibility and fog. In the study of Herman and Schumacher (2016), a model using machine learning algorithms was designed for more accurate weather prediction around the airport, while in the study of Kaewunruen et al. (2021), the deep learning method was used for the same purpose. In the studies of Alves et al. (2023) and Kim and Lee (2021), the machine learning method was used for more accurate wind predictions. In the studies of Menegardo-Souza et al. (2022) and Muñoz-Esparza et al. (2020), a machine-learning model was used to detect turbulence during flight.

Machine learning and aircraft irregular motion algorithms were used to predict unusual weather conditions around airports by Jan and Chen (2019). Machine learning was used to detect icing areas to prevent aircraft icing Sim et al. (2018).

In AI studies, many individual studies cannot be evaluated under any group. For example, in the study of Li et al. (2017), an xor-based algorithm was developed to design a system that can take control of an aircraft in the event of a hijacking or pilots' suicidal intentions. In the study of Habler and Shabtai (2018), a long short-term memory decoder was designed to detect fake messages sent from the Automatic Dependent Surveillance-Broadcast (ADS-B) system by an attacker or a hijacked aircraft. In the study of Ko et al. (2017), heuristic algorithms were used for more efficient and effective fleet assignment and routing under carbon restrictions due to EU-ETS requirements. In the study by Singh (2018), it was stated that airline companies wanted to reduce fuel consumption due to environmental and economic concerns, and a real-coded genetic algorithm was developed to reduce fuel consumption. In the study of Baumann and Klingauf (2020), a machine-learning method was used to model aircraft fuel consumption. In another study, Zhu and Li (2021) used a deep learning method to reduce fuel consumption. In the study of Wu et al. (2022), metaheuristic algorithms were utilized for hub and spoke network design and fleet planning.

When the literature is reviewed, it is seen that studies have also been conducted on aircraft hard landings. For example, Tong et al. (2018a) developed a deep prediction model based on Long Short-Term Memory to predict aircraft hard landings. Similarly, AI was used to predict aircraft landing speed to increase flight safety, and a model based on long short-term memory was created. Tong et al. (2018b) and Puranik et al. (2020) used the supervised machine learning technique to predict aircraft critical landings, and Kong et al. (2022) used the Bayesian deep learning method for the safety assessment of hard landing problems.

AI studies have also been conducted on education topics in the aviation sector. For example, in the study of Siyaev and Jo (2021), a metaverse was created in aircraft maintenance training, and topics such as deep learning, convolutional neural networks, and machine learning were tested. Mnaoui et al. (2022) examined a machine learning method proposed for use in emergency communication training of air traffic controllers. Kabashkin et al. (2023) examined the use and teaching of AI in aviation engineering curricula. In the study of Albelo and McIntire (2023), how aviation education professionals can use and adapt AI applications in the classroom was discussed.

As can be seen, many studies on AI in aviation have been conducted. However, the literature is not limited to the ones mentioned here. With recent technological advances, the number of these studies is constantly increasing. In this context, it is thought that the studies on AI in the air transportation sector, which is one of the leading sectors in technology development, should be analyzed in depth. One of the methods that enable in-depth analysis of the literature is bibliometric analysis. Bibliometric analysis helps reveal a general perspective by evaluating all studies related to a field instead of analyzing the studies individually. On the other hand, bibliometric analysis helps to reveal the trends and effectiveness of studies in a field (Bızel, 2023). Bibliometric analyses significantly contribute to the evaluation of existing literature by enabling analyses such as performance analysis, citation and co-citation analysis, bibliographic matching, co-author analysis, and common word analysis (Karakavuz, 2023). Bibliometric analyses are more reliable because they have a strong mathematical basis, provide quantitatively accurate findings, and reduce subjectivity bias (Donthu et al., 2021). In this context, using bibliometric analysis in this study was deemed appropriate.

3. Materials and Methods

In this study, a bibliometric analysis of the studies on AI in the air transport sector published in journals indexed by Scopus between 2003 and 2023 has been conducted and the findings obtained have been quantified and visualized. Data collection and data analysis processes are explained in detail below.

3.1. Data Collection

The data within the scope of the study were obtained from the Scopus database, which is used extensively by researchers. Scopus database is preferred for bibliometric analysis in social sciences because it contains more scientific articles than Web of Science, can present a large number of data together, and is a comprehensive database (Falagas et al., 2008; Singh et al., 2021). The Scopus database was searched using the keywords 'artificial intelligence' and 'aviation' for articles published only in English and, final versions. Only articles published between 2003 and 2023 were included in the study. On the other hand, studies in Biochemistry, Genetics and Molecular Biology, Medicine, Agricultural and Biological Sciences, Nursing, Pharmacology, Toxicology and Pharmaceutics, Immunology and Microbiology, Dentistry, and Veterinary Medicine were excluded. As a result of these limitations, a total of 1824 studies were reached. 1824 articles were examined, 112 of which were not related to air transportation and were removed from the study data. In this context, 1712 articles were found to be related to air transportation. Bibliometric aspects were investigated by analyzing the number of citations, average number of citations per study, most cited studies, most productive authors and countries, collaborations between countries, most frequently used keywords, co-occurrence, co-citation, and bibliographic coupling. Figure 1 shows the design of the study. Finally, the study data consists only of articles published in Scopus between 2003 and 2023, which constitutes a limitation of this study.

3.2. Data Analysis

Bibliometric analysis is a type of analysis that considers bibliographic characteristics such as collaborations, keywords, authors, and countries to learn about social networks and structures in a field and to determine which themes emerge in studies conducted in the field (Zupic and Čater, 2015). Bibliometric analysis provides insights into the evolution of science by systematically analyzing literature (Pessin et al., 2022). To reveal bibliometric features in the study, performance analysis was performed using R bibliometrix software, followed by science mapping analysis using VOSviewer software.

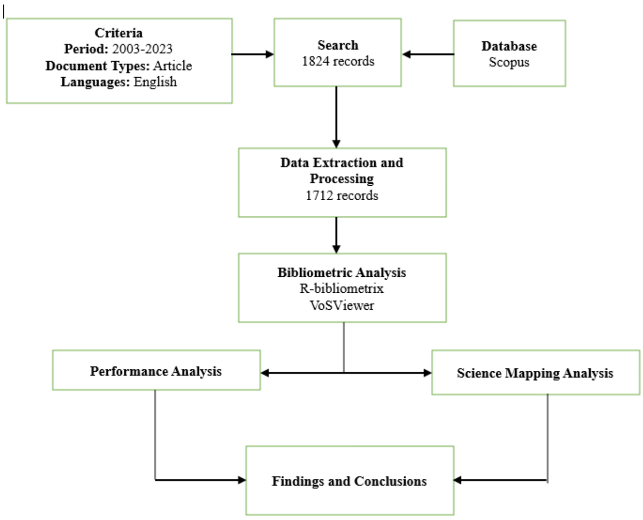

Figure 1. Bibliometric analysis flow chart.

3.2.1. Performance Analysis

Performance analysis is a type of bibliometric analysis in which quantitative data such as the amount and impact of production, authors, institutions and countries, number of citations, and the most cited publications can be obtained in a particular research area after the data are obtained (Moral-Muñoz et al., 2020). In performance analyses, authors present the quantitative information they deem necessary and valuable in their studies. In this study, the most productive authors and citation counts, most productive institutions, responsible author countries and international collaboration rates, country citation counts, word cloud analysis, and thematic analysis were carried out.

3.2.2. Science Mapping Analysis

Science mapping analysis aims to obtain an overview of scientific knowledge in a research area (Pessin et al., 2022). In other words, science mapping analysis is the graphical representation of how knowledge in a field is related in terms of countries, authors, and articles (Small, 1999). Network analysis is at the heart of scientific mapping analysis. Network analysis allows us to perform statistical analysis on the maps created to show different measurements of the whole network, measurements of relationships, or the overlap of different clusters (Aria and Cuccurullo, 2017). In this study, co-occurrence, co-citation, and bibliographic coupling analyses from scientific mapping analyses were performed.

4. Results

4.1. Results of Performance Analysis

In this study, bibliometric analysis of studies on AI applications in the air transportation sector published in journals scanned in the Scopus database was carried out. The data covers studies published between 2003 and 2023. Analyses were conducted on a total of 1712 articles. Table 1 shows the descriptive statistics of the published studies.

As seen in Table 1, 1712 articles were published in a total of 724 journals. While the annual growth rate of publications is 20.57%, the average age of documents is 5.12 years. While the authors used a total of 5259 keywords in their studies, the number of keyword plus determined by Scopus is 11097. Out of 1712 articles, only 94 articles have a single author. This shows that the rate of collaboration in AI studies is high. The author collaboration rate per document is 3.9. The international co-authorship rate is 22.84, indicating that the international collaboration rate is relatively low.

Table 1. Descriptive statistics for bibliometric data

Description	Results
Main Information About Data	
Timespan	2003:2023
Sources (Journals)	724
Documents	1712
Annual Growth Rate %	20.57
Document Average Age	5.12
Average Citations Per Doc	18.48
Document Contents	
Keywords Plus	11097
Author's Keywords	5259
Authors	4812
Authors of Single-Authored Docs	89
Authors Collaboration	
Single-Authored Docs	94
Co-Authors Per Doc	3.9
International Co-Authorships %	22.84

Figure 1 shows the historical development of scientific studies in literature. Accordingly, studies on AI in air transportation grew with a relatively small momentum between 2003 and 2017 but gained great momentum after 2017. The average number of citations per publication increased significantly in 2007, but this increase was not sustained in the following years.

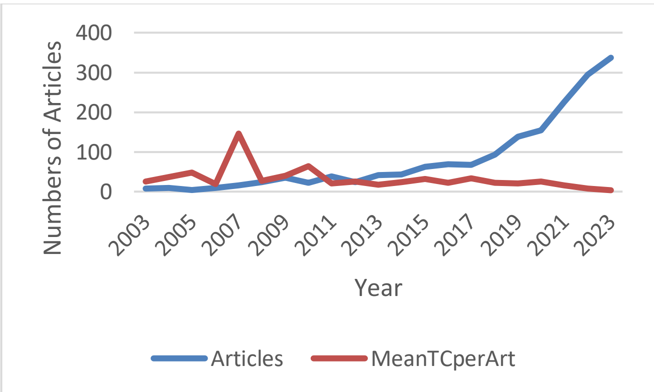

Figure 1. Number of publications and mean total citations by year

At the heart of progress in a scientific field are the authors of scientific production, who provide a better understanding of the boundaries of the scientific field Bakır et al. (2022). In this context, it is important to identify the most productive authors within the scope of performance analysis. The results of the analysis of the top 10 most productive authors are shown in Table 2.

As seen in Table 2, Zhang X is the most productive author in terms of the number of publications (A:31), number of citations (TC:726), and number of citations per article (TC/A:23,41). In terms of h-index, the most productive author is Zhang J with 13 publications receiving at least 13 citations. Considering the countries of the authors with the highest number of publications on AI in the air transportation sector, there are only 13 authors from outside Asian countries in the top 100. Of the 887 publications in the top 100, 800 were made by Asian authors. Therefore, it can be said that the Asian region is of great importance in the development of studies on AI in the air transportation sector. Lotka's Law analysis describes scientific productivity and the relationship between authors and the number of their articles by estimating an author's contribution to a publication (Kushairi and Ahmi, 2021). When the author productivity is analyzed with Lotka's law analysis, there are 3985 authors contributing to only 1 document, 464 authors contributing to 2 documents, 185 authors contributing to 3 documents, 72 authors contributing to 4 documents, 32 authors contributing to 5 documents, 21 authors contributing to 6 documents, 18 authors contributing to 7 documents, 3 authors contributing to 8 documents, 7 authors contributing to 9 documents, and 3 authors contributing to 10 documents. In other words, it can be said that most of the authors are involved in only one document.

Table 2. Most productive authors

Authors	A	TC	TC/A	h-index
Zhang X	31	726	23,41	12
Zhang J	30	626	20,86	13
Liu Y	27	410	15,18	10
Li J	25	295	11,8	9
Wang J	25	273	10,92	8
Li Y	23	290	12,6	9
Zhang Y	23	241	10,47	11
Wang Y	22	473	21,5	8
Chen H	20	224	11,2	8
Li X	20	182	9,1	6

TC: Total Citations, A: Articles
The ranking was made based on the number of publications.

Another analysis conducted within the scope of performance analyses is related to the organizations that most support AI efforts in air transport. Table 3 shows the top 10 organizations that support AI in air transport the most. As seen in Table 3, the organizations that support AI in air transportation the most are the organizations in China. While 302 of the 376 studies in the top 10 are supported by Chinese organizations, 27 are supported by British and 47 by American organizations.

Table 3. Most productive institutions

Institutions	Articles
Beihang University (China)	73
Nanjing University of Aeronautics and Astronautics (China)	73
Civil Aviation University Of China (China)	53
Civil Aviation Flight University Of China (China)	32
Cranfield University (UK)	27
Northwestern Polytechnical University (China)	25
Purdue University (USA)	24
Shanghai Jiao Tong University (China)	23
Sichuan University (China)	23
University of California (USA)	23

Another issue examined within the scope of performance analysis is international cooperation. The results of the analysis conducted in the context of the responsible author's countries are shown in Table 4. As seen in Table 4, although China is the country with the highest number of publications (A:428) and a quarter of all publications, the country with the highest international cooperation is France (MCP%: 38.9). The second country with the highest international collaboration rate is Australia with 38.1%. However, France and Australia represent only 4.6% of all publications.

Table 4. Corresponding author countries and international collaborations

Country	A	SCP	MCP	Freq	MCP %
China	428	348	80	0,25	0,187
USA	222	191	31	0,13	0,14
UK	67	45	22	0,039	0,328
Germany	65	47	18	0,038	0,277
India	60	47	13	0,035	0,217
Australia	42	26	16	0,025	0,381
Italy	42	29	13	0,025	0,31
Korea	38	27	11	0,022	0,289
France	36	22	14	0,021	0,389
Canada	35	23	12	0,02	0,343

SCP: Single Country Production, MCP: Multi-Country Production, A: Articles.

Another issue addressed within the scope of performance analysis is the total number of citations received by countries. Table 5 shows the total number of citations received by the top 10 countries.

Table 5. Country citation numbers

Country	TC	AAC
USA	6634	29,90
China	4857	11,30
Germany	2418	37,20
India	1505	25,10
Italy	1359	32,40
Canada	1246	35,60
UK	963	14,40
France	842	23,40
Australia	718	17,10
S. Korea	711	18,70

AAC: Average Article Citations, TC: Total Citations

As seen in Table 5, the country with the highest number of citations (TC: 6634) is the USA, followed by China (TC: 4857). In terms of the number of publications, China (A:428) has the highest number of publications, but in terms of the number of citations, America has received more citations than Chinese publications. On the other hand, Germany (AAC: 37.2) has the highest average article citation rate. Canada (AAC: 35.6) ranks second in terms of average article citations. This may be because researchers from Germany and Canada focus on current issues, study more general topics, conduct review studies, or conduct more qualified studies. Although China ranks first in terms of the number of publications and second in terms of total citations, the reason why China ranks last among the top 10 countries in terms of average article citations may be an indication that Chinese researchers tend to focus on very specific fields.

Another analysis performed within the scope of performance analysis is the word cloud analysis created from keywords. Figure 2 shows the word cloud created from the authors' keywords. While creating the word cloud, the keywords 'aviation', 'air transportation', 'civil aviation' and 'article' were not included in the analysis, considering that these keywords would be found in every study. As seen in Figure 2, the most used keywords in studies on AI in air transportation are air traffic control, aircraft, decision making, deep learning, machine learning, artificial intelligence, aircraft accidents, risk assessment, airports, and air navigation.

Figure 2. Wordcloud

Thematic analysis was the last analysis conducted within the scope of performance analysis. Thematic analysis is one of the most powerful analyses used to show the development of a scientific field (Bakır et al., 2022). The thematic analysis creates clusters based on recurring keywords and thus provides a more objective insight (Bajaj et al., 2022). Figure 3 shows the thematic map created using the Louven algorithm.

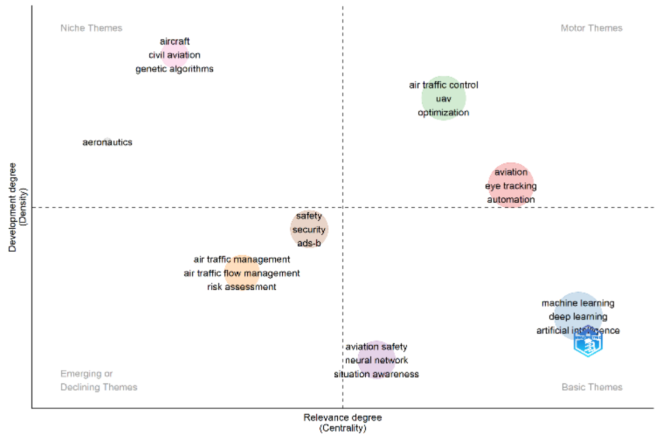

Figure 3. Thematic map

As seen in Figure 3, the motor themes (quadrant II) in AI studies in air transport are air traffic control, UAV, optimization, eye tracking, and automation. Basic themes (quadrant IV) are machine learning, deep learning, aviation safety, neural networks, and situation awareness. Emerging or declining themes (quadrant III) are safety, security, ads-b, air traffic management, air traffic flow management, and risk assessment. Finally, aircraft, genetic algorithms, and aeronautics emerged as niche themes (quadrant I). In this context, it can be said that genetic algorithms and aeronautics are more narrowly studied, while air traffic management, air traffic flow management, risk assessment, and ads-b are on the rise. On the other hand, it can be stated that machine learning, deep learning, neural networks, and situational awareness continue to be studied in AI studies from the past to the present. Finally, it can be mentioned that air traffic control, UAV and optimization, eye tracking, and automation are currently the most studied topics, and eye tracking and automation are on their way to becoming one of the main topics of the field.

4.2. Results of Science Mapping Analysis

Scientific mapping analyses are widely used in bibliometric studies (Karakavuz, 2023). In this study, co-occurrence analysis, co-citation analysis, and bibliographic coupling analysis were performed within the scope of scientific mapping analysis.

The first analysis performed within the scope of scientific mapping analyses in the study is co-occurrence analysis. Co-occurrence analysis is one of the important analyses for making inferences about scientific knowledge structures and trends in the research field Wang et al. (2020). This analysis helps to understand how researchers evolve and change in response to changes in concepts, issues, and societal trends Hassan and Duarte (2024). Figure 4 shows the co-occurrence analysis network realized within the scope of the study.

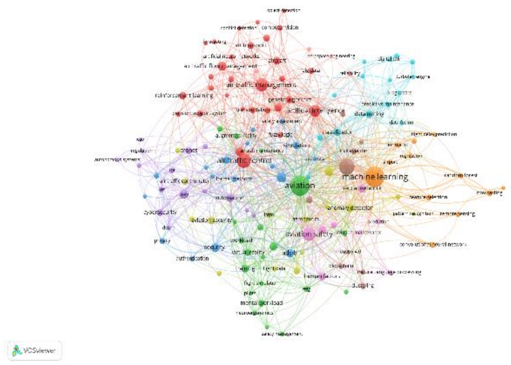

Figure 4. Co-occurrence analysis

As seen in Figure 4, ten different clusters emerged because of the co-occurrence analysis. The red cluster is the largest cluster with 30 items. In this cluster, the keywords air traffic management and air traffic control are the nodes, and topics such as prediction, conflict detection, optimization, and genetic algorithms were studied within the scope of air traffic topics. The keyword that coexists the most in this cluster is air traffic control with 53 occurrences, 36 links, and 57 total link strength. The green cluster constitutes the second largest group with 20 items. The node of this cluster is aviation, and studies were carried out on topics such as pilots, situational awareness, training, eye tracking, and attention. The most co-occurring keyword in this cluster is aviation with 100 co-occurrences, 70 links, and 137 total link strength. The third largest cluster is the blue cluster with a total of 17 items. The nodes of this cluster are risk assessment, safety, and security. This cluster focuses on safety and security issues in air-ground communication by studying topics such as identification, privacy, risk assessment, and ads-b. The keyword with the highest co-occurrence in this cluster is safety with 24 co-occurrences, 35 links, and 44 total link strength. The fourth largest cluster is the yellow cluster with a total of 15 items. The nodes of this cluster are deep learning and anomaly detection. In this cluster, topics such as collision avoidance and unmanned aerial vehicles are studied based on aviation safety and security issues. The most effective keyword of this cluster is neural networks with 20 co-occurrences, 22 links, and 29 total link strength. The fifth cluster again contains 15 items and is shown in purple. This cluster focuses on automation and regulation of drones, UAVs, and Unmanned Aircraft Systems (UAS). The most influential keyword in this cluster is UAV with 20 co-occurrences, 20 links, and a total link strength of 28. The sixth cluster again contains 15 items and is shown in light blue. The studies in this cluster mostly consist of studies on predicting the failures that may occur in aircraft maintenance. The most effective keyword of this cluster is data mining with 16 co-occurrences, 15 links, and a total link strength of 20. The seventh cluster consists of 12 items and is shown in orange. The node of this cluster is machine learning. This cluster includes studies that try to predict delays and turbulence in air traffic and airports. The most influential keyword of this cluster is machine learning with 100 co-occurrences, 59 links, and 143 total link strength. The eighth cluster consists of 9 items and is shown in brown. This cluster includes studies focused on topics such as deep learning and LTSM methods, blockchain, and aircraft maintenance. The most influential keyword of this cluster is deep learning with 67 co-occurrences, 46 links, and 81 total link strength. The ninth cluster has 8 items and is shown in pink color. The node of this cluster is aviation safety. In this cluster, there are mostly studies investigating human factors in ensuring aviation safety. The most influential keyword of this cluster is aviation safety with 48 co-occurrences, 39 links, and 61 total link strength. The tenth cluster has 4 items and is shown in light red. Studies in this cluster focus on topics such as space engineering, reliability, and uncertainty. Table 6 shows the keywords included in the Co-occurence analysis.

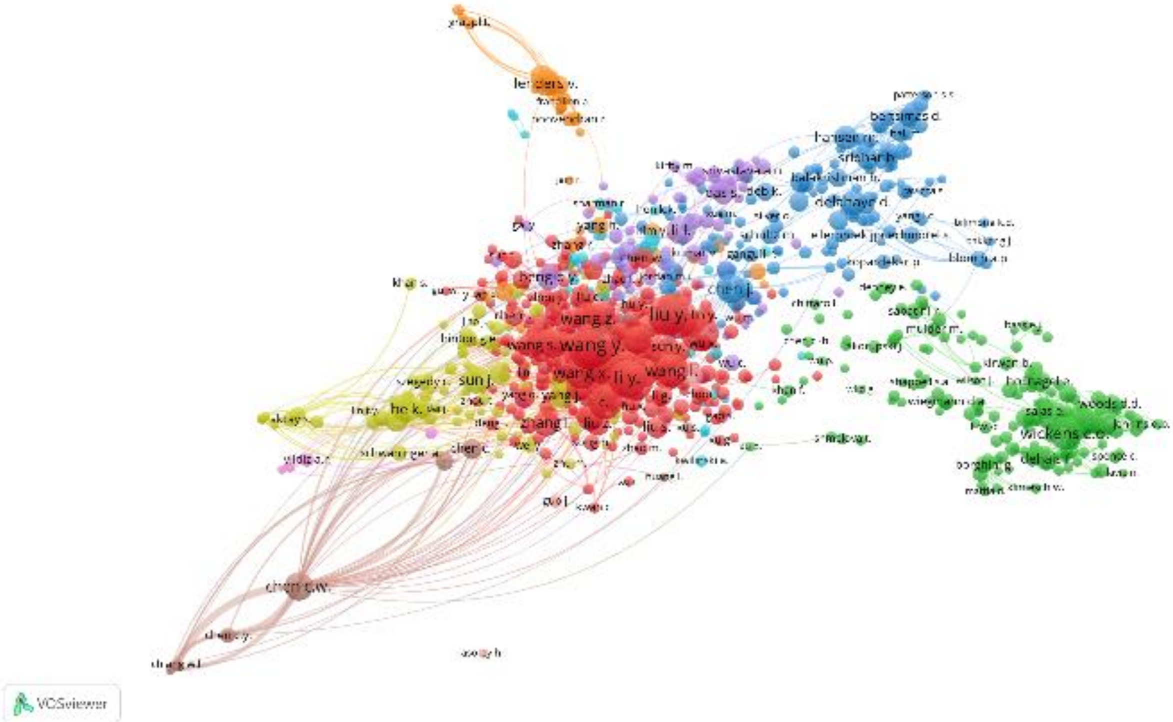

Figure 5. Co-citation analysis

As seen in Figure 5, 10 clusters emerged as a result of co-citation analysis. The first cluster is colored red, and the nodes of the cluster include authors such as Wang Y, Liu Y, Zhang H, Wang I, and Wang X. There are a total of 350 authors in this cluster. The most influential author of this cluster is Wang Y with 444 citations, 895 links, and 24196 total link strength. The second cluster is shown in green and there are 173 authors in this cluster. The nodes of this cluster include authors such as Wickens, C.D., Stanton N.A., Endsley M.R., Wiegman D.A., and Hollnagel E. The most influential author of this cluster is Wickens C. D. with 253 citations, 573 links, and 9344 total link strength. The third cluster is shown in blue color and there are 158 authors in this cluster. Authors such as Hansen M., Hansman R.J., Delahaye D., and Hwang I. are located at the nodes of this cluster. The most influential author of this cluster is Delahaye D. with 145 citations, 627 links, and 6154 total link strength. The fourth cluster is shown in yellow color and there are 100 authors in this cluster. The nodes of this cluster include authors such as Sun J., Yang J., Girshick R., He K., and Liu W. The most influential author of this cluster is Sun J. with 182 citations, 788 links, and 13049 total link strength. The fifth cluster is colored purple and contains 76 authors. The nodes of this cluster include authors such as Mahadevan S., Schmidhuber J., Hington G., Li L., Das, S., Srivastaya A.N., and Bengio Y. The most influential author in this cluster is Li L. with 188 citations, 777 links, and 8672 total link strength. The sixth cluster is shown in light blue and there are 40 authors in this cluster. The nodes of this cluster include authors such as Lee S., Kim S., Lee D., Chen F., Breiman I., and Chan P.W. The most influential author of this cluster is Breiman I. with 72 citations, 526 links, and 2321 total link strength. The seventh cluster is shown in orange and there are 33 authors in this cluster. The nodes of this cluster include authors such as Strohmeier M., Lenders V., Schafer M., and Maurer N. The most influential author of this cluster is Lenders V. with 155 citations, 410 links, and 6949 total link strength. The eighth cluster is shown in brown and there are 8 authors in this cluster. The nodes of this cluster include authors such as Chen C.W., Chen C.Y., Chen T., and Chen C. The most influential author of this cluster is Chen C. W. with 194 citations, 171 links, and 22261 total link strength. The ninth cluster is shown in pink color and there are 5 authors in this cluster. Kumar S. and Yıldız A.R. are located at the node of the cluster. The tenth and last cluster is colored in light red and there are 3 authors in this cluster.

Table 6. Co-occurrence keywords

Cluster 1 (Red)	**Cluster 2 (Green)**	**Cluster 3 (Blue)**	**Cluster 4 (Yellow)**	**Cluster 5 (Purple)**	**Cluster 6 (Light blue)**	**Cluster 7 (Orange)**	**Cluster 8 (Brown)**	**Cluster 9 (Pink)**	**Cluster 10 (Light red)**
Air traffic control	Aircraft maintenance	Ads-b	Aeronautics	AI	Artificial neural network	Air traffic	Aviation industry	Aviation maintenance	Aerospace engineering
Air traffic flow management	Attention	Authentication	Air traffic control (ATC)	Automation	Classification	Airport	Blockchain	Aviation safety	Mixed reality
Air traffic management	Augmented reality	Bayesian network	Anomaly detection	Autonomous systems	Data fusion	Convolutional neural network	Civil aviation	Human error	reliability
Air transport	Aviation	Formal methods	Aviation security	Communication	Data mining	Feature selection	Clustering	Human factors	Uncertainty
Air transportation	Education	Internet of things	Collision avoidance	Covid-19	Decision making	Flight delay prediction	Deep learning	Natural language processing	
Aircraft	EEG	Modeling	Flight data	Cybersecurity	Digital twin	Machine learning	Industry 4.0	Neural network	
Airport operations	Eye tracking	Petri nets	Flight safety	Decision-making	Fault diagnosis	Nowcasting	Long short-term memory	Prediction	
Artificial intelligence	Fatigue	Privacy	LTSM	Drone	Ontology	Random forest	Maintenance	Situation awareness	
Artificial intelligence	Flight Simulation	Risk assessment	Neural networks	Drones	Predictive maintenance	Regression	Text mining		
Artificial neural networks	Mental workload	Safety	Path planning	ICAO	Prognostics	Remote sensing			
Big data	Neuroergonomics	Safety assessment	Pattern recognition	IoT	Prognostics and health management	xgboost			
Computer vision	Pilot	Security	Performance evaluation	Regulation	Remaining useful life	Turbulence			
Conflict detection	Pilots	Simulation	Risk	Technology	Structural health monitoring				
Conflict detection and resolute	Principal component analysis	System Safety	Time series	UAS	Turbofan engine				
Decision support system	Safety management	Unmanned aerial vehicle	Unmanned aerial vehicle (UAV)	UAV	Vibration				
Decision support systems	Situational awareness	Unmanned aircraft							
Forecasting	Support vector machine	Unmanned aircraft systems							
Fuzzy logic	Training								
Genetic algorithm	Virtual reality								
Genetic algorithms	Workload								
Multi-criteria decision									
Multi-objective optimization									
Object detection									
Optimization									
Particle swarm optimization									
Reinforcement learning									
Sustainability									
Sustainable aviation									
Trajectory prediction									
Transportation									

The last analysis performed within the scope of science mapping analysis is bibliographic coupling analysis. Bibliographic coupling analysis is essentially a technique for finding conceptual similarities when citing a document (Pandey et al., 2023). In other words, if an article is included in the bibliography of two or more articles, it can be said that these articles are bibliographically merged Haghani et al. (2021). In this study, bibliographic coupling analysis was conducted based on journals. In this way, it is aimed to reveal which journals are related to each other in the field of air transportation. Figure 6 shows the bibliographic coupling analysis network.

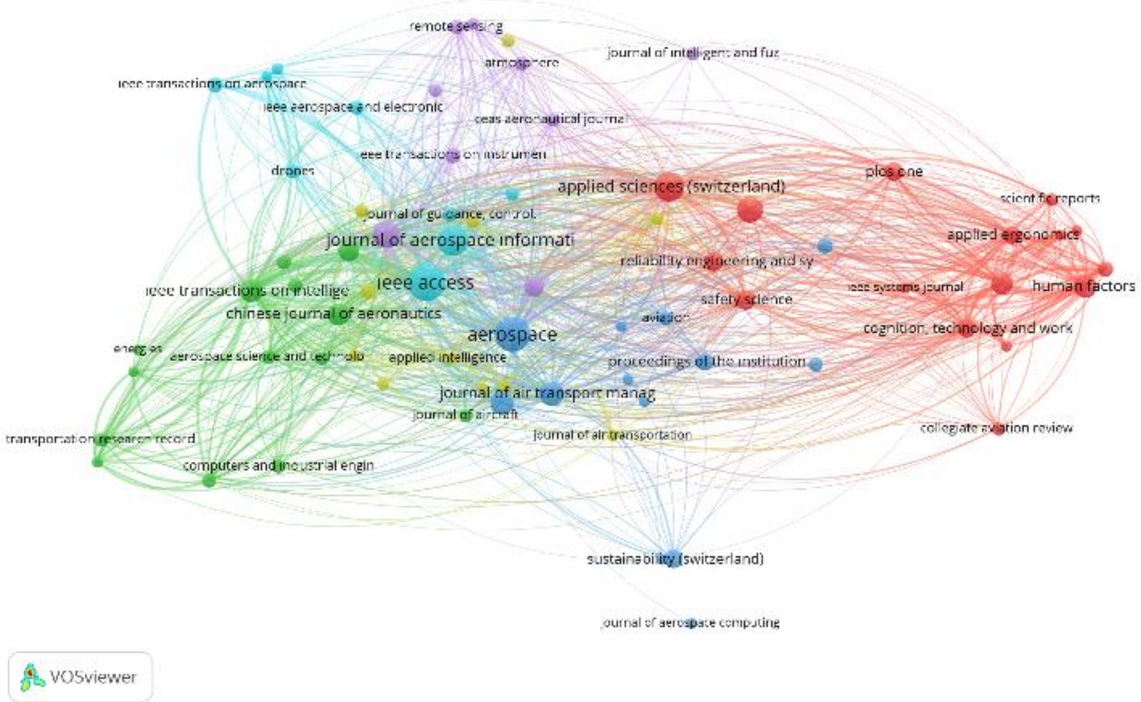

Figure 6. Bibliographic coupling analysis

As seen in Figure 6, six different clusters emerged because of bibliographic coupling analysis. The first cluster is shown in red color, and it can be mentioned that more journals in this cluster cover human factors and ergonomics topics related to AI. The most influential journal in this cluster is Applied Science (Switzerland), with 34 articles, 60 citations, and 580 total link strength. The second cluster is shown in green and it can be seen that there are more journals directly related to air transport in this cluster. The most influential journal in this cluster is IEEE Transaction on Intelligent Transportation Systems with 22 articles, 60 citations, and 881 total link strength. The third cluster is shown in blue, and it is seen that the journals in this cluster are mostly composed of journals that publish policy-oriented publications in the air transport sector. The most influential journal in this cluster is Aerospace with 50 articles, 68 citations, and 987 total link strength. The fourth cluster is shown in yellow color, and it is seen that the journals in this cluster mostly publish on engineering science. The most influential journal in this cluster is Engineering Applications of Artificial Intelligence with 9 articles, 41 citations, and 114 total link strength. The fifth cluster is shown in purple, and it is seen that the journals in this cluster publish on meteorology, applied sciences, and air transportation systems. The most influential journal in this cluster is Transportation Research Part C with 31 publications, 59 citations, and 1076 total link strength. The sixth and last cluster is shown in light blue, and it is seen that the journals in this cluster mostly publish on space sciences. The most influential journal in this cluster is IEEE Access with 54 articles, 67 citations, and 892 total link strength. On the other hand, it should also be mentioned that all clusters are interrelated. The air transportation system carries out its operations interconnected like a chain. Therefore, scientific progress or application in any field will have an impact on the entire system. Accordingly, it is quite normal for the clusters to have a strong relationship with each other.

5. Discussion and Conclusion

A review of the literature reveals that there has been a noticeable increase in studies on AI in the last five years. A similar situation can be mentioned in the studies in the air transportation sector. This situation requires knowing how, by whom, in which direction, and on which topics literature has developed. For this purpose, it is aimed to conduct a retrospective analysis of the studies on AI in the air transportation sector between 2003-2023 using the bibliometric analysis method. To achieve this goal, 1712 articles were obtained from the Scopus database, and analyses were performed on these articles. Performance analyses were performed using R biblometrix, and scientific mapping analyses were performed using VOSviewer software.

The results of the analysis show that a total of 4812 authors contributed to AI studies in air transportation in 1712 articles, 94 articles were single-authored, there was an average of 3.9 authors per document, and the international collaboration rate in these studies was 22.84%. When the studies are evaluated in terms of international cooperation, it can be said that only a quarter of them are international and the cooperation rate is relatively low. This can be considered as an indicator that the culture of cooperation in AI studies in the air transportation sector has not developed much. On the other hand, France (38.9%) and Australia (38.1%) have the highest rate of international collaboration. However, the share of these two countries in all publications is 4.6%. It is thought that the inclusion of more international collaborations in AI studies in an inherently international sector such as air transportation will contribute to increasing the benefits to be obtained. It is stated in the literature that increased collaborations increase the impact of the publication and the likelihood of citation (Glänzel et al., 1999) and facilitate joint learning (Laal et al., 2013).

As a result of the analysis, it was revealed that the studies on AI in the air transportation sector have accelerated after 2017. Of the 1712 articles in the analyzed sample, 1321

(77.16%) were published in 2017 and later. The result that the number of studies on AI has increased very rapidly after 2017 has also emerged in some studies (Yang et al., 2024). Innovations and developments in the field of computers and technology can be considered as the main reason for this. On the other hand, the use of AI applications in areas such as business, economy, agriculture, social development, medical sciences, unmanned driving, intelligent assistants, human resources, purchase intention prediction, and IoT also causes the number of academic studies to increase (Yang et al., 2024).

As a result of the analysis, it is seen that Zhang X. (A: 31, TC: 726) is the author who contributed the most to the field. Zhang J. (A: 30, TC: 626) ranked second and Liu Y. (A: 27, TC: 410) ranked third. On the other hand, when the countries that contributed the most to the field were examined, it was found that 25% of all publications were produced by China, the second place was the USA (13%) and the third place was the UK (3%) (see Table 2 and 3). On the other hand, when the institutions that support AI studies are examined, it is seen that 7 of the top 10 institutions are Chinese institutions (see Table 3). As can be seen, Chinese publications dominate the field both in terms of countries and authors. In many studies, it is mentioned that China is on its way to becoming a technology and science superpower (Wang and Feng, 2024). Some of China's policies in the last quarter century have led to an increase in the number and quality of academic publications. Some of these policies include the requirement for Chinese researchers to publish in the Science Citation Index or Social Science Citation Index to obtain a PhD degree, the possibility for researchers who have gone to developed countries to return to their home countries and work in both academic and practitioner positions, the sharing of knowledge with the people they work with, and the Chinese government's allocation of more resources to research and development activities (Karakavuz, 2023). With these policies, the pressure on Chinese researchers is increased and hence there is a noticeable increase in the number of academic publications.

As a result of the analysis, it was revealed that the topics that have been studied in the field for a long time and can be described as basic themes are machine learning, deep learning, neural networks, and situational awareness. In other words, it would not be wrong to say that the first academic studies on AI in aviation were carried out to increase or detect the situational awareness of aviation employees, and to say that machine learning, artificial neural networks, and deep learning methods are used to achieve this purpose. The current most studied topics (motor themes) are air traffic control, UAV, eye tracking, and automation. With the progress of the area, it is seen that AI studies in aviation are shifting to issues such as air traffic systems, UAVs and automation. One of the most popular issues of today is undoubtedly UAVs. UAVs are used in cargo transportation, military aviation, passenger transportation, agricultural practices and many other areas. Therefore, it is very common for the academic community to carry out studies for the development of this area. Air traffic control is an element that becomes even more apparent as the traffic volume in the airports increases. Therefore, the use of AI applications to solve the problems and difficulties within the air traffic system has been quite increasing in recent years. This is of course reflected in academic publications. One of the most studied issues in recent years is automation. In today's world, almost everything is autonomous to the electronic devices we have used in our homes. To reduce the impact of the human factor in aviation, aircraft, drones, air traffic control systems and other used equipment are tried to be autonomous in parallel with the developments in the AI field. As a matter of fact, this situation also manifests itself in academic studies. The emerging themes are safety, security, ads-b, air traffic management, air traffic flow management, and risk assessment. It can be mentioned that the use of AI has become popular to ensure the safety and security of air traffic management, to prevent data leaks and to carry out risk assessments more accurately. Finally, the niche themes are genetic algorithms and airplanes (see Fig 3). In the studies related to AI, a narrow researcher has established a connection between aircraft and genetic algorithms. This connection is thought to be established for purposes such as increasing the efficiency of the airplanes, developing safety and security issues and making aircraft autonomous.

The co-occurrence analysis, one of the science mapping analyses conducted for AI studies in air transportation, revealed 10 different clusters (see Fig 4). The largest cluster is shown in red color and this cluster, the keywords air traffic management, air traffic control, forecasting, and conflict were studied together. At the center of this cluster is the keyword air traffic control. This cluster includes studies carried out to reduce conflicts between aircraft (requesting priority, not losing the take-off-landing order, etc.) that occur during air traffic service. The second largest cluster is colored green, and in this cluster, the keywords aviation, pilots, situational awareness, and training worked together. The keyword aviation is at the center of this cluster. When the keywords in this cluster are examined, it is understood that the use of AI applications is being investigated in the training to be given to improve the situational awareness of pilots. The third largest cluster is shown in blue and the topics that worked together the most in this cluster are identification, risk assessment, safety, and ads-b. At the center of the cluster is the keyword safety. Studies on the necessity of correctly identifying risk factors to increase safety in this cluster have been examined in the context of AI.

Another science mapping analysis is co-citation analysis. In this study, co-citation analysis was performed on an author-based basis (see Fig 5). The analysis revealed 10 different clusters. The first cluster is shown in red, with Wang, Y. at the center of the cluster. The second cluster is colored green, with Wickens, C. D. at the center of the cluster. The third cluster is colored blue, with Delahaye, D. at the center of the cluster. When the co-citation analysis results are evaluated, it is seen that the authors give more citations to the authors in their geography in terms of co-citation. As stated in the study of Thelwall and Maflahi (2014), the authors read the publications from their own countries more and tend to ignore the articles from some other countries. On the other hand, in the study of Moed (2005), it is stated that the US authors give partially more citations to the articles in their own countries. Therefore, it is thought that the results in the co-citation analysis may be due to this situation. The last science mapping analysis performed was the bibliographic coupling analysis (see Fig 6). The analysis was performed based on journals. As a result of the bibliographic coupling analysis, 6 different clusters emerged. The first cluster is shown in red, and the Applied Science (Switzerland) journal is at the center of the cluster. The second cluster is colored green, and the center of this cluster is IEEE Transaction on Intelligent Transportation Systems. The third cluster is colored blue, and the center of this cluster is the journal Aerospace.

This study aims to provide an overview of the historical development of studies on AI for air transportation system and to define the structure of the research field. The main contribution of this study is to reveal the general structure of the research field and to serve as a guide for researchers who want to get acquainted with the existing literature. Through the study, researchers will be able to obtain statistical information such as the most productive authors, countries, and most cited studies in the field, and to identify gaps by monitoring the development direction of the literature.

In today's world, AI applications are no longer confined to the lab or a niche field of study but are now pervasive in every aspect of our lives. From creating communications, summarizing documents, and generating literature, to code engineering, translating languages, and synthesizing videos, AI work is emerging in every field, and the magnitude of its potential impact has caught even the most forward-thinking AI experts and technology visionaries off guard (Sellen and Horvitz, 2024). Therefore, raising awareness by comprehensively addressing past studies and existing literature will contribute to compensating for this unpreparedness, albeit to some extent. In this context, this study is expected to contribute to the understanding of existing literature to some extent. Finally, this study considers the air transportation system. In the future, separate studies on the components of the air transportation system such as airlines, airports, ground handling services, aircraft maintenance, aviation production, and air traffic control will contribute to a much clearer understanding of the effects of AI applications on the components of the sector.

Ethical approval

Not applicable.

Conflicts of Interest

The author declares that there is no conflict of interest regarding the publication of this paper.

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