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Trends and challenges of forecasting in the airline industry research

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ABSTRACT
This study aims to comprehensively review aviation forecasting research by identifying its bibliometric trends, evolving research areas, and thematic developments. It focuses on understanding the aviation industry's research gaps, highlighting emerging trends, and offering insights into future forecasting innovations. A systematic literature review in the Scopus database used Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) and bibliometric analysis. It identified key patterns, influential publications, and emerging topics. A science mapping analysis was executed to pinpoint research trends in airline forecasting using Biblioshiny to visualise the network analysis and thematic evolution keywords mapping. The study categorised research trends and identified underexplored areas for future investigation. The findings reveal significant shifts in aviation forecasting research, with three distinct phases of publication growth and a surge in output from 2016 onwards. Passenger demand forecasting remains the most researched topic, though its growth has stabilised. Emerging issues such as customer behaviour, financial forecasting, and dynamic pricing have gained prominence, driven by advancements in machine learning and big data analytics. The study also highlights transitioning from traditional statistical methods to more advanced predictive techniques, emphasising real-time decision-making and operational efficiency. Established research areas, such as air cargo forecasting and fleet scheduling, have become more standardised, reducing the need for further innovation.

KEY WORDS
airline, forecasting, bibliometric analysis, PRISMA

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Introduction

The airline industry is currently experiencing substantial growth in travel demand. International Air Transport Association (IATA) reports an annual compound average growth rate of approx. 3.7%. Projections indicate that by 2035, the global number of travellers is expected to soar to around 7.2 billion, nearly doubling the number of passengers recorded in 2016 (IATA, 2016). The aviation industry can address this projected growth by leveraging accurate forecasting across all operational and strategic levels. This remarkable increase in demand presents a significant

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challenge for the airline industry, as it requires precise forecasting to manage and optimise revenue expectations effectively.

Forecasting is fundamental to decision-making (Winkowski, 2019) and is critical across various aviation sectors. Accurate travel demand information is important for transportation systems, especially for the airline industry (Samli et al., 2021). In airline operations, accurate forecasting is essential for determining optimal flight frequencies, route allocations, and seat capacities to avoid overcapacity or shortages, thereby maximising load factors and improving overall profitability (Wang & Gao, 2021). Short-term decisions, such as flight schedules, pricing strategies, marketing campaigns, and crew rostering, rely heavily on demand forecasts. Long-term strategic planning, including fleet acquisition, emission, workforce allocation, resource investment, and network expansion, also depends on demand projections. Airport operators use demand forecasting as the foundation of airport master plans, which guide infrastructure expansion and significant capital investments to ensure sufficient capacity and operational efficiency (Sulistyowati et al., 2018). Policymakers rely on demand estimates to allocate budgets for air transportation and related sectors, while the aerospace industry depends on accurate forecasts for developing and manufacturing aircraft, engines, and components. Moreover, demand forecasts are critical in determining the stock market performance of airlines (Caiado & Lúcio, 2023), as investors and stakeholders closely monitor demand trends to assess airline companies' financial health and future profitability. Local communities also benefit from accurate air travel forecasts, as these estimates determine air transportation networks and regional connectivity.

Numerous research efforts have been devoted to addressing forecasting-related challenges in the aviation industry. Key areas of focus include predicting and mitigating flight delays (Li et al., 2023), optimising flight routing paths, addressing the impacts of weather and climate change, and improving spare parts inventory management and maintenance strategies to reduce operational disruptions. The growing emphasis on environmental sustainability has led researchers to explore demand forecasting for CO2 emissions reduction in the aviation sector (Huang et al., 2023).

Airlines were compelled to adopt new adaptive and robust revenue management strategies that continuously monitored key metrics to respond dynamically to market fluctuations (Vinod, 2022). These adjustments underscored the importance of incorporating flexible forecasting models that can adapt to sudden disruptions and evolving market conditions. Methods relying solely on historical data without traditional demand forecasting and optimisation have also been proposed to enhance forecasting accuracy in highly uncertain environments (van Ryzin & McGill, 2000).

Forecasting became incredibly challenging during the COVID-19 pandemic, as sudden disruptions rendered historical demand patterns less meaningful and necessitated new forecasting approaches. Studies have explored passenger demand variations across segments during the pandemic (Li et al., 2023) and the recovery of airfreight operations using time series analysis (İnan, 2022). Furthermore, Caiado and Lúcio (2023) proposed clustering methods to compare financial time series and analyse the pandemic's impact on the US stock market. Wang et al. (2020) studied predictors for international stock markets during the spread of COVID-19, while Ye et al. (2023) analysed the pandemic's impact on the airline industry. Their findings highlighted the importance of workforce planning and human resource management in adapting to the industry's disruptions.

Given the critical role of forecasting and the dynamic nature of the aviation industry, systematic reviews of relevant studies have become meaningful and necessary. Over the past decades, several significant efforts have been made to review and summarise advancements in this field to provide insights into effective forecasting practices and future research opportunities. Based on Zachariah et al. (2023), forecasting future demand for the aviation industry is critical, as it relies on a thorough understanding of various demand determinants. They also conducted a notable study evaluating aviation demand research and assessing the effectiveness of various forecasting techniques, providing valuable insights into the evolving landscape of demand modelling. Wang et al. (2022) provided a detailed review of the flight operation process, identifying flight delays as the most critical irregular flight issue. Their findings highlighted that delays are primarily caused by severe weather and other factors such as airline planning, air traffic control, airspace flow restrictions, and military activities, which also contribute to the problem.

Although extensive studies have been conducted, certain emerging and evolving areas in aviation forecasting remain underexplored. Addressing these gaps is the primary motivation for this literature review, which employs a bibliometric analysis to uncover key trends and research opportunities. This work highlights key focus areas for airline managers to gain a competitive advantage by concentrating on emerging research trends. For areas where research is becoming less relevant or more standardised, practitioners can focus on applying established best practices to maintain operational efficiency and optimise decision-making. This study aims to provide a holistic view of forecasting research in the aviation industry, with specific contributions as outlined below:

- RQ1: Identifying bibliometric research trends and global focus in forecasting or prediction in the aviation industry.
- RQ2: Evolving research areas and trends in the field of airline forecasting.
- RQ3: Thematic evolution and keyword shifts using co-citation analysis.
- RQ4: Topic mapping and emerging directions in aviation forecasting

The following chapters explore the identified challenges and trends in aviation demand forecasting, offering detailed bibliometric analysis and highlighting emerging research themes for future exploration. Chapter 1 examines the topics within the context of airline forecasting. Chapter 2 explains the methodology used for bibliometric analysis. Chapter 3 presents the findings from the bibliometric analysis, and the final chapter discusses the results and provides the conclusions.

1. Literature review

Forecasting presents a major challenge in the aviation industry and relies on accurate demand predictions. Moreover, revenue management (RM) depends on classifying demand based on historical demand patterns and consumer behaviour (Selçuk & Avşar, 2019). An essential focus within this industry is modelling demand over the sales horizon, spanning studies of air transport demand at international, regional, national, intercity, and airport levels (Zachariah et al., 2023). Over recent years, the collaborative efforts of academic researchers and industry professionals have significantly propelled advancements in aviation forecasting. Many studies have been conducted employing linear and nonlinear models to predict passenger and cargo demand, with some even delving into the intriguing realm of demand prediction based on customer sentiment (Iddrisu et al., 2023).

Numerous studies in the aviation sector have focused on forecasting and predictive analysis, covering aspects such as passenger and cargo demand, flight delays, weather and climate change, route adjustments, maintenance, spare parts management, emissions, and fuel consumption. These critical areas of research can generally be categorised into several key domains.

The most prominent key domain is in forecasting demand for passengers. The demand for air travel continues to rise, accompanied by dynamic changes in passenger preferences, making forecasting an exceptional challenge for the aviation industry. Consequently, commercial aviation heavily relies on reliable travel demand predictions (Zachariah et al., 2023). A comprehensive assessment has been conducted concerning the prediction of passenger demand (Zachariah et al., 2023; Banerjee et al., 2020; Wang & Gao, 2021), including ticket pricing (Abdella et al., 2021). The use of demand forecasting is leveraged by airlines and airports for capacity planning, such as predicting passenger connectivity (Guimarães et al., 2022), determining airport infrastructure needs (Nieto & Carmona-Benítez, 2021), forecasting cargo space in combination carriers (Tseremoglou et al., 2022), and personalised customer experiences by considering customer behaviour (Sznajder et al., 2023). As Zachariah et al. (2023) summarised, the methods used in demand forecasting include econometric, statistical, machine learning, artificial intelligence, and hybrid models. Additionally, many studies have compared statistical methods with machine learning approaches, such as the research by FAN et al. (2023), which compared time series forecasting methods with machine learning, assessing forecast accuracy through RMSE error values.

Following demand forecasting, flight delay prediction has emerged as the second most extensively studied area. This prominence is due to the significant impact that flight delays have on both operational efficiency and passenger satisfaction. Various factors, including severe weather conditions, air traffic control issues, airline scheduling problems, military activities, and other reasons, typically cause flight delays (Wang et al., 2022). Besides, flight delays can affect many factors, such as operational efficiency and airline service quality (Wang & Pan, 2022). The complexity of these factors necessitates the use of advanced predictive models. Wang et al. (2022) categorised flight delay prediction methods into traditional statistical analysis, simulation modelling and queuing theory, and machine learning methods. Conventional statistical analysis methods are usually used to predict data trends and characteristics. The methods used for flight delay predictions include time series, regression models, and correlation analysis. Several studies discussing time series were conducted by Wang et al. (2019), which addressed the flight delay situation by using time delay stability.

The flight delay prediction method based on simulation uses operations research to analyse, calculate the model, evaluate the results, and compare the appropriate case to achieve better predictions (Tascón & Díaz Olariaga, 2021; Lee et al., 2020). Flight delays have become increasingly prevalent, and forecasting related to climate change to meet the needs of airlines and issues associated with global warming and carbon emissions generated by aircraft (Oguntona, 2020). The machine learning method is based on artificial intelligence derived from a large amount of flight data. Several machine learning techniques include decision trees (Kang et al., 2021), Bayesian networks (Yang et al., 2023), random forests (Tang, 2021), k-nearest neighbours, support vectors, and deep learning.

Another airline forecasting topic is that contemporary climate science and weather forecasting studies increasingly integrate advanced computational techniques to address complex environmental challenges. Several studies focus on utilising machine learning and AI techniques (Choi et al., 2016), such as random forests, to improve the accuracy of weather predictions (Williams, 2014). This weather forecasting includes applications in wind forecasting and predicting exhaust gas temperature margins in aero-engines using transfer learning techniques (YAN et al., 2022). Additionally, significant attention is being given to developing data-driven models for wind forecasting and the prediction of thunderstorms, which are critical for improving the safety and efficiency of air travel (Andrés et al., 2021). The airline industry operates in a much more complex environment, which became especially true during the COVID-19 and post-COVID era, where passenger and cargo markets have gained significance. The situation resulted in numerous disruptions and uncertainties. COVID-19 has disrupted societies and economies worldwide, with the aviation sector experiencing one of the most catastrophic impacts (Suau-Sanchez et al., 2020). The COVID-19 pandemic caused a drastic drop in passenger air transport demand due to two forces: supply restriction and demand depression. Li et al. (2023) proposed a method separating the two COVID-19 forces and evaluating the respective impact on demand. It involves dividing passengers into segments based on passenger characteristics, simulating different scenarios, and predicting demand for each passenger segment in each scenario.

2. Research methods

This research uses a bibliometric analysis to assess the evolving interest in this topic, focusing on the number of publications during the specified period. The study was based on data retrieved from the Scopus database, which is more comprehensive, encompasses the most extensive peer-reviewed data, and is widely used in several bibliometric analyses (Asif et al., 2020). It identified the use of forecasting in the airline industry and the methods employed. Subsequently, Biblioshiny was used to create a classification of research subareas and developed to visualise the network analysis and the thematic evolution of keyword mapping. The Scopus database was used because it is recognised as the most extensive repository of abstracts and references from peer-reviewed literature (Pérez-Acebo et al., 2018). The ensuing section provides details regarding the specific database employed in this investigation.

- Database: Scopus
- Period of data: 1964 to 2023

This study involved a comprehensive literature assessment that adopts the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA) methodology. This approach allows for identifying and evaluating the most relevant and appropriate research through several criteria (Rahman et al., 2023). Fig. 1 established a knowledge base on forecasting in the airline industry. The methodology comprises the following steps:

1. Defining the search criteria. This step involves selecting keywords. While investigating the Scopus database, specific keyword strings were utilised to ensure the inclusion of all relevant publications, including “forecast” OR “forecasting” in conjunction with “airline”, OR “predict”, “demand”, AND “airline”.
2. Search and screening. The second phase entailed the quest for documents to scrutinise. Initially, 1465 documents were found. Subsequently, a language restriction was applied to focus on English. Several criteria for exclusion and inclusion were used to refine the selection and achieve a final set of articles meeting the study’s parameters. These articles were further assessed and chosen based on their relevance to the study’s objectives, incorporating keywords, abstracts, titles, and source type considerations.
3. Publication information processing. This step identified articles related to the author’s name, journal, and title to determine the presence of any duplications.
4. Document characteristics analysis. The study involved analysing information extracted from 820

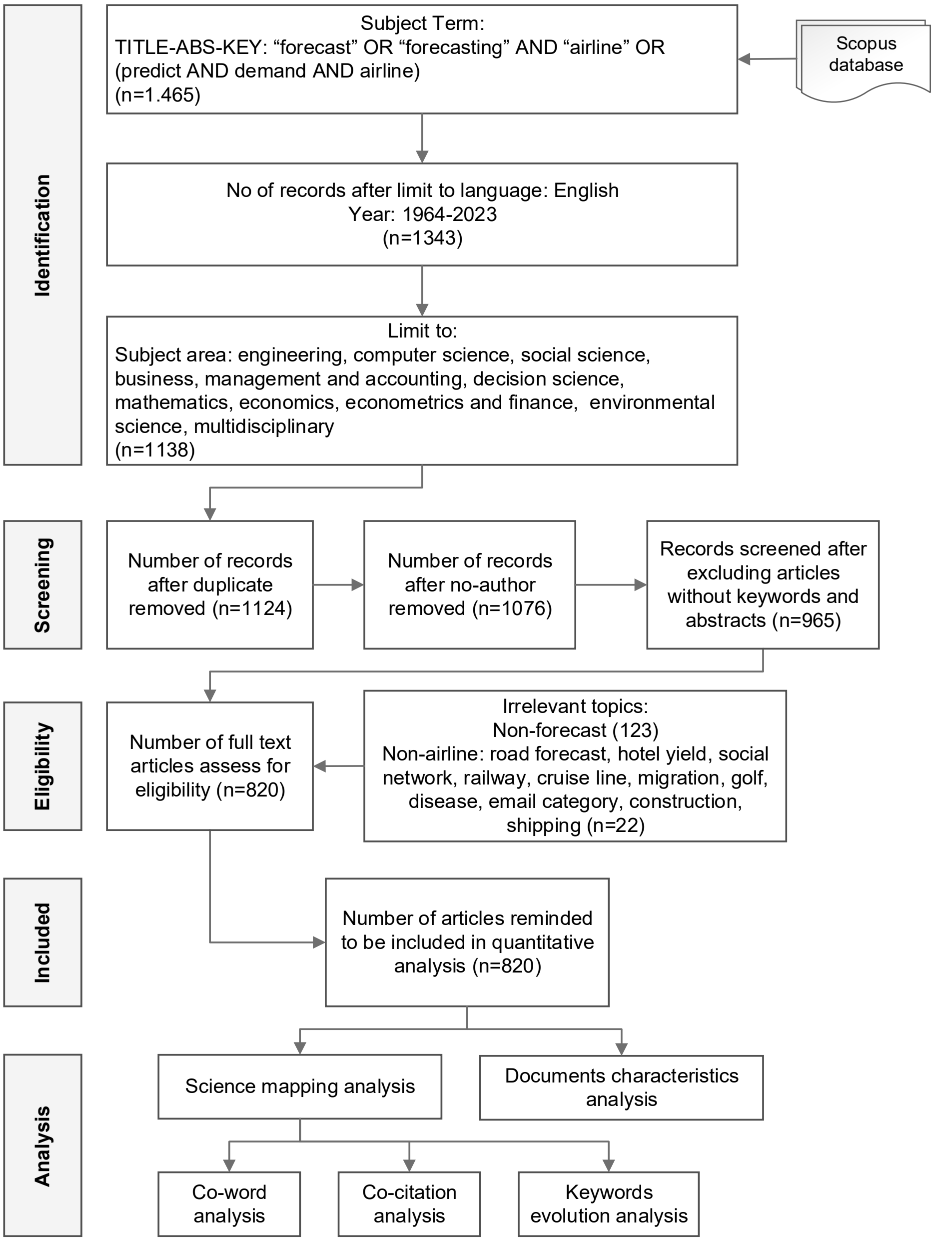

Fig. 1. Framework of the review paper

publications indexed in Scopus. Descriptive statistics were employed to conduct trend analyses of growth.

5. Scientific mapping analysis. In this step, the database was examined using various software tools. Biblioshiny was employed to analyse the network of keywords and authors and create thematic and keyword evolution maps.

6. A quantitative review of airline forecast and prediction. A quantitative analysis focused on numerous studies addressing various aspects of airline forecasting and prediction. Through this analysis, emerging subjects were identified, and the research requirements for the future of this field were charted.

3. Research results

3.1. RQ1: Bibliometric trends and global research focus

The bibliometric analysis encompasses 820 documents recorded from 1964 to 2023, providing an overview of the distribution of scientific publications identified in Scopus. The annual production of publications (Fig. 2) indicates three distinct phases. The first phase (1964–2000) had a consistent output of one to two publications annually. The second phase

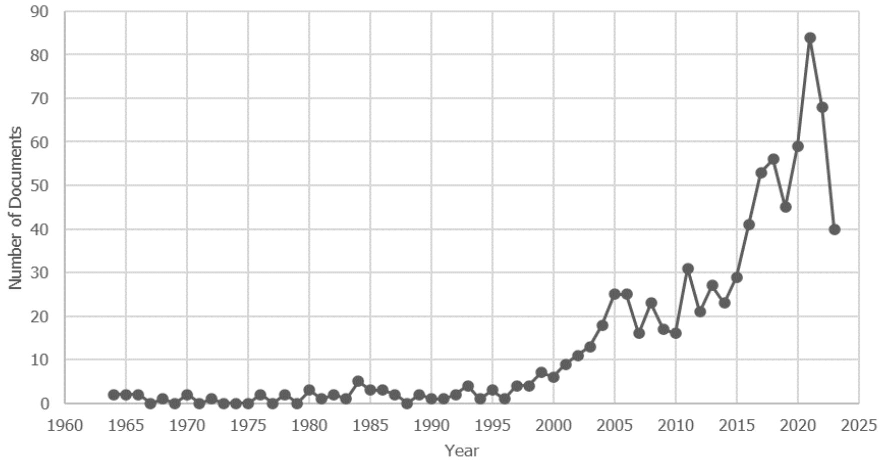

Fig. 2. Total publications per year

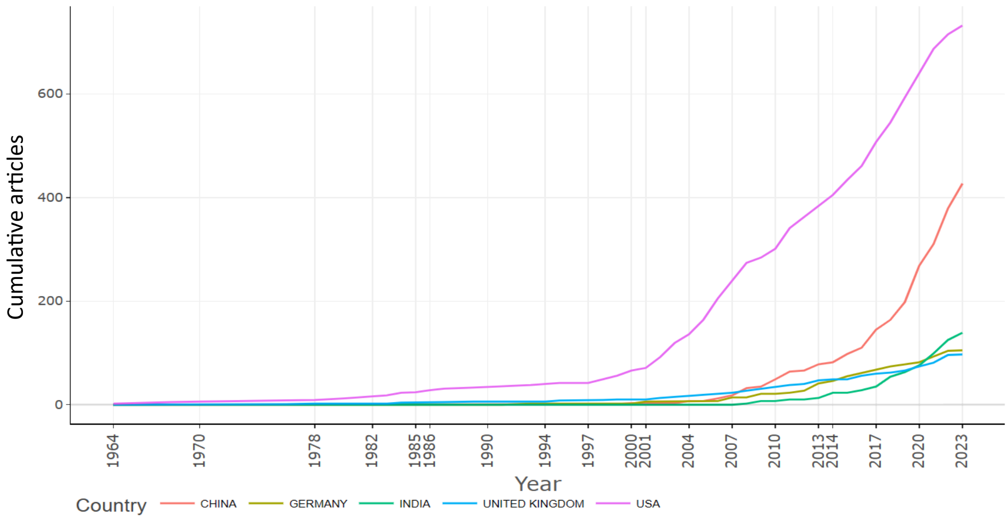

Fig. 3. Patterns of cumulative papers published in the six most productive countries

Tab. 1. Ten most globally cited documents

Most cited document	Publication year	Average citation per year	Total citations
(Colizza et al., 2006)	2006	45.78	824
(Gui et al., 2020)	2020	42.75	171
(Gudmundsson Et Al., 2021)	2021	34.67	104
(McGill & Van Ryzin, 1999)	1999	31.44	786
(Baptista et al., 2018)	2018	27.83	167
(Lamb et al., 2020)	2020	22.25	89
(Hadavandi et al., 2010)	2010	21.14	300
(Liu et al., 2021)	2021	21.33	64
(Elsaid et al., 2018)	2018	16.50	99
(Zhang & Graham, 2020)	2020	16.25	65

(2001–2015) saw a moderate increase, averaging 20 publications annually. The final phase (2016–2023) demonstrated significant growth, averaging 55 publications annually, reflecting an increased academic focus on aviation forecasting.

In the early 2000s, the USA led aviation research, primarily focusing on forecasting passenger demand (32% of studies). Flight delay prediction (15%) and weather (11%) were the second and third most prominent topics, respectively. In 2006, research on flight delays increased, while studies on economic issues declined. In China, aviation forecasting research experienced a steady upward trend starting in 2007. The topics most studied in China were flight delays (24%), passenger demand (19%), and spare parts (11%). Research on spare parts emerged in 2016, and studies on flight delays began in 2011. These trends are visually represented in Fig. 3, highlighting the topic distribution by country over time.

The top ten highly cited publications and authors on airline forecasting are listed in Table 1. The most frequently cited study is by Colizza et al. (2006), which models the global spread of diseases through large-scale airport networks using a stochastic computational framework. This framework incorporates the international air transportation network and population data to evaluate outbreak scenarios and containment policies. Another highly cited publication by Gui et al. (2020) uses big data and machine learning models to predict flight delays. Their findings indicate that while the Long Short-Term Memory (LSTM) model can handle aviation data, the random forest model provides higher accuracy and is more robust against overfitting. Gudmundsson et al. (2021) explored the relationship between economic strength and the airline industry's recovery following the COVID-19 pandemic, finding a direct correlation between financial shocks and passenger or cargo traffic.

3.2. RQ2: Evolving research areas and trends

This study identified and analysed 15 distinct research areas in aviation forecasting and prediction, as summarised in Table 2. The table illustrates the distribution and evolution of research focus across five periods, from 1964 to 2023. Passenger demand forecasting consistently emerged as the most researched topic, with 241 published papers reflecting its central role in airline operations and strategy. Flight delay prediction has seen significant publication growth since 2016, ranking second with 117 papers. This increase highlights the growing importance of minimising delays to enhance operational efficiency and customer satisfaction (Wang et al., 2022; Wang & Pan, 2022). Other areas, such as traffic demand, maintenance spare parts, risk analysis, and customer behaviour, show an upward trend, indicating increased interest in optimising operational aspects through personalised services and big data. In contrast, traditional topics like aircraft and engine research have

Tab. 2. Classification by field of airline forecasting

Type of forecasting/prediction	1964-2005	2006-2010	2011-2015	2016-2020	2021-2023	Total papers
Demand passenger	55	34	55	58	39	241
Flight delay	5	9	16	54	33	117
Air traffic	10	6	6	22	19	63
Weather	16	10	9	9	11	55
Maintenance-spare part	10	5	3	16	15	49
Financial	12	6	5	8	16	47
Route	6	5	7	19	9	46
Customer behavior and competition	3	1	2	18	16	40
Price	2	1	7	15	13	38
Aircraft and engine	15	3	4	9	1	32
Fleet and scheduling	5	8	5	3	4	25
Airport capacity	6	3	2	3	4	18
Fuel and emission	1	3	1	9	4	18
Risk	0	1	5	8	4	18
Cargo	2	2	4	3	2	13

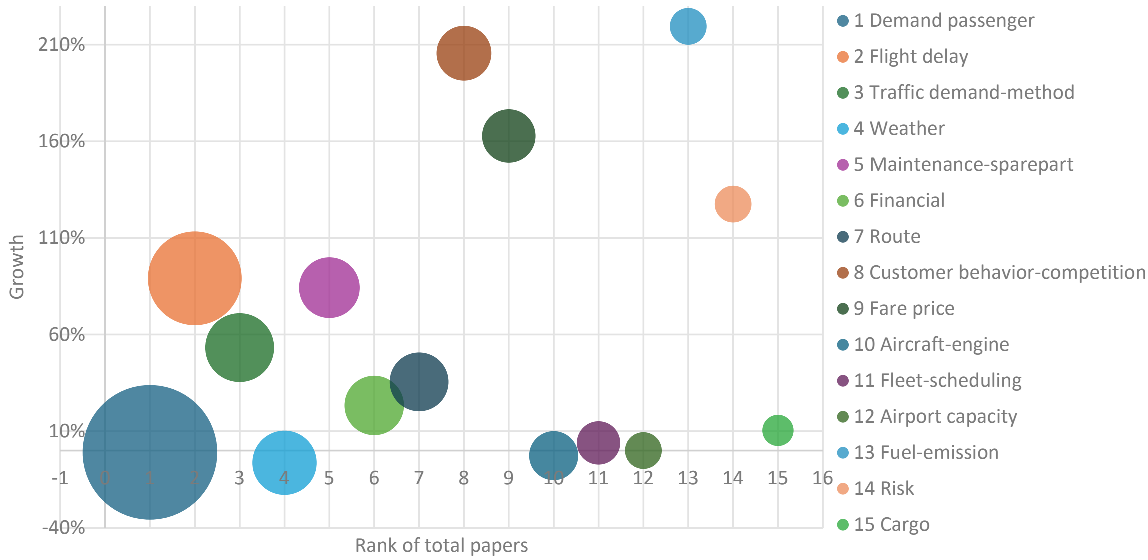

Fig. 4. Bubble chart analysis: growth vs rank of total papers

experienced a decline, suggesting advancements or shifting priorities. Fleet scheduling and airport capacity have also shown reduced publication volumes. Emerging areas, including customer behaviour, competition, and financial forecasting, have gained prominence, driven by the rise of big data and more nuanced market analysis.

Fig. 4 presents a bubble chart depicting the year-to-year growth of research publications across the 15 areas. Passenger demand forecasting ranks first in volume, as indicated by its large bubble size, but shows a low growth rate, indicating slower expansion despite its significance. Flight delay prediction ranks second and exhibits a high growth rate, signifying its rising importance. Mid-ranking topics, such as traffic demand and spare parts forecasting, display notable growth, likely due to advancements in data analytics and the need for precision in forecasting. Emerging areas, like customer behaviour, competition, and fare pricing show rapid growth, reflecting shifting academic interest. Under-researched topics, such as fuel and emissions and risk forecasting, are indicated by small bubble sizes, highlighting potential research opportunities. Traditional areas, like aircraft and engine forecasting, show minimal growth and low volume, suggesting a shift in research priorities towards emerging challenges and operational complexities.

3.3. RQ3: Thematic evolution and keyword shifts

The study collected and analysed keywords from research publications from 1964 to 2023. Keyword occurrence frequency was employed to identify the most used terms and to determine potential future research directions. The evolution of research themes over time is illustrated in Fig. 5, highlighting different thematic transformations from 1964 to 2023. The keyword "revenue management" demonstrated consistent use throughout this period. Keywords such as

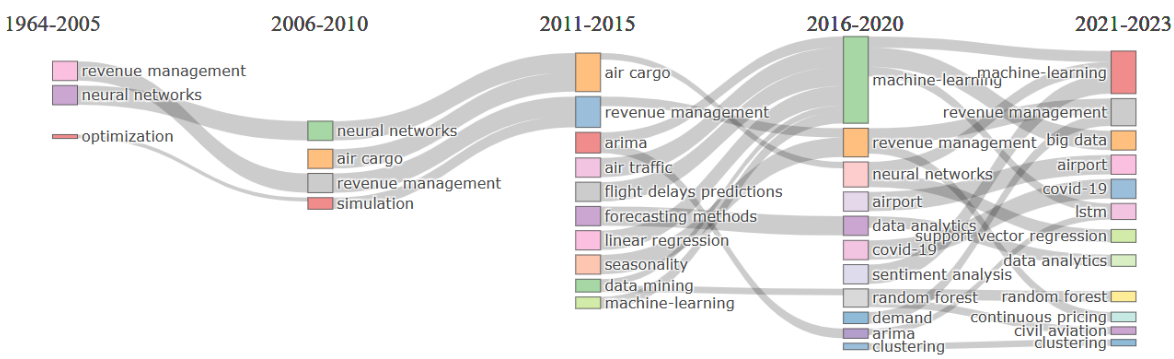

Fig. 5. Thematic evolution of author's keywords

"data mining", "machine learning", and related forecasting methodologies began to emerge around 2011 and have since evolved to include terms like "random forest", "data analytics", "sentiment analysis", and "LSTM". Air cargo research was particularly prominent between 2006 and 2015 but has declined. "Flight delay" research, prevalent from 2011 to 2015, became closely associated with machine learning studies. Between 2021 and 2023, research themes shifted towards advanced technologies and the impact of COVID-19, with machine learning remaining a central focus alongside innovations in big data, continuous pricing, and random forest methodologies.

3.4. RQ4: Topic mapping and emerging directions in aviation forecasting

Fig. 6 visually maps the evolution of trending research topics over time, illustrating the frequency and emergence of key terms in aviation forecasting. In the early years, foundational topics, such as technological forecasting, flight dynamics, and industrial economics, were prevalent, reflecting the industry's initial focus on operational fundamentals. Over time, there was a marked shift towards more advanced computational methods and data-driven research. By the mid-2000s, terms like machine learning, deep learning, and prediction modelling began to dominate, indicating the growing integration of emerging technologies into aviation research. The COVID-19 pandemic, which emerged as a dominant research topic by 2020, further reshaped aviation research priorities. Studies on the industry's recovery prospects emphasised several core strategies, including operational resilience (Linden, 2021), lessons learned from successful recovery stories (Czerny et al., 2021), and the critical role of digital transformation in enhancing industry adaptability (Halpern et al., 2021). Furthermore, the research explored defining attributes for resilience and sustainability in aviation, underlining the industry's need to withstand future disruptions. Colizza et al. (2006) demonstrated the applicability of stochastic models in predicting epidemic transmission through airports. Li et al. (2023) expanded on this by leveraging forecasting models to evaluate the impact of the COVID-19 pandemic on passenger demand and operational strategies. Simultaneously, research increasingly focused on enhancing prediction accuracy and improving operational efficiency. Terms such as learning algorithms, flight delay prediction, and predictive maintenance became more frequent, reflecting the industry's shift towards data-driven decision-making to optimise real-time operations. Collectively, these emerging trends illustrate how the aviation sector is evolving to integrate advanced forecasting methods and technological innovations, particularly in response to global disruptions.

Fig. 7 further illustrates the evolution of analytical methods over time. Traditional statistical methods, such as regression analysis and time series modelling, were dominant from 1964 to 2005, with a 100% usage rate. However, their prevalence steadily declined, reaching just 11% by 2021–2023. Simulation and queuing theory methods, which were first employed between 2006 and 2010, peaked at 33% during that period but subsequently declined to 6% in the latest period. In contrast, machine learning methods — including decision trees, random forests, and deep neural networks — rose rapidly, becoming the dominant analytical approach by 2021–2023 with an 83% usage rate. This trend underscores the field's increasing reliance on machine learning to manage complex aviation challenges and improve prediction accuracy.

Emerging topics and strategic opportunities. Topic mapping reveals several emerging themes that airline managers can leverage to gain a competitive edge. Machine learning, deep learning, and customer behaviour analysis are critical for developing accurate demand forecasts, predictive maintenance, and customer-centric strategies. Sentiment analysis highlights the growing emphasis on passenger feedback and experience in operational decisions, while continuous pricing reflects the trend toward dynamic and real-time pricing strategies to maximise revenue. Practitioners can enhance operational decision-making and develop adaptive, real-time responses to evolving market conditions by focusing on these emerging topics.

Sinking topics and standardisation. Conversely, topic mapping highlights areas where research interest has stabilised or declined. Air cargo forecasting, fleet scheduling, and traditional statistical methods have become more standardised, reflecting their diminished relevance in addressing new challenges. The industry has primarily developed best practices for these areas, reducing the need for further research. Practitioners in these domains should focus on applying proven solutions and optimising existing processes to maintain operational efficiency without significant innovation.

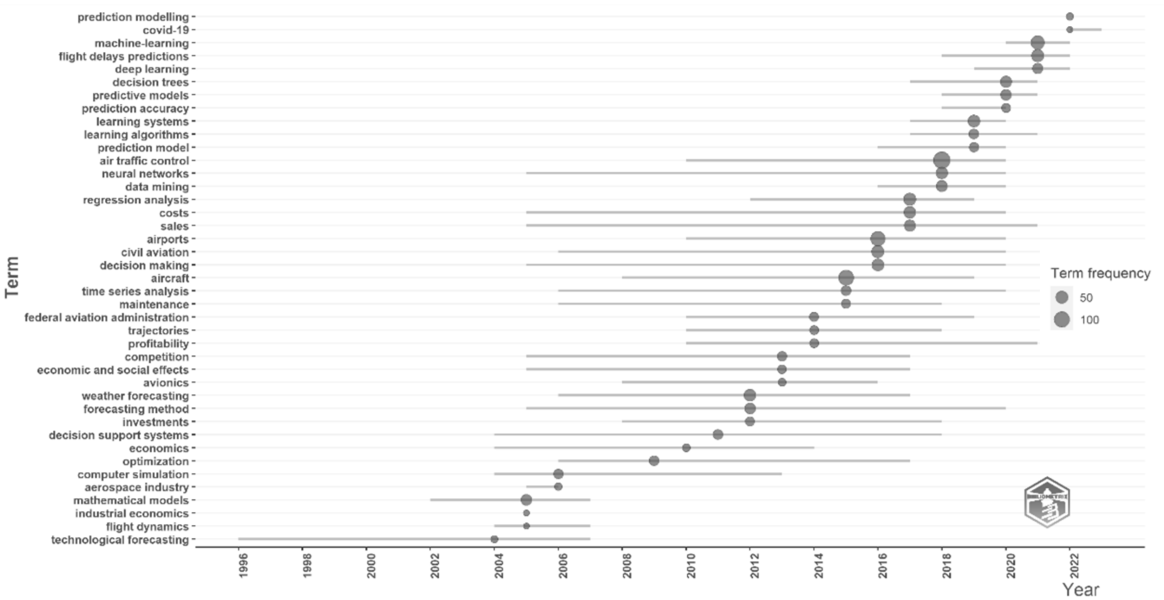

Fig. 6. Mapping of trend topics

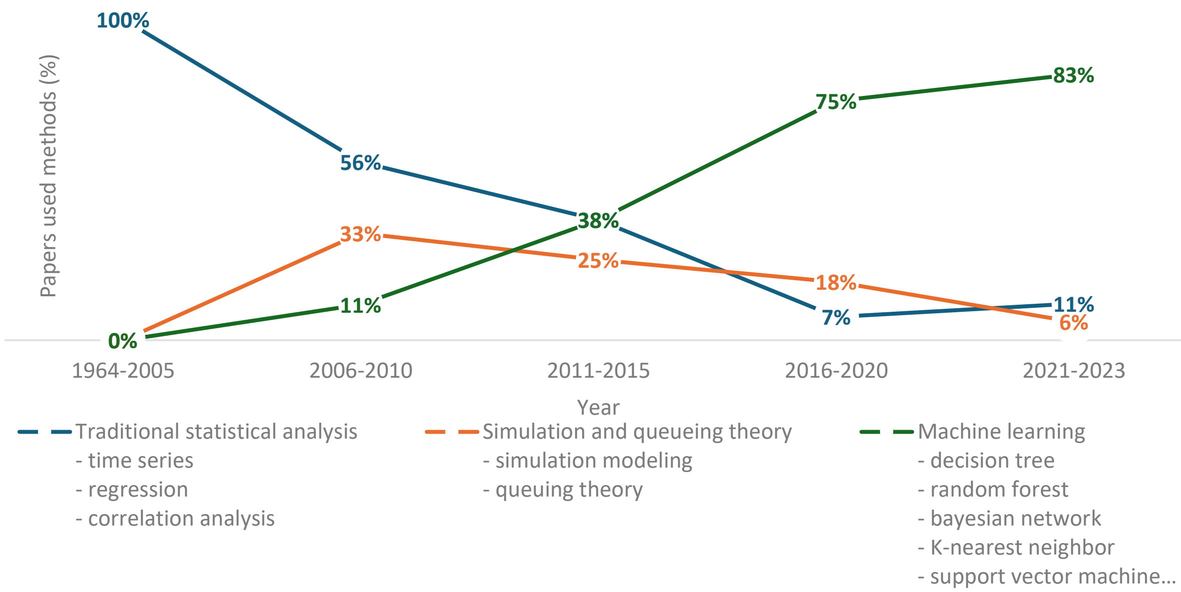

Fig. 7. Number of articles using machine-learning methods

4. Discussion of the results

This section synthesises key findings across bibliometric trends, thematic evolution, and technological advancements to address the four research questions (RQ1–RQ4).

RQ1. The bibliometric analysis of aviation forecasting research revealed significant shifts in publication trends and geographical research focus from 1964 to 2023. Three distinct phases of publication growth were identified, with a notable increase in research output from 2016 onwards, signalling heightened academic interest. This growth aligns with global advancements in data analytics and the increasing complexity of aviation operations. Geographically, the USA initially led aviation forecasting research, with passenger demand forecasting being the most studied topic (32%). The focus later expanded to flight delay prediction and weather-related studies. China followed with a steady upward trend in aviation research, particularly on flight delays and spare parts forecasting, reflecting the country's expanding aviation industry. These findings indicate that regional aviation market needs and economic priorities significantly influence research directions. Highly cited publications reflect the integration of advanced methodologies such as machine learning and stochastic modelling. For instance, Colizza et al. (2006) applied network-based stochastic models to disease transmission through airports, demonstrating the relevance of aviation research in broader public health contexts. The prominence of machine learning models like random forest and LSTM in predicting flight delays underscores the shift towards more data-driven, predictive analytics approaches in aviation forecasting.

RQ2. The study identified 15 distinct research areas, with passenger demand forecasting consistently dominating the field due to its strategic importance for airline operations. Flight delay prediction has grown significantly since 2016, driven by operational efficiency improvements and rising customer expectations. Emerging topics, such as customer behaviour, financial forecasting, and competition analysis, have gained traction, influenced by the proliferation of big data and evolving market dynamics. Conversely, traditional research areas such as aircraft and engine performance have declined, likely due to advancements in these fields or shifting research priorities. The bubble chart analysis illustrates varying growth rates across research areas. Passenger demand forecasting remains the most studied topic but shows slower growth, reflecting its established status. In contrast, flight delay prediction and emerging areas like customer behaviour exhibit rapid growth, indicating increasing interest and potential for future research. Under-researched areas such as fuel and emissions forecasting present opportunities for innovation, particularly in light of sustainability and regulatory challenges.

RQ3. The evolution of research themes highlights a transition from traditional statistical methods to machine learning and big data-driven approaches. Early studies relied heavily on time series and regression analyses, but more advanced techniques have largely supplanted these methods. By 2021–2023, machine learning methods, including decision trees, random forests, and deep neural networks, became dominant, reflecting their superior accuracy and adaptability in managing aviation complexities. Key terms like "machine learning", "data mining", and "sentiment analysis" emerged post-2011 and have evolved to encompass more specialised methodologies. COVID-19 research themes emerged prominently after 2020, further underscoring the aviation industry's adaptive response to global crises. Continuous pricing and predictive maintenance also surfaced as critical areas, indicating a strategic shift towards real-time decision-making and dynamic operational adjustments.

RQ4. Topic mapping revealed distinct patterns in emerging and declining research areas. Emerging areas, like machine learning, customer behaviour analysis, and sentiment analysis, are poised to transform aviation forecasting by enabling more accurate demand forecasts and customer-centric strategies. Continuous pricing further highlights the shift towards dynamic pricing models for revenue optimisation. On the other hand, areas like air cargo forecasting and fleet scheduling have become more standardised, reducing the need for further research. These areas have established best practices, indicating industry maturity. However, underexplored topics such as fuel and emissions forecasting remain critical for addressing sustainability and regulatory compliance, presenting opportunities for future research and innovation. The COVID-19 pandemic catalysed a shift in research priorities, emphasising the importance of resilience, adaptability, and digital transformation in aviation recovery. Applying stochastic models and forecasting tools further underscores the industry's proactive approach to mitigating risks and enhancing operational efficiency. Future research should focus on deepening the understanding of predictive technologies and expanding studies on resilience and sustainability to navigate future disruptions effectively. Expanding this area could help the industry develop robust long-term strategies to withstand financial shocks and market disruptions, ensuring sustainable recovery and growth. Conversely, topic mapping highlights areas where research interest has stabilised or declined. Air cargo forecasting, fleet scheduling, and traditional statistical methods have become more standardised, reflecting their diminished relevance in addressing new challenges. The industry has largely developed best practices for these areas, reducing the need for further research. Practitioners in these domains should focus on applying proven solutions and optimising existing processes to maintain operational efficiency without significant innovation.

Despite topic diversification, certain themes remain under-researched, presenting key challenges in airline forecasting. However, fuel and emissions forecasting remains a niche research area critical for addressing sustainability and regulatory concerns. Expanding research in this direction presents an opportunity for innovation in sustainability initiatives and compliance strategies. Economic resilience in the face of financial shocks, particularly post-pandemics, is crucial for developing robust long-term operational strategies. The pandemic's impact has also highlighted the importance of economic resilience research, which remains under-explored. Expanding this area could help the industry develop robust long-term strategies to withstand financial shocks and market disruptions, ensuring sustainable recovery and growth. Addressing these challenges will be essential for the aviation sector to adapt to evolving complexities and achieve sustainable industry resilience.

Conclusions

This study has successfully addressed its objectives and research questions (RQ1–RQ4) by comprehensively analysing aviation forecasting trends, thematic evolution, and emerging opportunities. Bibliometric analysis revealed significant shifts in publication trends from 1964 to 2023, driven by advancements in data analytics and aviation complexity. Passenger demand forecasting remains the most researched area due to its strategic importance for airline operations, while emerging topics in customer behaviour, financial forecasting, and competition analysis have gained prominence. Thematic evolution highlighted the transition from traditional statistical methods to machine learning and big data-driven approaches, underscoring aviation's increasing reliance on predictive analytics. Topic mapping emphasised emerging areas in sentiment analysis and dynamic pricing, reflecting evolving customer expectations and the need for real-time decision-making. Established areas like air cargo forecasting and fleet scheduling have become more standardised, indicating industry maturity and reduced research demand.

This work highlights key focus areas for airline managers to gain a competitive advantage by concentrating on emerging research trends and data-driven approaches. For stabilised research areas like fleet scheduling, practitioners can focus on applying established best practices to maintain operational efficiency and optimise decision-making processes. Future research should prioritise underexplored areas in fuel and emissions forecasting, economic resilience, and sustainability to address evolving regulatory and environmental challenges. Additionally, advancing research on real-time pricing, customer behaviour analysis, and predictive maintenance will ensure sustainable growth and resilience in the aviation industry as it adapts to new complexities and global disruptions.

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