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Review

How big data enriches aviation research: A critical review of flight data applications

Ziming Wang[1], Lingxiao Wu[1,✉], Dabin Xue[2], Ang Li[1]

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ABSTRACT: The growing variety of flight data, the expanding scope of its applications, and the continuous improvement in data quality have collectively accelerated the digital transformation of the aviation industry. Advances in multi-source data fusion and analytical methods have further unlocked the potential of flight data for operational insights and decision support. This study first summarizes the main characteristics of different flight data sources and then provides a comprehensive review of the literature on flight data applications. The reviewed studies are grouped into three key domains: operations and maintenance, safety supervision, and strategic policies and sustainable development. Undoubtedly, the use of flight data will continue to expand in the foreseeable future. These data will support a deeper understanding of flight performance, airline operations, and airspace systems. They will also help international aviation organizations, airlines, engineers, and researchers improve decision-making, optimize resources, and develop more reliable and environmentally responsible aviation systems. More cross-disciplinary research using flight data is expected to emerge in the coming years. We believe this study offers a new perspective that can support the future development of flight data research.

KEYWORDS: Flight Data Analysis, Aviation Operations and Maintenance, Aviation Safety, Strategic Policies, Sustainable Aviation

1 Introduction

Big data technologies are widely regarded as a major advancement in the aviation industry and are expected to reshape most aviation operations in the coming one to two decades. The concept of the Flight Data Recorder (FDR) emerged in the late 1940s to early 1950s. Dr. David Warren, an Australian scientist, is recognized as the inventor of the modern FDR, inspired by a mysterious air crash in 1953 (Raza et al., 2024). In the 1960s, the International Civil Aviation Organization (ICAO) mandated the installation of FDR and Cockpit Voice Recorder (CVR) on commercial aircraft. Regulatory bodies such as the U.S. Federal Aviation Administration (FAA) and the European Union Aviation Safety Agency subsequently specified standards for recorded parameters, such as throttle position and control surface deflections (Verma, 2024). As technology has advanced, flight data systems have become increasingly sophisticated, encompassing sources such as FDRs, Quick Access Recorder (QAR), and Automatic Dependent Surveillance – Broadcast (ADS-B) systems. These sources significantly enhance data quality and integrity, enabling comprehensive analysis of aircraft status and behavior from takeoff to landing. This data supports key activities such as accident investigation, safety inspections, and crew training.

In recent years, the rapid growth of publications and the increasing diversification of flight data have continuously expanded the scope of flight data applications. Emerging flight data can improve traditional aviation research in three main ways. First, the global coverage and accessibility of flight data extend the research focus beyond individual routes or specific regions to a worldwide scale. For example, the availability of global flight data has enabled the reconstruction of aircraft routes at cross-country and international levels, supporting worldwide air traffic analyses (Hurter et al., 2014), and has facilitated assessments of aviation-induced environmental impacts from regional to global perspectives (Han et al., 2025; Xue et al., 2025a). Second, the high resolution and real-time nature of flight data enhance the accuracy of operational behavior analysis. For instance, such data have been employed to improve the precision of aircraft trajectory extraction and prediction, as well as traffic monitoring (Balakrishna et al., 2010). Third, the granularity and richness of individual aircraft data allow researchers to move beyond the limits of traditional macro-level statistics and conduct analyses at the micro-level. For example, flight data have been used to predict aviation safety incidents (Song et al., 2025) and to support nationwide carbon emission accounting (Wang et al., 2024). Fig. 1 illustrates a conceptual framework that links flight data sources with modeling approaches and application domains.

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[1] Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China. [2] State Key Laboratory of Solar Activity and Space Weather, National Space Science Center, Chinese Academy of Sciences, Beijing 100190, China.

✉ Corresponding author. E-mail: lingxiao-leo.wu@polyu.edu.hk

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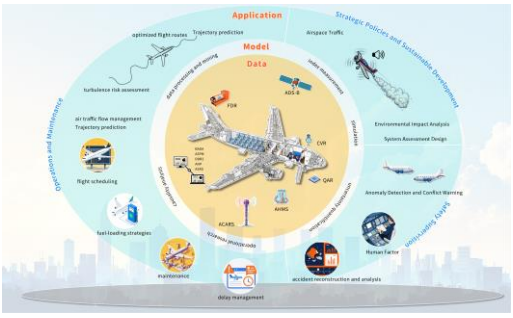


Fig. 1. Conceptual framework of flight data sources, modeling approaches, and application domains in aviation research.

As the quality and accessibility of flight data continue to improve, its applications are expected to expand rapidly. In this context, it is important for scholars, practitioners, and government agencies to understand the current state of flight data use. This paper therefore focuses on: (1) summarizing major flight data types and their application landscape; (2) examining how flight data enhances industry efficiency and supports practical problem-solving; and (3) discussing future application potentials. Importantly, we believe the insights in this paper will benefit relevant academic communities, practitioners, and government stakeholders in two ways: for those already working with flight data, it highlights emerging applications that may help refine or extend ongoing work; and for newcomers, it illustrates the potential of flight data to support innovation.

Although several prior studies have reviewed methods applied to specific types of flight data, most have focused on a single data source or its use in data mining and flight safety (Gavrilovski et al., 2016; Kožović et al., 2023; Tian et al., 2021; Wang et al., 2014). In the broader transportation literature, recent reviews have examined specific methodological domains, such as machine learning-based microscopic traffic flow modeling, or specific application domains, such as maritime decarbonization (Rowan et al., 2025; Wang et al., 2026). To the best of our knowledge, no comprehensive and up-to-date review currently exists that covers flight data as a whole and its broad applications to diverse aviation challenges. Thus, it is both timely and essential to synthesize previous work and project the future direction of flight data research. This study aims to provide a comprehensive overview of recent advances in flight data applications and to inspire new research perspectives.

The remainder of this paper is organized as follows. Section 2 provides an overview of flight data, including its definition, development, and limitations. Section 3 describes the methods and structure of the literature review. Sections 4, 5, and 6 review applications of flight data across three areas: operations and maintenance (OM), safety supervision (SS), and strategic policies and sustainable development (PD). Section 7 discusses emerging research trends in flight data applications. Finally, Section 8 discusses potential directions for future research on flight data applications.

2 Flight data sources and characteristics

Flight data are widely used in modern aviation research, such as safety management and operational optimization. Different data sources have been developed to meet specific operational and research needs. They differ in the types of information recorded, data resolution, coverage, and accessibility. This section provides a comprehensive overview of the major categories of flight data, their sources, and core characteristics.

As fundamental infrastructure for flight data collection, the FDR and CVR together form the "black box" system essential for aviation safety investigations. The FDR is the earliest and most widely adopted device for recording flight information. Modern systems capture over 1,000 parameters at 4–8 Hz, providing high-precision data for accident investigation and performance analysis. Developed in parallel with the FDR, the CVR is designed to capture cockpit audio, including pilot conversations, audible alarms, and radio communications with air traffic control. CVRs typically use a loop recording structure that retains the most recent 120 minutes of audio (NTSB, 2019). The two recorders provide different types of information for accident investigation. FDR data describe changes in aircraft operating conditions, while CVR recordings help investigators understand crew actions and communications during the flight. Due to the sensitive and legally protected nature of the data, access to both FDR and CVR data is strictly regulated under ICAO provisions (ICAO, 2018).

Compared with the FDR, the QAR is more commonly used for routine flight monitoring by airlines. It receives flight parameters through the aircraft's data acquisition system and can record more than 2,000 parameters, with some measurements sampled at frequencies above 32 Hz. Typical parameters include airspeed, altitude, flap positions, landing gear status, and engine thrust (Kim et al., 2022). These records support trend analysis, safety assessment, pilot training, and serve as the primary source for Flight Operational Quality Assurance (FOQA) programs (Wang et al., 2014). However, QAR data is usually controlled by airlines and belongs to non-public datasets. External researchers typically need to sign agreements with airlines to obtain access.

Since the widespread deployment of ADS-B in the 2000s, it has become an important source of aircraft trajectory and traffic information (Schäfer et al., 2014). It relies on the onboard GPS system and transponder to continuously broadcast the aircraft's position data at a frequency of approximately once per second, with data features including latitude, longitude, altitude, ground speed, vertical speed, heading, and call sign. These information are transmitted regularly and can be received by ground stations, satellites, and other equipped aircraft. These data can serve as aircraft surveillance and assist pilots and air traffic controllers in perceiving the situation (Kožović et al., 2023). Historical ADS-B data are available through platforms such as OpenSky Network and FlightRadar24, which provide widely accessible datasets.

In contrast to traditional surveillance technologies, the Aircraft Communications Addressing and Reporting System (ACARS) establishes a distinct communication channel for transmitting flight data. Introduced in the 1970s as a digital alternative to voice communication, ACARS functions as a text-based data link between aircraft and ground stations (Roy, 2001). It transmits various types of information, including engine health status, fault codes, crew reports, weather data, and fuel consumption. Some of this information can be transmitted in near real time, particularly on flights using satellite communication links. Some ACARS data are available through subscription-based services such as FlightAware, but complete records are generally controlled by airlines and remain difficult for researchers to access.

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In addition to the onboard data described above, there are several databases, including the Base of Aircraft Data (BADA), the Demand Data Repository 2 (DDR2), the Aviation System Performance Metrics (ASPM), Aircraft Noise and Performance (ANP), and the Aviation Safety Reporting System (ASRS). Among them, BADA, developed by EUROCONTROL, is a model-based database that characterizes the performance behavior of commercial aircraft. Its data are derived from fitting manufacturer-provided performance manuals with actual flight records, covering standard flight performance during climb, cruise, and descent for major aircraft types (Nuic et al., 2010). BADA is provided in a parameterized model form that includes fuel consumption, flight time, power settings, and speed–altitude relationships, and is widely used for trajectory prediction, route planning, environmental impact assessment, and airspace capacity modeling. The BADA model series (e.g., BADA 3 or BADA 4) is publicly accessible (EUROCONTROL, 2016, 2012), and researchers may obtain it free of charge through EUROCONTROL authorization. DDR2, also operated by EUROCONTROL, supports flight flow forecasting, strategic planning, and airspace capacity analysis in Europe (EUROCONTROL, 2017), storing airline-filed flight plans and corrected trajectories in XML format.

ASPM, maintained by the FAA and publicly available (Federal Aviation Administration, 2021), is a statistical database used to assess the operational efficiency of major U.S. airports and flights. This data is updated daily and features planned and actual departure and arrival times, taxi times, delays, airport capacity, and weather related factors. These data are used to examine operational trends and support airport planning and capacity analysis. ANP provides standardized aircraft noise and performance data. It is mainly used for noise contour mapping, environmental assessment, and evaluation of measures to reduce aircraft noise. For aviation safety, ASRS was established in 1976 as a voluntary and confidential reporting program jointly supported by NASA and the Federal Aviation Administration of the United States. Its database contains structured event information and narrative reports submitted by aviation personnel. After removing the identification information, these reports will be made public. They are used to study human factors, safety culture, and procedural issues in aviation.

Table 1 compares the attributes and classifications of the main flight data sources reviewed in this article. These databases are not an exhaustive list of all available sources, but are often discussed in literature, representing different types of flight data.

From the perspective of data attributes, Table 1 highlights the differences in the structural composition of the dataset. FDR and QAR contain detailed aircraft operating parameters recorded at relatively high sampling rates. They are particularly useful for flight performance analysis and anomaly detection. In contrast, BADA provides aircraft performance models, while ASPM contains data on airline and airport operations. BADA is typically used for trajectory and performance simulation, while ASPM supports operational analysis and airport planning. These databases lack real-time details and are more commonly used for macro level performance evaluation. Additionally, a few data sources, such as CVR, ASRS, and ACARS, provide voice or textual information that holds unique value for safety analysis and human factors research.

Table 1. Flight data attributes and classification.

			FDR	QAR	CVR	ADS-B	BADA	ASPM	ANP	ACARS	ASRS	DDR2
Data Attribute	Timestamp		√	√	√	√	×	√	×	√	√	√
	Aircraft Identification		√	√	×	√	×	√	×	√	×	√
	Altitude		√	√	×	√	○	√	○	√	×	√
	Airspeed		√	√	×	√	○	√	○	√	×	√
	Air Temperature		√	√	×	×	○	×	○	○	×	×
	Aircraft Weight		√	√	×	×	√	×	○	×	×	×
	Vertical Speed/Climb Rate		√	√	×	√	○	√	○	○	×	√
	Attitude Angles		√	√	×	×	×	×	×	×	×	×
	GPS Position		√	√	×	√	×	√	×	○	×	√
	Heading/Track Angle		√	√	×	√	○	√	×	○	×	√
	Engine Parameters		√	√	×	×	○	×	√	○	×	×
	Control Surface Positions		√	√	×	×	×	×	×	×	×	×
	Flight Phase		√	√	×	○	×	√	×	○	×	√
	Waypoints/Route Info		○	○	×	×	×	√	×	√	×	√
	Autopilot/Flight Mode Settings		√	√	×	×	×	×	×	×	×	×
	Navigation Deviations		√	√	×	×	×	×	×	○	×	×
	Health Monitoring Signals		×	×	×	×	×	×	×	○	×	×
	Fault Codes/Maintenance Data		×	×	×	×	×	×	×	○	×	×
	Cockpit Voice (Audio)		×	×	√	×	×	×	×	×	×	×
	Radio Communication (ATC)		×	×	√	×	×	×	×	√	×	×
	Text/Narrative Reports		×	×	×	×	×	×	×	√	√	×
Data Classification	Acquisition	Primary	√	√	√	√	×	×	×	√	×	×
		Secondary	×	×	×	×	√	√	√	×	√	√
	Frequency	High	√	√	√	×	×	×	×	×	×	×
		Medium	×	×	×	√	×	×	×	√	×	×
		Low	×	×	×	×	√	√	√	×	√	√
	Source	Airline/Operator	√	√	×	×	×	×	×	×	×	×
		Onboard/Avionics	√	√	√	×	×	×	×	√	×	×

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		Regulator/Research	×	×	×	√	√	√	√	×	√	√
	Accessibility	Open/Public	×	×	×	√	×	×	√	×	√	×
		Licensed/Shared	×	√	×	×	√	√	×	√	×	√
		Restricted/Sensitive	√	×	√	×	×	×	×	×	×	×
	Data Structure	Time Series	√	√	×	√	×	×	×	×	×	×
		Text/Audio	×	×	√	×	×	×	×	√	√	×
		Model/Table	×	×	×	×	√	√	√	×	×	√

Note: √ indicates that the attribute is typically present in the data source; ○ indicates partial, indirect, or model-based availability; × indicates that the attribute is typically not available.

Building on these attribute differences, flight datasets can be further classified by acquisition mechanism. In terms of acquisition, datasets such as FDR, QAR, and CVR are primary data, collected in real time or near real time by sensors, avionics systems, or communication modules. These datasets typically have high sampling frequencies greater than 1 Hz or medium sampling frequencies triggered by events or periodic reporting. They include rich parameters with detailed measurements and can capture key flight events. In contrast, datasets such as BADA, ASPM, and DDR2 represent secondary data, aggregated from historical records, schedules, or subjective reports. Although they lack the fine-grained precision of raw measurements, they are standardized in structure, broad in coverage, computationally efficient, and generally fall within the category of low-frequency data, making them suitable for macro-level statistics and long-term analyses. In terms of data sources, flight data includes both operator-generated data collected through airline or operator-owned systems, such as QAR and AHMS, and automatically recorded onboard data, such as FDR, CVR, and ACARS. Due to concerns related to privacy, safety, and commercial sensitivity, access to such datasets is typically restricted. As a result, studies based on these data often face limitations such as small sample sizes and limited reproducibility. In contrast, datasets released by regulatory authorities, research organizations, or open data platforms, such as BADA and DDR2 provided by EUROCONTROL, ASPM maintained by the U.S. FAA, and ANP published by the ICAO, generally exhibit higher levels of accessibility, either through open dissemination or via authorized access mechanisms. These datasets facilitate cross-airline and cross-regional analyses and provide critical empirical support for transportation research and aviation policy development. Finally, regarding data structure, flight datasets exhibit substantial diversity. They include high-frequency multidimensional time series such as FDR and ADS-B, audio and textual data such as CVR and ASRS, and performance models and static tables such as BADA and DDR2. These different types of flight data vary in acquisition mechanisms, availability, temporal resolution, and structural format, collectively forming a heterogeneous, multi-scale, multi-source flight data ecosystem that provides complementary and synergistic support across a wide range of aviation applications.

From an application perspective, differences among flight-data sources determine their suitability for different aviation problems and involve trade-offs between information richness, coverage, accessibility, and application requirements. For example, QAR records detailed flight parameters and is mainly used to analyze aircraft states and performance. In comparison, ADS-B covers aircraft movements across wider areas and is more suitable for large-scale traffic and airspace analysis. Other data sources also have similar trade-offs. FDR and QAR contain detailed information about aircraft status, but access to these records is often limited and the available samples may also be limited. This makes it difficult to conduct comparative research across fleets or operators. ADS-B data covers a wider range of flight and can be used for trajectory and traffic analysis. However, they did not provide equivalent detailed information about onboard aircraft systems and performance. ACARS, CVR, and ASRS provide additional information for safety investigations and human factors studies, but are generally not suitable for continuous trajectory analysis. BADA, ASPM, and DDR2 have different purposes. BADA provides aircraft performance models, while ASPM and DDR2 contain operational and flight information. These sources can be used for simulation, traffic analysis, and planning, and cannot replace detailed onboard measurements. Therefore, no single data source is universally superior; the appropriate choice depends on the research objective, required level of detail, scale of analysis, and data accessibility.

Beyond the mainstream data sources mentioned above, aviation operations involve a variety of additional technical data streams. These include Flight Management System (FMS) logs that record navigation intent and trajectory planning; Aircraft Health Monitoring System (AHMS) data that monitor airframe condition and fault progression; Aircraft Condition Monitoring System (ACMS) data; Maintenance Management System (MMS) data; data links from the Diagnostic and Analysis System for Health (DASH); Airport Surface Detection Equipment (ASDE); Ground Delay Program (GDP) data; and Daily Aircraft Movement Record (DAMR) data. Furthermore, datasets can be obtained from platforms such as FlightAware and OpenSky. These data sources are often task-specific, structurally heterogeneous, and difficult to access. Aviation operations are also strongly influenced by external factors, particularly meteorological (Gultepe et al., 2019) and space weather conditions (Xue et al., 2024). As a result, researchers also use weather data from sources such as the National Oceanic and Atmospheric Administration (NOAA), airport and airspace infrastructure data, terrain and obstacle information, and data on socioeconomic conditions and travel demand. These additional sources help researchers analyze aviation operations, safety, and environmental impacts.

3 Literature review method and structure

The promising practical applications of flight data have gradually gained recognition in the academic community. Beyond data mining and flight safety, the applications of flight data extend to broader and more advanced domains. Currently, flight data are used across various fields of aviation research, spanning disciplines such as statistics, information technology, psychology, biology, and environmental science. This paper aims to provide a comprehensive overview of flight data, its processing methods, and its applications in addressing various problems, while also stimulating new

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perspectives on its use across different disciplines. Given the applied nature of flight data usage, numerous technical reports and practical project documents also exist. However, this review focuses primarily on peer-reviewed academic literature in order to ensure consistency. Throughout the review, we conducted detailed and in-depth literature searches, identifying, analyzing, and summarizing relevant themes, methodologies, and trends to provide a panoramic overview of flight data research.

A two-stage literature search strategy was adopted to identify the flight-data types used in aviation research and systematically examine their applications. In the first stage, a broad search was conducted to identify studies related to flight data in aviation research. The search covered the period from 2000 to June 1, 2025 and was conducted in Scopus, Google Scholar, the Science Citation Index (SCI), and IEEE Xplore, using the following search string: ("flight data" OR "flight data analytics" OR "flight data recorder") AND ("aviation" OR "aircraft" OR "air transport" OR "air transportation" OR "air traffic"). The purpose of this initial search was to identify the flight-data types commonly discussed and used in aviation research. Based on the flight-data sources identified from the initial literature, a second-stage search was conducted for each data type in the same databases to identify studies applying these data to aviation-related problems. Only a very limited number of relevant studies were identified for 2000–2003. Therefore, the temporal analysis presented in this review begins in 2004.

During the screening process, studies were included when they used flight data as a source of information or analytical input to investigate or address an aviation-related research or practical problem. Studies primarily concerned with the development, processing, transmission, storage, reconstruction, or quality assessment of flight data themselves, without applying these data to an aviation-related problem, were excluded. Review articles, editorials, non-English publications, and studies without sufficient information to assess their relevance were also excluded. To further improve the comprehensiveness of the literature search, backward and forward snowballing was subsequently conducted on the relevant studies identified through the database searches. Additional studies were screened using the same inclusion and exclusion criteria.

Following the literature search and screening process, 233 studies were included in the final review, comprising 225 journal papers and 8 conference papers. Table 2 lists journals with at least two published papers that apply flight data. Publication years were divided into seven periods, each spanning 3-4 years. Among the 233 reviewed studies, 187 were published in these journals. The top five journals contributed nearly half of the publications: Aerospace, Transportation Research Record, Transportation Research Part C: Emerging Technologies, Transportation Research Part D: Transport and Environment, and Applied Energy. This distribution reflects the multidisciplinary nature of flight data research, covering core areas such as aerospace science, new transportation technologies, environmental impacts, and energy utilization. It also demonstrates the broad academic interest and sustained growth momentum in flight data applications. The data in the table indicate a significant increase in publication volume over time, particularly during the 2020-2022 and 2023-2025 periods, highlighting rapid growth in research activity in this field. The most recent period shows the greatest diversity in journal distribution, suggesting that research focus has expanded to encompass a wider range of application areas.

Table 2. Publication counts by journal and time period.

	2004-2007	2008-2010	2011-2013	2014-2016	2017-2019	2020-2022	2023-2025	Total
Aeronautical Journal	0	0	1	0	2	4	0	7
Aerospace	0	0	0	0	0	10	10	20
Aerospace Science and Technology	0	0	1	0	2	0	1	4
Aircraft Engineering and Aerospace Technology	1	0	0	0	1	5	8	15
Applied Energy	0	0	0	0	0	0	3	3
Applied Sciences Basel	0	0	0	0	1	2	4	7
Atmosphere	0	0	0	0	0	2	2	4
Chinese Journal of Aeronautics	0	0	2	0	2	1	0	5
Energy	0	0	0	0	0	0	2	2
Engineering Applications of Artificial Intelligence	0	0	0	0	0	0	2	2
IEEE Access	0	0	0	0	0	4	3	7
IEEE Transactions on Intelligent Transportation Systems	0	0	0	2	0	5	2	9
IEEE Transactions on Vehicular Technology	0	0	0	0	0	3	0	3
Journal of Advanced Transportation	0	0	0	0	0	1	1	2
Journal of Aerospace Information Systems	0	0	0	1	0	2	2	5
Journal of Air Transport Management	0	0	0	0	1	5	2	8
Journal of Aircraft	1	1	2	0	0	1	0	5
Reliability Engineering System Safety	0	0	0	1	0	3	4	8
Safety Science	0	0	0	0	3	1	1	5
Sustainability	0	0	0	0	2	1	1	4
Transportation Research Part A: Policy and Practice	0	0	0	1	1	0	0	2
Transportation Research Part C: Emerging Technologies	0	1	0	1	4	8	3	17
Transportation Research Part D: Transport and Environment	0	0	1	0	6	6	3	16
Transportation Research Part E: Logistics and Transportation Review	0	0	0	1	2	3	2	8
Transportation Research Record	0	0	1	4	2	6	6	19
Total	2	2	8	11	29	73	62	187

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The literature in this review is organized primarily according to application domains rather than data sources or methodologies. The same flight data can be used to investigate different aviation problems, while similar methods may be applied in different research areas. We therefore divide the reviewed studies into three domains: OM, SS, and PD. These domains cover flight- and airline-level operations, aviation safety, and broader policy and sustainability issues, respectively. Among the 233 studies reviewed, 114 fall within OM, 83 within SS, and 36 within PD.

4 Operations and maintenance

4.1. Flight scheduling optimization

The deep use of flight data is shifting flight scheduling toward dynamic, data-driven coordination. One key application is fuel-burn analysis. Researchers have combined QAR and ADS-B data with machine learning models to improve fuel consumption prediction (Uzun et al., 2019). This precision supports optimized fuel-loading strategies, enabling algorithms to calculate minimum safe fuel loads with sufficient reserves (Wang et al., 2025; Zou et al., 2025). This can reduce unnecessary fuel carriage and the associated fuel consumption and carbon emissions.

Building on this foundation, flight planning has become increasingly precise. Historical flight records and weather forecasts are combined with simulation and data-driven methods to identify suitable routes under different operating conditions. Kim et al. (2015) developed an airport capacity estimation model based on historical operational data, which provides a quantitative foundation for flight schedule allocation and air traffic flow management. Yuan et al. (2024) further demonstrated the potential of collaborative optimization by applying multi-agent reinforcement learning for interval management of multiple aircraft. This line of research also extends to airport capacity planning.

For delay management, predictive models using ADS-B, ACARS, and historical delay data can forecast delays, identify causes, and prevent propagation (Gui et al., 2020; Hao et al., 2014; Penn et al., 2015). Operations research methods, such as integer programming, can then adjust takeoff and landing slots or optimize ground-holding strategies (Jia and Wang, 2025). Beyond routine delay management, flight data are increasingly used for disruption management, in which irregular operations caused by severe weather, space weather (Xue, 2025), infrastructure failures, or airspace restrictions necessitate large-scale rescheduling (Ohi and Kim, 2020). Data-driven recovery models leverage real-time flight data to support aircraft and crew reassignment and slot reallocation, aiming to reduce recovery time and limit the propagation of disruption across the network (Yildiz et al., 2023).

4.2. Flight status and trajectory modeling

Trajectory prediction is a core task in OM, integrating historical and real-time data to estimate future flight paths. Early studies mainly relied on physics-based models such as BADA, limited by model simplifications and insufficient real-time capability (Schuster et al., 2012). With the increasing availability of ADS-B and QAR data and the development of machine learning approaches, trajectory prediction can correct deviations in real time (Zhang et al., 2018). Furthermore, deep learning models such as CNN-LSTM (Ma and Tian, 2020) and Transformer-based architectures (Tong et al., 2023) extract spatiotemporal features from trajectories, enabling stable predictions across multiple routes and long horizons, and providing a foundation for subsequent flight parameter estimation.

In terms of flight parameter prediction, research has focused on estimating key operational indicators, such as estimated arrival time, taxi-out time, and climb performance, to support resource optimization. Alligier et al. (2015) and Alligier and Gianazza (2018) estimate aircraft mass and speed intent, improving trajectory prediction during the climb phase and demonstrating the close coupling between parameter estimation and trajectory modeling.

Accurate assessment of flight states is essential for safe operations, with turbulence detection and prediction being particularly critical. The eddy dissipation rate (EDR), a key indicator, is widely used in turbulence risk assessment. Huang et al. (2019) and Lee et al. (2022) estimated EDR and compared algorithms using QAR data. Gao et al. (2020) combined an unsteady vortex-lattice method with acceleration-based EDR estimation to improve stability during maneuvering flight.

Building on trajectory and parameter prediction, flight efficiency assessment can be carried out from a system-level perspective. Lange et al. (2019) used ADS-B data to examine differences in ground operation times among airlines, revealing how business models influence operational efficiency. Recent studies have further explored data-driven trajectory optimization for improving operational and environmental performance (Nguyen et al., 2025).

4.3. Aircraft health monitoring and maintenance

By integrating onboard data sources such as QAR, ACMS, and ACARS, airlines can implement full-spectrum health management, shifting from scheduled maintenance to predictive maintenance based on actual equipment condition, thereby improving safety, efficiency, and cost-effectiveness. Flight data enables component-to-system-level health assessment, supporting evaluation of engines (Xinlei et al., 2017), environmental control systems (Jianzhong Sun et al., 2019), and bleed air systems (Duan et al., 2023), which informs optimal maintenance timing. Real-time data, particularly from ACARS, allows in-flight fault detection and early preparation by maintenance teams (Sun, 2009), reducing aircraft downtime and enhancing operational efficiency.

4.4. Critical assessment of operations and maintenance applications

By reviewing the application of flight data in combat prediction, scheduling, and aircraft maintenance, we have found that there are still two major limitations at present. Firstly, the connection between data analysis and operational decision-making is still limited. Many studies focus on improving the accuracy of predictions, such as trajectory, fuel consumption, delay, or aircraft health. However, few studies have explored how to effectively incorporate these outputs into decision-making and apply them in practical problems.

Secondly, the accessibility of flight data is also an important issue that limits its widespread application. Many models are developed and tested based on data from specific airlines, aircraft types, airports, or regions. This results in their performance being uncertain under other conditions. In addition, QAR provides detailed information about aircraft systems, but these records are often difficult to obtain. ADS-B data is easier to access and covers a wider range of flights, but they contain less onboard system information. This requires researchers to weigh the information

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richness, accessibility, and universality of different data when selecting data for research.

5 Safety Supervision

5.1. Anomaly detection and conflict warning

In abnormal flight state detection, in addition to detecting anomalies in aircraft components (Cui et al., 2021; Jiang et al., 2011; Su et al., 2022), research has also focused on identifying behavioral and performance anomalies across different flight phases. A key point is that detecting abnormal flight operations forms the basis of risk identification. Li et al. (2016) clustered QAR data and identified operational behaviors that deviate from normal patterns, thereby providing early warning support. These operational anomalies are particularly important during landing. Wang et al. (2018) conducted a systematic analysis of long-landing and hard-landing events and highlighted the critical role of flare operations in landing performance. Barry (2021) and Guo et al. (2023) further examined the identification and early warning of runway safety risks and potential controlled flight into terrain hazards.

In conflict detection and resolution (CDR), following the seminal review by Kuchar and Yang (2000), a wide range of new CDR methods have been proposed, spanning both strategic conflict management and tactical collision avoidance. With the increasing availability of flight data, many recent studies have incorporated data-driven approaches into CDR applications. For example, Lu et al. (2021) used ADS-B data to assess lateral collision risk on oceanic parallel routes. For airport surface operations, Kunzi (2013) developed an ADS-B-based ground conflict alerting system to reduce collisions between aircraft and ground vehicles. Furthermore, by integrating trajectory prediction with spatiotemporal modeling, Bao et al. (2024) assessed conflict risk in complex interweaving segments of terminal airspace.

Data from different sources can also provide complementary information for safety analysis. ASRS reports contain descriptions of safety events, while QAR and ADS-B provide quantitative information on aircraft operations and trajectories. Combining ASRS reports with QAR and ADS-B data links narrative descriptions with quantitative evidence. Liu et al. (2024) detected high-risk events in imbalanced ASRS data, showing that multi-source integration broadens anomaly detection and provides richer contextual information for conflict alerting.

5.2. Accident reconstruction and analysis

In the aviation safety framework, flight data-based accident reconstruction and analysis support the shift from reactive response to proactive prevention. Studies combine different data sources, analytical methods, and expert knowledge to examine accident causes and predict safety risks. These analyses can support preventive safety measures and help reduce the risk of future accidents.

High-fidelity accident reconstruction relies on both textual data and spatiotemporal status parameters. Large text corpora from the ASRS offer valuable resources for identifying systemic risks (Kuhn, 2018; Nikšić and Arıkan Öztürk, 2023; Rose et al., 2022). Ziółkowski and Skłodowski (2018) integrated QAR and CVR data to reconstruct the final minute of flight control actions before the TU-154M crash in Poland. Similarly, Vuorio et al. (2023) combined CVR, FDR command records, psychological profiles, and toxicology reports in four commercial aircraft-assisted suicides, constructing an evidence chain from behavioral intent to operational execution. These studies show that accident reconstruction has expanded beyond physical trajectory recovery toward comprehensive behavioral and cognitive analysis.

For causal analysis of accidents, Ni et al. (2024) and Zhou et al. (2024) enabled rapid classification of unsafe events and interpretable causal tracing. In addition, Liu et al. (2025) combined entity recognition with Bayesian networks to analyze threats and errors. Their method identified possible sequences of contributing factors. Generative language models have also been used to analyze ASRS reports (Tikayat Ray et al., 2023). These models can support report summarization and causal factor identification. Such methods may support the long-term goal of zero-accident aviation.

5.3. Human factor

By collecting and analyzing multi-source flight data, regulators and airlines can more accurately identify pilots' abnormal states, operational errors, and changes in cognitive workload during flight, enabling a shift from passive response to proactive safety management. Specifically, the use of flight data in pilot behavior monitoring covers several dimensions, including fatigue and sleep inertia detection (Ruiz et al., 2010), identification and classification of unsafe operations (Li et al., 2022), pilot performance evaluation (Marinov et al., 2020), situation awareness modeling (Irwin and Kelly, 2021), and prediction of air traffic controller and pilot coordination behavior (Pham et al., 2020). These aspects are interconnected and together form a multi-layered framework for behavioral monitoring and intervention.

5.4. Critical assessment of safety supervision applications

This section reviews the use of flight data in safety monitoring, anomaly detection, risk assessment, and accident analysis. Three main limitations are identified. First, the identification of abnormal events does not necessarily translate into reliable safety-risk assessment. Many studies use historical events to detect abnormal flight conditions. These datasets often contain few abnormal cases and may not represent all operational situations. Moreover, an operational deviation does not always indicate a safety risk. Further research is needed to assess whether detected anomalies are associated with actual safety events. Their potential consequences for flight safety also need to be examined.

Second, the interpretability and causal understanding of data-driven safety models remain limited. Machine-learning models can achieve high prediction accuracy, but their results are often difficult to explain. This makes it difficult to understand the factors contributing to safety risks. In addition, statistical relationships do not necessarily indicate causal effects. More research is needed to explain model predictions and investigate the possible causes of safety events.

Third, the integration and generalizability of safety data remain challenging. QAR, ADS-B, and ASRS provide different types of safety information. Combining these sources can improve safety analysis, but differences in data formats and temporal resolution make integration difficult. In addition, many models are developed using data from specific airlines, airports, or aircraft types. Their applicability to other operating conditions remains uncertain. Improving data integration and testing models in different

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operational environments are therefore important directions for future research.

6 Strategic Policies and Sustainable Development

6.1. Environmental impact analysis

Flight data are essential for assessing environmental impacts and building high-resolution carbon and pollutant inventories. From a micro-level operational perspective, Xue et al. (2025b) quantified the fuel-saving and CO_2-reduction potential of continuous descent operations using QAR data. From a macro-level perspective, Lu et al. (2024) integrated QAR data with flight schedules to generate a high spatiotemporal – resolution CO_2 emission map. For noise assessment, ADS-B and flight-tracking data are essential. Pretto et al. (2024) optimized airport noise prediction models using high-resolution trajectory data, while Giladi (2020) employed ADS-B data to identify and separate aircraft noise events in real time, thereby enhancing monitoring accuracy.

These environmental analyses directly support the formulation and evaluation of aviation environmental policies. Liao et al. (2022) used ADS-B data to examine the impact of COVID-19 on the baseline of CORSIA, providing key evidence for adjustments to the international carbon-offset mechanism. Wang et al. (2024), using ADS-B data, conducted fine-grained carbon accounting for developing countries, showing how aircraft types and operational patterns affect emission-reduction potential and guiding differentiated climate policies.

6.2. Airspace traffic evaluation and prediction

With widespread ADS-B and radar surveillance, researchers reassess airspace capacity and layout using real traffic patterns to reveal congestion mechanisms and evaluate potential structural adjustments (Ma et al., 2019). Flight data are also used to predict air traffic flows. Machine learning and spatiotemporal neural networks can improve demand forecasting at sector and terminal levels (Zhang et al., 2025). These predictions help balance traffic demand and airspace capacity under different operating conditions. Optimization models further consider uncertainties in traffic demand, airspace capacity, and weather. They are used to support rerouting, flight-level allocation, and delay management (Sandamali et al., 2022). In addition, surveillance data are used to assess air traffic complexity. The resulting indicators provide information on controller workload and operational risks (Chen et al., 2025). Overall, they can help evaluate changes in airspace structures and their effects on system performance, illustrating how data-driven traffic management promotes efficient and environmentally sustainable aviation.

6.3. System assessment design

Flight data are playing an increasingly important role in evaluating air transportation systems. They provide evidence on operational efficiency, safety, and resilience, helping regulators and policymakers make decisions based on data rather than experience alone.

For example, Mitkas et al. (2022) deployed ADS-B ground receivers to capture more than 90 million messages and constructed key indicators, including fleet composition, approach speed, arrival spacing, and runway occupancy. This evaluation framework not only helps identify operational bottlenecks and optimize the allocation of airspace and ground resources but also supports the assessment of the efficiency and sustainability of the national aviation system.

6.4. Critical assessment of strategic policies and sustainable development applications

Compared with operational and safety applications, the use of flight data for strategic policy and sustainable development remains limited but is growing rapidly. First, environmental assessments are sensitive to data availability, resolution, and modeling assumptions. QAR provides detailed aircraft-level information, while ADS-B offers broader coverage but less information on aircraft performance. Combining these data with performance and emission models may introduce additional uncertainty. Differences in data sources and modeling methods also make results difficult to compare across studies.

Second, data-driven airspace evaluation and system assessment face challenges in transferability, practical validation, and comprehensive decision-making. Existing studies use flight data to predict traffic flows and optimize airspace operations. They also develop indicators for emissions, traffic complexity, controller workload, and runway utilization. However, improvements in prediction accuracy or optimization results do not necessarily lead to better operational outcomes. Assessments focusing on a single indicator may overlook trade-offs among efficiency, safety, capacity, and environmental performance.

7 Summary

Based on the reviewed literature, this section first presents the publication trend and the relationships among different research areas. Then, we demonstrate the evolution of research topics and summarise the major methods applied.

7.1. Overall trend of publications

To assess the current stage of this technology and forecast future research trends, we fitted a Technology Life Cycle curve using publication data from 2004 to 2027 (Fig. 2). Both the Logistic and Gompertz models fit well (R^2=0.955 and 0.944), with inflection points around 2018, indicating a transition into a mature growth phase. The shaded areas indicate different stages of the research life cycle. The projection for 2023–2027 suggests that research activity may gradually stabilize.

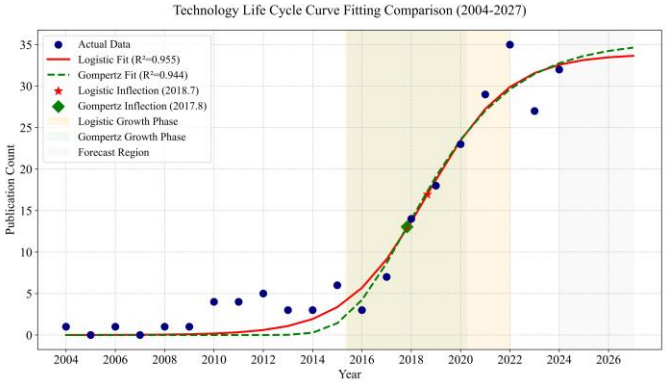


Fig. 2. Technology life cycle curve fitting comparison.

7.2. Evolution of research topics

Fig. 3 illustrates the distribution of the 233 flight data studies across three research areas from 2004 to May 2025, providing an overview of how research interests in this field have evolved. Research in this field has expanded rapidly since 2017. Among the three areas, OM consistently dominates in publication volume, followed by SS and

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PD. Notably, PD-related studies have only started to appear in recent years, reflecting the growing attention to sustainable aviation strategies.

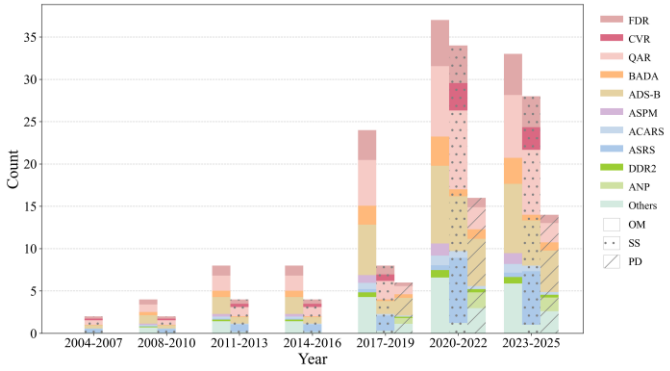


Fig. 3. Distribution and trends of research topics and datasets over the years.

Corresponding to the evolution of research focus, Fig. 3 further summarizes the composition and temporal distribution of datasets used in the reviewed studies. ADS-B is the most widely used source (63 studies), followed by QAR (59), Others (34), and FDR (33), together accounting for over two-thirds of all publications and highlighting their central role in data-driven aviation research. In contrast, datasets such as CVR, ASPM, ACARS, and DDR2 appear far less often, suggesting limited access or narrower applicability. The table also shows that some datasets, including ASPM, ACARS, and DDR2, began appearing only after 2017, indicating their relatively recent adoption in aviation research. Overall, dataset use was limited before 2010 but expanded rapidly after 2014, peaking between 2017 and 2022. The continued rise projected for 2023–2025 (89 publications) indicates sustained research interest and growing availability of flight data.

Fig. 3 also shows how different flight data sources are used across the three research areas: OM, SS, and PD. The stacked bars within each clustered column represent the relative number of publications using a specific data source within each research area. QAR, FDR, and ADS-B data are closely associated with OM studies. In the SS domain, ASRS, ACARS, and ASPM play significant roles. These datasets contain incident reports, communication records, and airport performance information. They are used to examine safety incidents, identify potential risk factors, and evaluate safety management practices. PD covers fewer studies but has grown rapidly in recent years. Research in this area mainly uses BADA, DDR2, and ANP data.

7.3. Summary of major methods

This section summarizes the methods used in the reviewed literature. These methods can be grouped into six categories: data processing and mining, index measurement, simulation, uncertainty quantification, causality analysis, and operations research.

In flight data analytics, data processing and mining remain the core foundation, integrating machine learning, deep learning, and natural language processing models for trajectory prediction (Shafienya and Regan, 2022), anomaly detection (Cui et al., 2021), and operational performance analysis (Xiuyi Li et al., 2022). At the same time, traditional statistical modeling and network analysis methods are used to cluster flight patterns (Xu Li et al., 2022) and characterize the structure of air traffic networks (Ma et al., 2019). These methods are often combined with visualization techniques to enhance pattern recognition. Index measurement provides another approach to safety and performance evaluation. Studies have developed metrics for airspace capacity and complexity, airport efficiency, and emissions (Mitkas et al., 2022; Wang et al., 2024). Gao et al. (2020) proposed dynamic indices based on control theory to evaluate operational stability, resilience, and responses to disturbances. These indicators can be used to compare different operating conditions and provide inputs for simulation and optimization models.

Simulation provides an experimental platform for validating findings in flight data research. Flight performance simulations typically rely on BADA models, engine emission factors, and meteorological data to reconstruct 3D trajectories, energy states, or emission distributions (Ekici et al., 2023). High-resolution emission modeling and ADS-B-based emission inventories are other applications (Klenner et al., 2022), supporting scenario analyses of airspace structures and flight procedures. However, simulation results depend on the input data and model assumptions. Flight operations are also affected by uncertain factors, including weather changes, crew behavior, and traffic fluctuations. Uncertainty quantification is therefore important for evaluating prediction reliability and operational risks. Studies commonly adopt stochastic processes (Yildiz et al., 2023), Bayesian models (Junzi Sun et al., 2019), Monte Carlo propagation (Zhu et al., 2021), and ensemble learning approaches to estimate confidence intervals and quantify operational risk.

In explanatory analysis, causal analysis is widely used to understand the underlying causes of operational events. It has been used to reveal the causal effects of weather, traffic density, or operational behavior on delays, safety risks, and trajectory deviations (Barry, 2021; Liu et al., 2025; Zhou et al., 2023).

Finally, operational research methods transform data analysis and metric outputs into actionable decisions. Operations research methods use flight data to support operational decision-making. Methods such as mixed-integer programming and column generation have been applied to flight scheduling, trajectory optimization, and other operational problems (Jia and Wang, 2025; Lu et al., 2022; Matsuno and Matsuda, 2025), converting data-driven insights into practical operational strategies and playing a central role in airline decision-support systems.

Overall, various methods serve different analytical purposes, and any single method is difficult to support complete decision-making based on flight data. Data mining helps with prediction, but some models lack interpretability. Index based methods make the results easier to understand, but they may overlook complex operational relationships. Simulation allows researchers to examine different scenarios, but the results depend on the assumptions made. Uncertainty quantification helps evaluate the reliability of analysis results, but this information is not always considered in subsequent decision-making. Causal analysis can help explain observed relationships, but it requires reliable assumptions to determine causality. Operations research uses analytical results to support operations research decisions, although its effectiveness depends on the quality of input data. The main challenge at present is to select and combine appropriate methods based on research questions. For example, when the results are used for scheduling or resource

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allocation, prediction errors are not always considered. Similarly, environmental assessment can estimate emissions without evaluating the effectiveness of specific operational measures. Strengthening the connections between these methods can improve the reliability and practical value of flight data applications.

7.4. Evolution of subjects

Fig. 4 shows how the disciplinary distribution of flight data research has changed over time. During 2004–2009, the reviewed studies were mainly associated with Engineering, Computer Science, and Psychology. Engineering and Computer Science continued to provide the technical foundation for research in this field. The range of disciplines expanded in subsequent years, with Transportation, Operations Research, and Environmental Sciences becoming more prominent. This trend highlights the increasing complexity and maturity of the field, as well as its growing alignment with global goals in green aviation and data-driven decision-making.

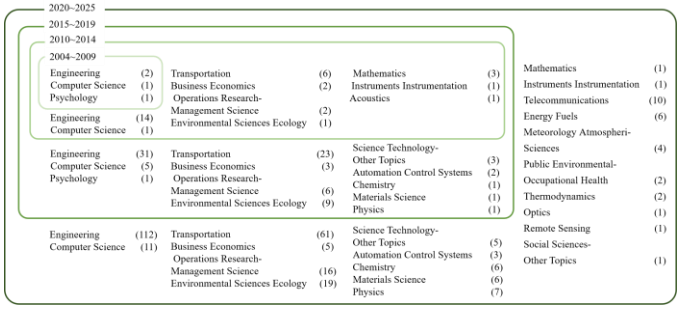


Fig. 4. Evolution of main research subjects.

8 Challenges and Future Research Directions

Despite the growing use of flight data across operational, safety, and sustainability applications, several challenges continue to limit their wider application. Table 3 summarizes the major research gaps identified from the reviewed studies across these three application domains. Data availability and quality remain important concerns. Many models also require further validation across different operating conditions. In addition, causal relationships are difficult to establish, and analytical results are not always used in system-level decisions. Future research should improve data quality and model reliability. Greater attention should also be given to applying research findings in practical aviation decision-making.

Table 3. Research gaps in flight-data applications.

Application domain	Research focus	Existing studies	Research gaps
OM	Flight delay prediction	Hao et al. (2014); Penn et al. (2015); Gui et al. (2020)	Existing models lack robust multi-source data integration and uncertainty quantification, limiting their effectiveness for operational decision support under heterogeneous delay patterns.
	Aircraft scheduling and disruption management	Jia and Wang (2025); Ohi and Kim (2020)	Integration of real-time data-driven delay predictions into scheduling optimization under large-scale network disruptions remains limited.
	Trajectory prediction	Schuster et al. (2012); Zhang et al. (2018); Ma and Tian (2020); Tong et al. (2023)	Long-term prediction accuracy and robustness under extreme weather, congestion, and non-standard operations require substantial improvement.
	Aircraft health monitoring and maintenance	Sun (2009); Xinlei et al. (2017); Duan et al.(2023)	Scarce labeled fault data limits supervised learning; existing unsupervised methods lack interpretability and cross-platform generalizability.
SS	Abnormal flight and component anomaly detection	Li et al. (2016); Cui et al. (2021)	Threshold-based methods miss novel multi-parameter anomalies; data-driven approaches lack reliability and interpretability for high-dimensional flight data.
	Conflict detection and warning	Kunzi (2013); Lu et al. (2021); Bao et al. (2024); Liu et al. (2024)	Modeling intent uncertainty in interactive traffic and balancing timeliness versus false alarms remain key operational challenges.
	Accident reconstruction	Ziółkowski and Skłodowski (2018); Vuorio et al. (2023)	Incomplete or inconsistent multi-source evidence limits accurate sequence reconstruction; advanced fusion and inference techniques are needed.
	Accident causal analysis	Ni et al. (2024); Zhou et al. (2023); Tikayat Ray et al. (2023)	Current methods identify correlations, not causation; establishing robust causal chains from observational data remains a core bottleneck.
	Human-factor analysis	Ruiz et al. (2010); Marinov et al. (2020); Irwin and Kelly (2021); Pham et al. (2020)	Objective, real-time cognitive state monitoring is lacking; existing indirect methods lack large-scale operational validation.
PD	Environmental impact analysis	Xue et al. (2025b); Pretto et al. (2024); Giladi (2020); Liao et al. (2022); Wang et al. (2024)	Assessment accuracy is highly sensitive to data resolution and model assumptions, leading to limited cross-study comparability and policy uncertainty.
	Airspace capacity evaluation	Ma et al. (2019)	Static/linear assumptions fail to capture nonlinear capacity dynamics from traffic–weather–control interactions; big-data-based methods are underdeveloped.
	Traffic-flow prediction	Sandamali et al. (2022); Zhang et al. (2025)	Sector/terminal-specific models lack robustness and generalizability under changing conditions; a unified adaptive framework is absent.
	Traffic complexity assessment	Chen et al. (2025)	Relationship between data-driven complexity indicators and actual controller workload/safety risk requires further empirical validation.
	Aviation system assessment	Mitkas et al. (2022)	Multi-dimensional evaluation balancing efficiency, safety, capacity, sustainability, and resilience within a unified framework remains scarce.

First, an important challenge in flight-data applications is data quality. For example, operational data may contain missing values,

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noise, or anomalous observations. These issues will affect trajectory prediction and related tasks. Systematic approaches such as data validation, anomaly detection, and data reconstruction are therefore needed to reduce these errors. However, uncertainty may still remain after processing. Researchers need to assess the remaining uncertainty and examine how it affects later models and decisions. This can help reduce the risk of unreliable results.

Second, for privacy and security reasons, access to flight data is often restricted. Data sources such as FDR, CVR, AHMS, and ACARS may contain highly sensitive information about aircraft operations. Moreover, there are significant differences in data ownership and sharing policies among different organizations. These limitations may make data difficult to obtain and affect the reproducibility of research. Privacy protection analysis methods can be one of the feasible paths to enable partial analysis to be carried out without directly sharing sensitive records, such as federated learning allowing participants to train models locally, exchanging only model parameters or gradients. This type of method mainly reduces the dependence on sharing the original dataset at the computational level. The controlled data sharing arrangement provides another option. Researchers can only analyze data in a controlled computing environment, and cannot export raw records. They also have sub controls on researcher qualifications, data anonymization, project review, analysis environment, and output disclosure. However, clear rules are still needed to define who can access data and how to use it. When recording information of interest, there may also be issues of responsibility and ethical use. More consistent documentation and data governance practices can help support research while protecting privacy, security, and business interests.

Third, integrating flight data from different sources remains difficult because consistent standards are still lacking across many datasets. Different sources may use different data formats and variable definitions. Their sampling frequencies and spatial or temporal resolutions may also differ. These differences complicate data integration and make it harder to compare results across airlines, aircraft types, airports, and regions. Developing interoperable data architectures and more consistent data representations addresses these differences. What's more, data-fusion methods may also help align information from different sources and make better use of their complementary information. This could support the development of more complete datasets for flight-data analysis. At the aircraft level, flight records can be connected to aircraft parameters and weather observations to view the status and flight performance of aircraft in real time. From the time series data of engine and system parameters, abnormal patterns and slow performance degradation may be found. This information is very useful for fault prediction, health-state assessment, and predictive maintenance of each aircraft. Spare-parts supply chain management may also get help from these records. At the level of airspace and network, traffic records and ADS-B trajectories are combined with airport operational data to realize traffic prediction and capacity balancing. The same information can also be used for the research of delay propagation, dynamic sectorization, and network-level robustness optimization. For sustainable aviation, aircraft performance models such as BADA or ANP could be used alongside ADS-B or FDR trajectories and weather records to estimate CO_2 and other emissions at a finer spatial and temporal scale. Linking operational records with aircraft energy-consumption and monitoring data may also help assess emission-reduction strategies and emerging low- and zero-emission aircraft technologies. These analyses could inform policy evaluation, technology pathway selection, and sustainable aviation planning.

Beyond these data-related issues, selecting suitable analytical methods is another challenge. As mentioned in Section 7.3, data mining, index-based methods, simulation, uncertainty quantification, causal analysis, and operations research all have their own premises and limitations, so it is difficult to cover all stages of flight-data analysis and decision-making with only one method. For example, when prediction errors affect the next diagnosis, predictive models may need to consider uncertainty. Causal analysis may be more suitable if the purpose is to evaluate the involvement of operational and policy. Optimization models can then use data-driven predictions together with unprotected information to support operational decisions. These methods do not have to be combined in all studies. Which method to choose should depend on the problem studied and the diagnosis considered.

Advances in Artificial intelligence (AI), digital twins, and edge computing may expand the use of flight data. AI can help with anomaly detection and traffic prediction, and also be used for trajectory optimization and aircraft health monitoring. Digital twins may be helpful for monitoring system status and evaluating various operational scenarios. Edge computing may allow data analysis in the aircraft when abnormal situations need to be dealt with quickly. Whether these technologies are really useful cannot be judged by predictive accuracy alone. Data quality and uncertainty can affect the results, even when an algorithm performs well in experiments. Model interpretability and computational requirements also matter, particularly when a method must fit existing operational procedures. Therefore, it is necessary to test these technologies in actual operations.

Another concern is model performance in settings different from those used for model development. The results can depend on the original data and the operating environment. Airports and airlines may have different operating patterns. Aircraft types, weather, traffic conditions, and airspace structures can also be different. Therefore, a model tested in a setting may produce different results when it changes in other places and operating conditions. Validation across Airports, airlines, and aircraft types, and using different time-period data, will help to find these differences. Testing models in actual operations is also needed to examine whether they are interpretable, computationally manageable, and compatible with existing procedures. Good results on a particular dataset alone provide limited evidence of how well a model will work in other operational settings.

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Author contributions

Ziming Wang: Writing – original draft, Software, Methodology, Visualization, Data curation. **Lingxiao Wu:** Writing – review & editing, Formal Analysis, Supervision, Conceptualization. **Dabin Xue:** Writing – review & editing, Visualization, Formal Analysis, Conceptualization. **Ang Li:** Writing – review & editing, Formal Analysis, Data curation, Conceptualization.

Replication and data sharing

The data and replication package are available on ETS-Data at https://doi.org/10.26599/ETSD.2026.9190108.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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Author biography



Ziming Wang received the master's degree in Management Science and Engineering from Shanghai University, Shanghai, China. She is currently a Ph.D. student in the Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University. Her research interests focus on air traffic management and big data analysis in aviation. Her research has appeared in Transportation Research Part D/E.



Lingxiao Wu is an assistant professor in Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University. His research interests lie in the design and implementation of methods that combine operations research and data analytics for solving problems arising in logistics management and transportation. His research has appeared in leading international journals, including Operations Research, Transportation Research Part B/E, and Transportation Science.



Dabin Xue is a researcher at the National Space Science Center, Chinese Academy of Sciences, appointed through a talent recruitment program. His research focuses on space weather effects and air traffic management. As a first or corresponding author, he has published in leading international journals, including Communications Earth & Environment, npj Space Exploration, and Space Weather. His work on space weather impacts on aviation was selected as a Research Highlight by Nature Reviews Earth & Environment.



Ang Li is an assistant professor in the Department of Aeronautical and Aviation Engineering, The Hong Kong Polytechnic University. Her research areas focus on Advanced Air Mobility (AAM), Air Traffic Management (ATM), multimodal system, leveraging machine learning, reinforcement learning, and operations research. Her research has appeared in Transportation Research Part A/C/E and EJOR.

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