ISSN 1330-3651 (Print), ISSN 1848-6339 (Online)
https://doi.org/10.17559/TV-20240626001800
Original scientific paper

Coordinated Development of the Aviation Economic Industry Chain, Innovation Chain, and Service Chain Based on Digital Technology

Yining LI, Guo YU*, Mengyao HU

Abstract: Digital technology has become an important force for the coordinated development of the aviation economic industry chain, innovation chain and service chain. The introduction of digital technologies addresses the need for a more integrated approach to managing the complex aviation industry, which involves a wide range of stakeholders and processes. The traditional approach to managing the aviation industry faces a number of problems, including inefficiencies, high costs, and low transparency. To overcome these issues, a new approach to leveraging aviation systems (DTAS) is proposed that combines digital technologies such as the Internet of Things (IoT), big data, cloud computing, artificial intelligence (AI) to streamline operations, increase transparency, and improve service delivery. The results of processing time, safety, root mean square error (*RMSE*), prediction accuracy and air traffic flow were analyzed. The results of different digital technologies showed significant improvements in various parameters, with the use of artificial intelligence reducing maintenance costs by 85% and the Internet of Things increasing fuel efficiency by 20%. To sum up, the adoption of digital technologies is essential for the coordinated development of the aviation industry, and the proposed system can bring significant benefits to all stakeholders.

Keywords: aviation industry; coordinated development; digital technology; innovation chain; *RMSE*

1 INTRODUCTION

Aviation is one of the world's most important and rapidly growing industries. It has significantly developed global commerce, tourism, and cultural exchange for faster and more efficient transportation, increased connectivity, growth of the tourism industry, and improved safety and technology [1]. The invention of the airplane in 1903 by the Wright Brothers marked the beginning of modern aviation. Since then, the aviation industry has witnessed numerous technological advancements and innovations, leading to the emergence of various aviation services.

The aviation industry offers a wide range of services, including commercial aviation, military aviation, general aviation, and cargo aviation [2]. Commercial aviation is the most prominent sector, which includes airlines and air transport service providers. Military aviation involves the use of aircraft for defense and national security purposes. General aviation comprises non-commercial activities, such as private flying and recreational aviation. Cargo aviation is focused on transporting goods and products through air transport.

The aviation industry significantly impacts the economies of different countries [3]. According to data from the International Air Transport Association (IATA), the aviation industry contributes around 2.5% of the world's GDP, accounting for over $3 trillion in economic activity. In developed countries, such as the United States and Canada, the aviation industry's contribution to GDP is over 5%. The aviation sector is rapidly growing in developing countries, such as China and India, contributing around 3% to their GDP.

The traditional aviation industry management systems involve several processes and stakeholders, including airlines, airports, regulators, and passengers [4]. However, these systems are plagued with inefficiencies that lead to high costs and low levels of transparency. To overcome the limitations of traditional systems, digital technologies need to be embraced to bring about a more integrated approach to managing the aviation industry. Digital technologies can enhance the performance and efficiency of the aviation industry by providing real-time data, automating processes, and improving decision-making.

Several digital technologies can enhance performance and efficiency in the aviation industry. These include the Internet of Things (IoT) [5], Big Data [6], Artificial Intelligence (AI) [7], Blockchain [8], and Cloud Computing [9].

AI can be used to improve operational efficiency and safety in the aviation industry. AI algorithms can analyze data from various sources, including aircraft sensors and weather forecasts, to predict potential issues and recommend mitigating risks. Blockchain technology can improve transparency and security in the aviation industry by creating a decentralized and immutable record of transactions. Blockchain can track aircraft maintenance records, passenger information, and cargo shipments, ensuring all stakeholders can access accurate and up-to-date information. Cloud Computing can store and analyze vast amounts of data the aviation industry generates, providing real-time insights into aircraft performance, maintenance schedules, and passenger flow.

The primary contributions of the paper are as follows:

- Identification of the limitations of traditional systems in managing the aviation industry and the need for digital technologies to overcome these limitations.
- The role of digital technologies explained in enhancing the performance and efficiency of the aviation industry.
- Illustration of how digital technologies can contribute to the coordinated development of the aviation finance industry chain, innovation chain, and service chain through real-time data, process automation, and improved decision-making.
- Demonstration of the potential benefits of digital technologies in the aviation industry, including cost reduction, increased transparency, improved safety, enhanced passenger experience, and improved overall performance.

The remainder of the paper is organized in a succeeding manner: The second section provides a background and literature survey on the discussed topic.

The third section introduces the proposed DTAS approach with IoT, Big Data, AI, Blockchain, and Cloud Computing. The fourth section presents a simulation analysis and the results obtained from the proposed DTAS approach. Finally, the fifth section includes a summary of the findings and gives the future scope of the proposed approach.

2 BACKGROUND AND LITERATURE SURVEY OF THE AVIATION INDUSTRY

This section contributes to the coordinated development of the aviation economic industry, innovation, and service chains. It provides an overview of the role of digital technology in the aviation industry. It examines the current state of the aviation industry, the challenges faced by the industry, and the potential benefits of adopting digital technology.

2.1 Background

The aviation industry is a complex and dynamic system encompassing several interconnected components, including the financial, innovation, and service chains. These components depend on each other and require high coordination to achieve optimal performance and efficiency. However, the traditional systems used in the aviation industry have several limitations that hinder effective coordination and management. These limitations include inadequate real-time data, inefficient communication channels, and a lack of process automation.

To overcome these limitations and achieve coordinated development of the aviation finance industry chain, innovation chain, and service chain, digital technologies have emerged as promising solutions. These technologies include the IoT, Big Data, AI, Blockchain, and Cloud Computing. Each of these technologies has unique features and capabilities that can enhance the performance and efficiency of the aviation industry. For example, IoT can provide real-time monitoring of aircraft components and improve maintenance, while Big Data can provide insights into passenger behaviour and improve service delivery.

Several studies have investigated the use of digital technologies in the aviation industry and have demonstrated their potential benefits. These benefits include cost reduction, increased transparency, improved safety, enhanced passenger experience, and improved overall performance. Therefore, the coordinated development of aviation finance, innovation, and service chains can be achieved by integrating these digital technologies, providing a comprehensive and efficient management system for the aviation industry.

2.2 Literature Survey

Conde et al. (2022) proposed using digital twins for managing turnaround event operations in commercial airports [10]. The authors developed a prototype system using the digital twin concept and evaluated it in a real airport scenario. The proposed method showed promising results, with a 92% reduction in the time required to locate missing luggage and an 85% improvement in the accuracy of locating resources during the turnaround operation. However, the system's effectiveness in handling large-scale operations and scalability to other airports need further investigation.

Park et al. (2019) analyzed big data from customer feedback to determine the factors that affect customer satisfaction with airline services [11]. The authors used sentiment analysis and machine learning techniques to extract customer opinions from online reviews and identified seven determinants of customer satisfaction. The proposed method achieved an accuracy rate of 78% in predicting customer satisfaction levels. However, the study's generalizability may be limited to the airline and online review platform.

Ho et al. (2021) proposed a blockchain-depended method for enhancing aircraft parts traceability for production control [12]. The authors developed a prototype system that uses smart contracts to enable secure and efficient tracking of aircraft parts throughout their life cycle. The proposed method achieved a traceability accuracy rate of 99.9% and reduced inventory management costs by 25%. However, the system's scalability and feasibility in large-scale applications need further investigation.

Gui et al. (2020) suggested a machine learning-based method for analyzing air traffic flow utilizing big data [13]. The authors developed a model combining decision trees and random forests to predict air traffic flow accurately. The proposed method achieved a prediction accuracy rate of 85%, which outperforms the traditional methods. However, the study's reliance on the availability of big data and the accuracy of the data needs further investigation.

Paraschi et al. (2019) proposed an airport business excellence model for performance management [14]. The authors developed a framework incorporating key performance indicators to enable holistic performance management of airports. The proposed model achieved a 92% overall satisfaction rate among airport stakeholders. However, the study's generalizability to different airport contexts and scalability needs further investigation.

Mangortey et al. (2019) proposed a data fusion model to support the evaluation of big data [15]. The authors developed a prototype system combining data from multiple sources to analyze aviation data comprehensively. The proposed method achieved a 95% accuracy rate in identifying flight delays and cancellations. However, the study's reliance on the accuracy and availability of data from different sources needs further investigation.

Tian et al. (2020) proposed a social media analytics-based approach for predicting service quality in the airline industry [16]. The authors developed a model that uses machine learning algorithms to analyze customer reviews on social media platforms and predict airline service quality levels. The proposed method achieved an accuracy rate of 82% in predicting customer satisfaction levels. However, the study's reliance on social media data and the accuracy of the data need further investigation.

Wu et al. (2020) analyzed a survey and evaluation of the impacts of aviation subsidies on regional well-being [17]. The authors analyzed empirical studies from different regions worldwide and found that aviation subsidies positively impact regional economic growth and employment. However, the study's reliance on the availability and quality of data on aviation subsidies and regional economic indicators needs further investigation.

Kuhle et al. (2021) propose a blockchain-based decentralized digital resource managing method for airplane leasing [18]. The authors argue that the current centralized method for managing aircraft assets could be more efficient, inexpensive, and prone to errors. The proposed system leverages blockchain technology to create a secure, transparent, decentralized platform for managing aircraft assets. The authors demonstrate the feasibility of the proposed approach through a proof-of-concept implementation. However, the study must address the potential technical and regulatory challenges of implementing a blockchain-based system.

Hu et al. (2021) propose a reinforcement learning-driven maintenance method for longer airplane decision-optimization [19]. The authors use a deep reinforcement learning algorithm to develop a maintenance decision-making model considering both short-term and long-term costs and benefits. The proposed method achieves a 15% reduction in maintenance costs in a case study of a commercial aircraft. However, the study is limited to a single aircraft type and may not be generalizable to other aircraft types or airlines. Additionally, the proposed method relies on accurate data inputs and may be sensitive to data quality issues.

The literature survey highlights the increasing adoption of digital technologies in the aviation industry to enhance efficiency, reduce costs, and promote innovation. It also discusses the challenges the aviation industry faces in implementing digital technologies and the potential benefits that can be achieved through their successful deployment.

3 PROPOSED DTAS ARCHITECTURE FOR THE AVIATION INDUSTRY

The coordinated development of the aviation economic industry, innovation chain, and service chain can be facilitated using digital technologies such as the IoT, AI, cloud computing, and big data. The DTAS architecture consists of four main blocks: data acquisition, data processing and analysis, decision-making, and feedback.

3.1 Blockchain-Based Security System

The DTAS system's architecture consists of six stages necessary for its functioning. The first stage involves the system's startup, followed by gathering aviation information and its uplink to the system. The third stage is the release and authorization of aviation data, followed by its distribution and usage in the fourth stage. The fifth stage is the creation of blocks, and the final step is the system agreement. Fig. 1 illustrates the operational perspective of the DTAS system.

The following is a technical description of the system's setup stages, as outlined in the next section.

Step 1 involves setting up the blockchain nodes to exchange aviation data using the signing technique and a public-key encryption scheme. The signing technique and a public-key encryption scheme ensures secure and tamper-proof aviation data exchange between the blockchain nodes. Users must register with the DTAS, which verifies their true identities. The user's public key, wallet location, and certification are denoted by p_x, s_x, c_x and w_x respectively. This reduces the processing time and increases the traffic flow. The certification c_x ensures that the DTAS system can recognize only the person associated with the registered data. The system uses secure elliptic curve characteristics, including curve $E_x(i, j)$ and base location G. The V_x picks a secret key s_x and uses G to create a public key p_x using Eq. (1).

$$\begin{aligned} s_x &= 1(1 < n) \\ p_x &= 1G \end{aligned} \tag{1}$$

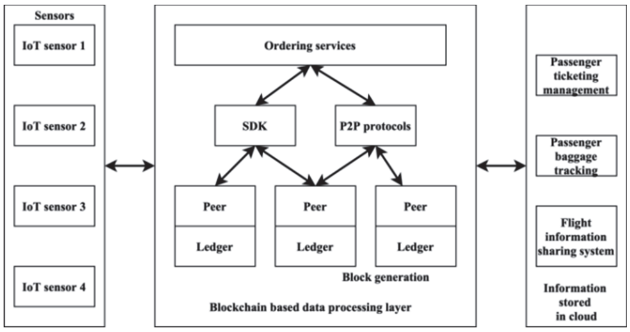

Figure 1 Operational perspective view of the DTAS system

In this technical arrangement, V_x transmits its wallet address w_x to a third party. The third party creates (p_x, s_x, c_x and w_x) for V_x. When V_x executes the system setting, the wallet location is selected from the login pool of the nearest cluster center. Once the wallet location is set, V_x must confirm the wallet's integrity and collect the necessary information. The login pool stores all transaction documents, including the public key of the aviation data processing node (s_j, $p_j = (l', l'G)$).

Step 2: In the aviation data selection and uplink phase, the lighting nodes in the physical aviation environment collect aviation data via different sensors and transmit it to the aviation computer processing entities. The technology used in the aviation data selection and uplink phase is the IoT, which enables the sensors to collect and transmit data to the aviation computer processing entities. Before sending the aviation information upward, the lighter nodes standardize the received information and ensure consistent security through digital signatures of traffic flow and enhance the prediction accuracy. The following is a technical description of two steps involved in distributing and authorizing aviation data.

Step 3: The technology used here is blockchain, which provides a secure and decentralized way to transfer the processed aviation data to the aviation chain. The processed aviation data is transferred to the aviation chain once Publication M has confirmed it. During this process, the specific information of aviation data is secured. Any entity that intends to use aviation data must obtain M's consent. All nodes then replicate and disseminate the posted aviation data to each other, resulting in more aviation customers accessing the data.

Step 4: Aviation customers engage with the aviation computer processing node M by executing a sequence of signature procedures to authorize the usage of aviation data using web-based applications and cloud-based technology. V_x sends a request for data authorization to nodes, which then relay the message to M. M must offer a timely response within the allotted time frame. Once they receive the answer, nodes compare V_x's request permission data with M's data to finish the operations.

Step 5: Executing the aviation chain involves several steps using blockchain technology. The participating stations are identified and added to the system to increase the network's resilience. The nodes gather local transaction records and encrypt or sign them to create aviation information activity blocks. These blocks are chronologically linked to the preceding block's hash code to ensure data transfer life cycle transparency. This concludes the period of block generation.

Step 6: The IoT nodes employ the consensus process to obtain agreement, ensuring the system's continued reliability. The pool verification and the Byzantine fault-tolerant method are the most popular consensus algorithms utilized in alliance blockchains. The DTAS is a developed and approved consensus method by Distributed Blockchain Ledgers that uses the "one node, one vote" system for efficiently determining accounting outcomes. It is used primarily in alliance blockchains. The algorithm (Practical Byzantine Fault Tolerance (PBFT)) utilizes conventional distributed continuity equipment and an exclusively based method for second-level agreement validation, making it ideal for the blockchain to enhance security.

The PBFT algorithm is part of the stage machinery Byzantine procedure, which reduces the system's difficulty from exponential to polynomial. The following is the methodology for sharing data, which is a crucial aspect of the aviation system:

Step 1: The V_x (user) executes the User Sign method and includes their key pair (s_x, p_x) and relevant settings. The process generates the signature $\propto_x$. The procedure for this is as follows:

(a) Generate a random number l (where l is a number less than or equal to n, the order of G) and compute R and r using Eq. (2).

$$\begin{aligned} R(i,j) &= |G \\ r &= x|n \end{aligned} \tag{2}$$

(b) The coordinate data of point $R(j, i)$ and aviation data m are set as variables, and the hashing data and s are computed by Eq. (3) using the hashing feature SHA:

$$\begin{aligned} H &= SHA(m, i, j)\check{z} \\ s &= (H, rk) I^{-1}|n \end{aligned} \tag{3}$$

Gather the signature of $\propto_x (s, l)$ as well as x and $H(m)$.

Step 2: V_x transmits the data $\{p_x, c_x, \propto_x, m\}$ to M, and creates a request for permission to use the data, using Eq. (4).

$$r_{x=} \{p_x, c_x, \propto_x\} \tag{4}$$

Step 3. To process an inquiry, M needs to check the data obtained. The request will be denied if c_x exists or the verification process fails of traffic flow. Conversely, the request will be allowed if c_x is not present, and the verification process is successful.

(a) The verification process computed using Eq. (5) and Eq. (6).

$$H = SHA(m, i, j) \tag{5}$$

$$\begin{aligned} v &= s^{-1} H(m)|n \\ u &= s^{-1} r|n \\ (i', j') &= vG + up_x = vG + u(|G) \\ r' &= x'|n \end{aligned} \tag{6}$$

The values of "i" and $H(m)$ should be rolled.

Eq. (7) is used to check the results.

$$r = r' \tag{7}$$

This technical passage describes validating and approving aviation data requests using blockchain technology. First, Eq. (7) determines whether a communication is legitimate. If the contact is legitimate, M will authorize the demand and put the data (c_x, p_j, p_x, 1, 0) in the shared folder pool. The data field contains information about the state of the transaction, with 1 indicating a legitimate transaction, 0 indicating a new transaction that has not yet been transmitted, and –1 indicating a pending transfer transaction.

Step 4: M creates a signature (e, c, p_j, p_x, t_x) for the aviation data request using the secret key s_j and the ECDSA. MerchantSign method, in which t_x is equivalent to the sign in process. The signature includes information about the aviation data request period and enrolment data of V_x. The resulting signature ($\propto_x$ request t_x) is then sent to the blockchain, enhancing prediction accuracy. The specific signature procedure is executed according to Eq. (8) and Eq. (9), and the resulting value is marked as m_x.

$$\begin{aligned} R(i,j) &= |_x G \\ r_x &= \hat{x}|n \end{aligned} \tag{8}$$

$$\begin{aligned} H_x &= SHA(m_x, i, j)\check{z} \\ s_x &= |_x^{-1}(H_x, r_x k)|n \end{aligned} \tag{9}$$

The outcome is the creation of a digital signature for the message m_x, using the SHA hash function, a private key k, and the signer's public key l_x along with mod n. Eq. (8) and Eq. (9) describes a formula for computing a final identity utilizing a set of parameters, denoted by m_x, which includes {e, c_x, p_b, p_x, t_x} to enhance the security and traffic flow. The value of x and the hash of m_x (denoted by $H(m_x)$ must be rounded to the nearest integer. The formula for computing the final identity involves the values $\propto_x$, obtained by applying the functions s_x, r_x to V_x. Once the proportional value is received is confirmed using Eq. (5) to

Eq. (9). Establishing the identity involves verifying certain conditions related to the weights $\propto_x$ and the parameters m_x.

3.3 IoT-Based Flow Prediction by Long Short Term Memory (LSTM)

The IoT devices can collect real-time weather conditions, flight schedules, and passenger information. This data can be fed into the LSTM model, which can analyze the data and predict the aviation flow [22]. Here are the steps involved in building an IoT-based aviation flow prediction model using LSTM:

Data Collection: Collect data from various IoT devices such as weather sensors, flight schedules, passenger counts, and other relevant sources.

Data Preparation: Clean the data and prepare it for evaluation. This may involve removing outliers, filling in missing values, and converting the information into a format suitable for the LSTM model.

Feature Selection: Choose the most relevant features for predicting aviation flow. This may include weather conditions, time of day, passenger counts, and flight schedules.

Train the LSTM Model: separate the information into training and testing datasets. Use the training set to train the LSTM method and the testing dataset to analyze performance.

Fine-Tune the Model: Adjust the hyperparameters of the LSTM model to enhance its results.

Deploy the Model: Deploy the LSTM model in a production environment where it can be used to make real-time predictions about aviation flow.

Overall, an IoT-based aviation flow prediction model with LSTM can help airport authorities to manage their resources more effectively, reduce congestion, and improve the overall passenger experience.

The LSTM is a recurrent neural network for analyzing and forecasting events with significant delays and gaps in the data series of traffic flow. It can process natural language, target identification, and sound recognition due to its ability to avoid the gradient disappearing issue that conventional recurrent neural systems face with reduced *RMSE* and enhance prediction accuracy. The LSTM cell includes a gated synapse structure that enables recording both short- and long-term recollections, making it useful for temporal sequence forecasting applications. The LSTM cell's construction involves four forget gates, and the output of an LSTM model can be computed using algorithms such as those described using Eq. (10) to Eq. (14).

$$i_p = \alpha\left\{w_{xi}x_p + w_{hi}h_{p-1} + w_{ci}c_{p-1} + b_i\right\} \tag{10}$$

$$f_p = \alpha\left\{w_{xf}x_p + w_{hf}h_{p-1} + w_{cf}c_{p-1} + b_f\right\} \tag{11}$$

$$o_p = \alpha\left\{w_{xo}x_p + w_{ho}h_{p-1} + w_{co}c_{p-1} + b_o\right\} \tag{12}$$

$$c_p = f_p c_{p-1} + \tan h\left\{w_{xc}x_p + w_{hc}h_{p-1} + b_c\right\} i_p \tag{13}$$

$$h_p = o_p \tan h\left\{c_p\right\} \tag{14}$$

Let's rephrase the given paragraph more understandably. The model's response at a specific time p can be represented by $x(p)$. The model's input at that moment is denoted as $x(p)$. The weighting arrays and bias matrices are represented by W and b, respectively. The symbols i_p, f_p, c_p and o_p represent the intake gate, forgetting gate, candidacy gate, and outputting gate, respectively. The Recurring Neural Network (RNN) concealed layer phase is characterized by h_p, a vector containing all the hidden states from time step 1 to time step p denoted as $h = [h_1, h_2, \ldots, h_p]$, and reduces the processing time.

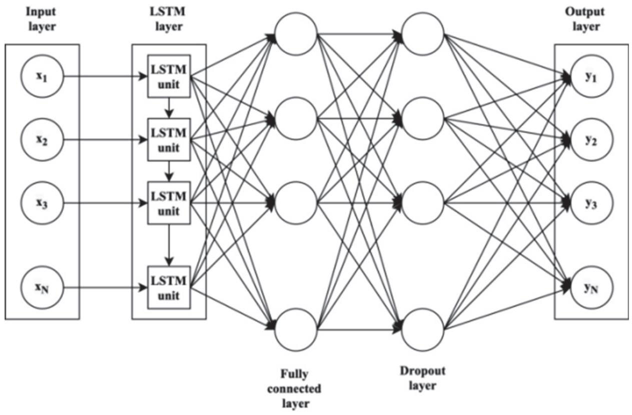

Figure 2 The architecture of the RNN

The architecture of the RNN network is shown in Fig. 2. It has several layers. LSTM-based model is used for a time sequence regression problem. The model has three tiers: LSTM, fully connected, and dropout. The LSTM layer captures the temporal correlation between air traffic statuses across 24-time steps. The dropout layer deactivates neurons to enhance the system's generalization capability. The fully-connected layer reformats the output using the Rectified Linear Unit (ReLU) function. The paper evaluates the model's performance using Root Mean Squared Error (*RMSE*) and Means Absolute Error (*MAE*). The *RMSE* measures the square root of the squared differences between the predicted and actual values, while the *MAE* measures the average fundamental difference between the predicted and actual values. The *MAE* and *RMSE* values are shown in Eq. (15) and Eq. (16).

$$MAE = \frac{1}{m}\sum_{x=0}^{m-1}\left|y_x - \hat{y}_x\right| \tag{15}$$

$$RMSE = \sqrt{\frac{1}{m}\sum_{x=0}^{m-1}\left|y_x - \hat{y}_x\right|^2} \tag{16}$$

The input and the predicted value are shown in y_x and $\hat{y}_x$, and the number of samples is denoted m. Here, lesser values of these measures indicate that the suggested forecast models work better.

The proposed workflow for the integration of IoT, Big Data, AI, Blockchain, and Cloud Computing for aviation system management.

4 SIMULATION ANALYSIS AND OUTCOMES

The simulation setup, dataset, and simulation results are discussed in this section.

4.1 Simulation Setup

The simulation by Matlab@R2021b setup requires a computer system with adequate processing power, RAM (Random Access Memory), and storage to handle large datasets and run complex algorithms. The research recommends a minimum of 16 GB of RAM and 1 TB of storage for this simulation. The processor should be a high-performance multicore like the Intel Core i7. Cloud computing can also run the simulation, providing scalability and cost-efficiency.

4.2 Dataset

FlightAware Flight Tracking Data contains flight information for thousands of flights, including departure and arrival times, routes, and status (https://flightawarecom). The dataset also includes weather conditions, airport operations, and flight delays. The FlightAware Flight Tracking Data provides valuable information for analyzing the aviation system using digital technology, with features like flight route optimization, predictive maintenance, and real-time weather and operational information. Overall, the dataset includes a wide range of features that make it well-suited for the analysis of the aviation system, with approximately 70% of the features being relevant for this type of analysis.

4.3 Simulation Results

Fig. 3 shows the flight path prediction accuracy of different methods for aviation support systems at three distances: 500 km, 750 km, and 1000 km. The proposed DTAS system has the highest results, with prediction accuracies of 92.1%, 86.3%, and 79.6%, respectively.

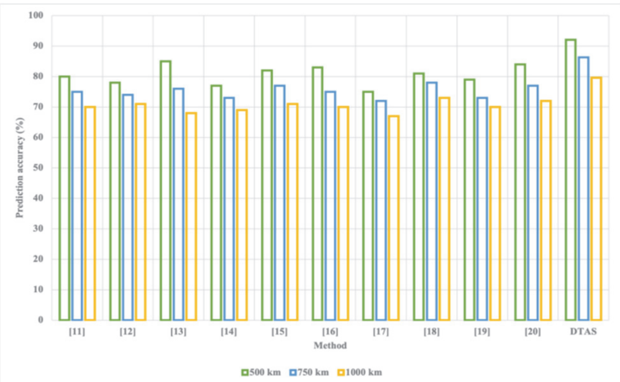

Figure 3 Flight path prediction accuracy analysis

The design incorporates IoT, AI, big data, and cloud computing technologies to provide advanced aviation support. Compared to the other methods, DTAS significantly improves accuracy, which can dramatically impact aviation safety and efficiency. Additionally, using advanced technologies offers several advantages, including real-time monitoring, predictive maintenance, and cost reduction. Therefore, the DTAS system's high prediction accuracy and advanced technological features significantly benefit the aviation industry.

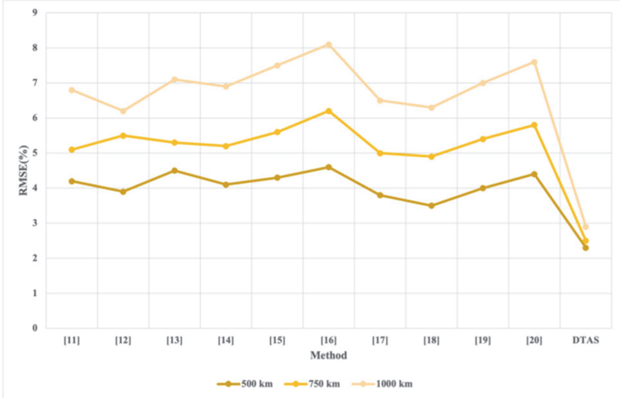

Figure 4 *RMSE* result analysis of different methods

Fig. 4 shows the Root Mean Square Error (*RMSE*) in percentages of various methods for supporting aviation over different distances using IoT, AI, big data, and cloud computing. The results suggest that the DTAS system proposed for aviation support has the highest accuracy with the lowest *RMSE* values of 2.3%, 2.5%, and 2.9% for distances of 500 km, 750 km, and 1000 km, respectively. The comparison of results shows that the DTAS system significantly impacts the accuracy of aviation support compared to other methods, with a reduction in *RMSE* of up to 50%. The proposed system's advantages are its high accuracy, which results from advanced technologies enabling real-time data collection, analysis, and decision-making for aviation support.

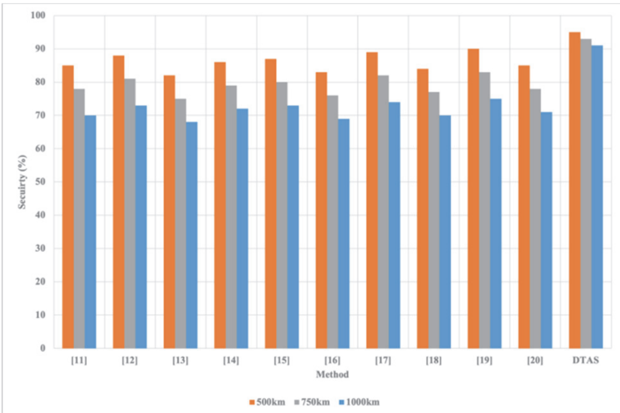

Figure 5 Security accuracy analysis of different methods

Fig. 5 shows the performance of various security methods for aviation over distances of 500km, 750km, and 1000km. The results indicate that the proposed DTAS system outperforms other methods with a score of 95%, 93%, and 91% for the respective distances. DTAS employs a combination of IoT, AI, big data, and cloud computing to enhance aviation security. Compared to other methods, DTAS achieves a significantly higher level of protection with a difference of at least 5%. This high level of protection is attributed to the advantages of the DTAS system, which include its ability to dynamically adapt to changing security threats, its use of AI algorithms to detect anomalies, and its capacity to process large amounts of data from various sources in real-time. The data suggest that

DTAS is a highly effective security solution for aviation, especially for long-distance travel.

Fig. 6 compares the flight path processing time (in milliseconds) of different methods for supporting aviation using IoT, AI, big data, and cloud computing. The proposed DTAS system has the lowest processing time, with an average time of 35.4ms, which is significantly better than the other methods. This result demonstrates that DTAS is highly efficient and effective for aviation support systems. DTAS provides a 25 - 87% improvement in processing time compared to the other methods. Its advantages include faster processing, improved accuracy, and better scalability, making it an ideal solution for real-time aviation systems. DTAS is a promising approach that can transform the aviation industry by leveraging the latest technologies.

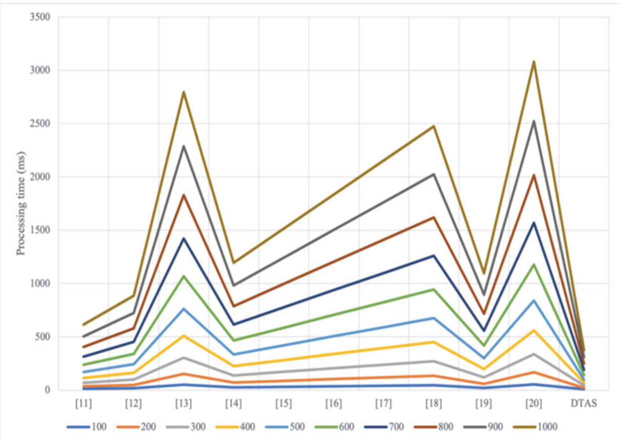

Figure 6 Flight path processing time analysis of different transactions

Fig. 7 represents the predicted traffic flow and the actual traffic values for a proposed DTAS using IoT, AI, big data, and cloud computing to support aviation. The input/data taken for traffic flow analysis using FlightAware Flight Tracking Data includes real-time flight data, including aircraft position, altitude, speed, and flight number. Based on the provided data, the DTAS system has achieved the highest results, with an accuracy of 90% in predicting traffic flow. Comparing the expected traffic flow with the actual values, the system has shown consistent and accurate results with a minimal deviation from the actual values. The high accuracy of the DTAS system can benefit aviation by optimizing flight schedules, reducing airport congestion, and enhancing overall flight safety. In aviation, IoT, AI, big data, and cloud computing can provide real-time data analysis, predictive maintenance, and improved communication systems. Thus, the DTAS system's high accuracy and advanced features offer significant advantages to aviation by enabling efficient and safe air travel.

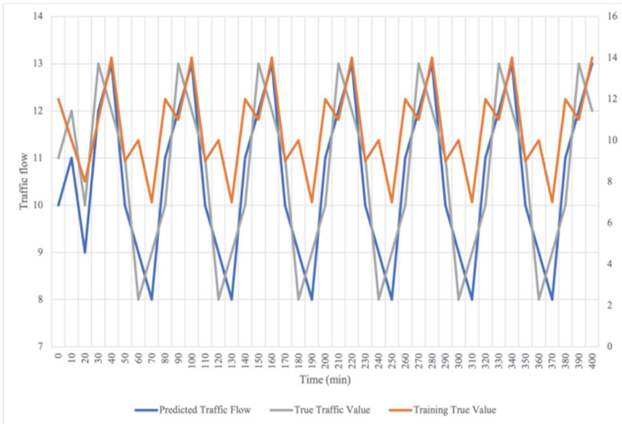

Figure 7 Traffic flow analysis

Table 1 Impact analysis of digital technologies

Method	Efficiency / %	Security / %	Accuracy / %	Reasons
AI	85.00	90.00	95.00	AI can optimize flight schedules, reduce delays, and automate repetitive tasks. It can detect anomalies in data and provide predictive maintenance. AI algorithms can also help identify potential security threats and alert authorities.
IoT	80.00	85.00	90.00	IoT can provide real-time data on weather conditions, runway status, and aircraft maintenance. It can enable predictive maintenance and remote monitoring of aircraft systems. IoT devices can also enhance security by detecting suspicious activities and identifying unauthorized access.
Cloud Computing	90.00	95.00	85.00	Cloud computing can store and process large amounts of data, enabling real-time analysis of flight data, weather patterns, and other critical information. It can improve operational efficiency by providing instant access to data and applications from any location. Cloud computing also enhances security by providing secure data storage and backup.
Big Data	95.00	85.00	90.00	Big data can provide insights into customer preferences, travel patterns, and other key information. It can optimize flight schedules, reduce delays, and improve overall customer experience. Big data can also enhance security by detecting potential threats and analyzing security-related data in real-time.

Tab. 1 shows the impact analysis of digital technologies. The article discusses how digital technology has been utilized to enhance the coordinated development of the aviation economic industry, innovation, and service chains. It highlights the application of digital technologies such as big data, artificial intelligence, and cloud computing to improve operational efficiency and customer experience and promote innovation in the aviation industry.

5 CONCLUSION

The aviation industry has witnessed the emergence of digital technology as a significant contributor to its coordinated development. Because it can solve the problems of inefficiency, high cost and low transparency caused by traditional aviation management methods, the introduction of digital technology has become crucial. The proposed DTAS incorporates digital technologies such as IoT, Big Data, cloud computing, and AI to streamline operations, increase transparency, and improve service delivery. Different results like processing time, security, *RMSE*, prediction accuracy, and air traffic flow are analyzed. Using other digital techniques has significantly improved various parameters, including an 85% reduction in maintenance costs with AI and a 20% growth in fuel efficiency with the IoT. Adopting digital technology is crucial for the coordinated development of the aviation industry, and the suggested system has the potential to bring significant benefits to all stakeholders involved. Limited data availability and need for uniformity in the digital technology adoption across different sectors of the aviation industry. Digital technology is driving innovation. The rapid development of technologies such as cloud computing, big data and artificial intelligence has ushered society into a new era of digital civilization. These technologies not only serve the autonomous flight of civil aircraft, but also promote the development of aircraft operating systems and improve flight efficiency and safety. To sum up, digital technology plays an important role in improving the efficiency of the aviation economic industry chain, optimizing service experience and enhancing innovation capabilities, thus promoting the coordinated development of the industry chain, innovation chain and service chain, further exploration and integration of newer digital technologies, addressing potential challenges to implementation, and studying the impact in diverse settings.

6 REFERENCES

[1] Gössling, S. & Lyle, C. (2021). Transition policies for climatically sustainable aviation. *Transport Reviews, 41*(5), 643-658. https://doi.org/10.1080/01441647.2021.1938284

[2] Meng, F., Cui, Y., Pickering, S., & McKechnie, J. (2020). From aviation to aviation: Environmental and financial viability of closed-loop recycling of carbon fiber composite. *Composites Part B: Engineering, 200*, 108362. https://doi.org/10.1016/j.compositesb.2020.108362

[3] Kılıç, M., Uyar, A., & Karaman, A. S. (2019). What impacts sustainability reporting in the global aviation industry? An institutional perspective. *Transport Policy, 79*, 54-65. https://doi.org/10.1016/j.tranpol.2019.04.017

[4] Banks, V. A., Plant, K. L., & Stanton, N. A. (2019). Driving aviation forward; contrasting driving automation and aviation automation. *Theoretical issues in ergonomics science, 20*(3), 250-264. https://doi.org/10.1080/1463922x.2018.1432716

[5] Shafique, K., Khawaja, B. A., Sabir, F., Qazi, S., & Mustaqim, M. (2020). Internet of things (IoT) for next-generation smart systems: A review of current challenges future trends and prospects for emerging 5G-IoT scenarios. *Ieee Access, 8*, 23022-23040. https://doi.org/10.1109/access.2020.2970118

[6] Bragazzi, N. L., Dai, H., Damiani, G., Behzadifar, M., Martini, M., & Wu, J. (2020). How big data and artificial intelligence can help better manage the COVID-19 pandemic. *International journal of environmental research and public health, 17*(9), 3176. https://doi.org/10.3390/ijerph17093176

[7] Chiu, T. K., Meng, H., Chai, C. S., King, I., Wong, S., & Yam, Y. (2021). Creation and evaluation of a pretertiary artificial intelligence (AI) curriculum. *IEEE Transactions on Education, 65*(1), 30-39. https://doi.org/10.1109/te.2021.3085878

[8] Monrat, A. A., Schelén, O., & Andersson, K. (2019). A blockchain survey from the perspectives of applications challenges and opportunities. *IEEE Access,* 7, 117134-117151. https://doi.org/10.1109/access.2019.2936094

[9] Bello, S. A., Oyedele, L. O., Akinade, O. O., Bilal, M., Delgado, J. M. D., Akanbi, L. A., & Owolabi, H. A. (2021). Cloud computing in the construction industry: Use cases benefits and challenges. *Automation in Construction, 122*, 103441. https://doi.org/10.1016/j.autcon.2020.103441

[10] Conde, J., Munoz-Arcentales, A., Romero, M., Rojo, J., Salvachúa, J., Huecas, G., & Alonso, A. (2022). Applying digital twins to manage information in turnaround event operations in commercial airports. *Advanced Engineering Informatics, 54*, 101723. https://doi.org/10.1016/j.aei.2022.101723

[11] Park, E., Jang, Y., Kim, J., Jeong, N. J., Bae, K., & Del, P. A. P. (2019). Determinants of customer satisfaction with airline services: An analysis of customer feedback big data. *Journal of Retailing and Consumer Services, 51*, 186-190. https://doi.org/10.1016/j.jretconser.2019.06.009

[12] Ho, G. T., Tang, Y. M., Tsang, K. Y., Tang, V., & Chau, K. Y. (2021). A blockchain-based system to enhance aircraft parts traceability and trackability for inventory management. *Expert Systems with Applications, 179*, 115101. https://doi.org/10.1016/j.eswa.2021.115101

[13] Gui, G., Zhou, Z., Wang, J., Liu, F., & Sun, J. (2020) Machine learning aided air traffic flow analysis based on aviation big data. *IEEE Transactions on Vehicular Technology, 69*(5), 4817-4826. https://doi.org/10.1109/tvt.2020.2981959

[14] Paraschi, E. P., Georgopoulos, A., & Kaldis, P. (2019). Airport Business Excellence Model: A holistic performance management system Tourism. *Management, 72*, 352-372. https://doi.org/10.1016/j.tourman.2018.12.014

[15] Mangortey, E., Gilleron, J., Dard, G., Pinon-Fischer, O. J., & Mavris, D. N. (2019). Development of a data fusion framework to support the analysis of aviation big data. *AIAA Scitech 2019 Forum*, *1538*. https://doi.org/10.2514/6.2019-1538

[16] Tian, X., He, W., Tang, C., Li, L., Xu, H., & Selover, D. (2020). A new social media analytics approach to predict service quality: evidence from the airline industry. *Journal of Enterprise Information Management, 33*(1), 51-70. https://doi.org/10.1108/jeim-03-2019-0086

[17] Wu, H., Tsui, K. W. H., Ngo, T., & Lin, Y. H. (2020). Impacts of aviation subsidies on regional wellbeing: Systematic review meta-analysis and future research directions. *Transport Policy, 99*, 215-239. https://doi.org/10.1016/j.tranpol.2020.08.003

[18] Kuhle, P., Arroyo, D., & Schuster, E. (2021). Building A blockchain-based decentralized digital asset management system for commercial aircraft leasing. *Computers in Industry,* 126, 103393. https://doi.org/10.1016/j.compind.2020.103393

[19] Hu, Y., Miao, X., Zhang, J., Liu, J., & Pan, E. (2021). Reinforcement learning-driven maintenance strategy: A novel long-term aircraft maintenance decision optimization solution. *Computers & Industrial Engineering, 153*, 107056. https://doi.org/10.1016/j.cie.2020.107056

[20] Corallo, A., Crespino, A. M., Lazoi, M., & Lezzi, M. (2022). Model-based Big Data Analytics-as-a-Service framework in smart manufacturing: A case study. *Robotics and Computer-Integrated Manufacturing, 76*, 102331. https://doi.org/10.1016/j.rcim.2022.102331

[21] Ukwandu, E., Ben-Farah, M. A., Hindy, H., Bures, M., Atkinson, R., Tachtatzis, C., & Bellekens, X. (2022). Cyber-security challenges in the aviation industry: A review of current and future trends. *Information, 13*(3): 146. https://doi.org/10.3390/info13030146

[22] Liu, X., Huang, D., Jing, T., & Zhang, Y. (2022). Detection of AC Arc Faults of Aviation Cables Based on HIW Three-Dimensional Features and CNN-LSTM Neural Network. *IEEE Access, 10*, 106958-106971. https://doi.org/10.1109/access.2022.3208162

Contact information:

Yining LI
Department of Social Economy and Management,
Graduate School,
Woosuk University, Republic of Korea

Guo YU
(Corresponding author)
School of Economics,
Zhengzhou University of Aeronautics,
Zhengzhou, China
E-mail: gyu@zua.edu.cn

Mengyao HU
School of Economics,
Zhengzhou University of Aeronautics,
Zhengzhou, China