Prediction of Physical Training Demand and Dynamic Course Adjustment Model for Flight Attendants Based on the Evolution of Civil Aviation Industry Standards

Yanzi Cai, Xiaobin Xu
Zhejiang Yuying College of Vocational Technology, Hangzhou 310018, Zhejiang, China
Corresponding author: Xiaobin Xu (e-mail: xuxiaobinsci@163.com)

ABSTRACT With the continuous evolution of civil aviation industry standards, flight attendant physical training requires dynamic adaptation to changing occupational demands. Aiming at lagging standard response, insufficient quantitative demand prediction, and rigid curriculum systems, this study constructs a four-dimensional quantitative index system for civil aviation standard evolution. An Improved Sparrow Search Algorithm–Random Forest (IMSSA-RF) prediction model is proposed, and a dynamic course adjustment mechanism linking standards, demand, and training is designed. Based on 495 panel data samples from 15 colleges and 30 airlines during 2014–2024, the IMSSA-RF model achieves 95.7% prediction accuracy, outperforming ARIMA, RF, and LSTM models. The dynamic curriculum adjustment improves the physical fitness pass rate by 37.2% and job adaptation by 41.5%. Emergency physical fitness and high-altitude safety are identified as the core driving factors. The model provides a systematic and quantitative scheme for precision training and adaptive curriculum design. It also has engineering relevance for aviation scenarios involving wearable monitoring, wireless emergency communication, and electromagnetic-compatible cabin safety systems.

INDEX TERMS flight attendants, occupational physical fitness, demand prediction, wireless monitoring, aviation safety

I. INTRODUCTION

A. RESEARCH BACKGROUND

As a strategically pivotal industry in the transportation sector, the civil aviation industry is rapidly advancing toward safer, more refined, intelligent, and high-quality operations. It achieves industrial upgrading through smart airport operations and maintains global competitiveness. The continuous improvement and dynamic evolution of the industry standard system have become important guarantees for the high-quality development of the industry. As the core subject of civil aviation cabin services and safety assurance, flight attendants' professional physical fitness is not only the foundation for ensuring cabin emergency response and high-altitude operation safety, but also the key to improving cabin service efficiency and meeting passengers' high-quality service needs. The requirements for flight attendants' professional physical fitness in the civil aviation industry continue to improve and refine with the evolution of industry standards [1,2]. Since the release of China's first "Physical Examination and Appraisal Standards for Civil Aviation Flight Attendants" in 1996, the Civil Aviation Administration of China has successively issued/revised more than ten core standards, including "Occupational Skills Standards for Aviation Flight Attendants", "Cabin Emergency Response Operation Specifications", and "Management Rules for Civil Aviation Personnel Physical Examination Certificates". The evaluation indicators for flight attendant occupational physical fitness have gradually expanded from a single basic physical fitness requirement to a comprehensive index system of basic physical fitness, emergency physical fitness, high-altitude adaptation physical fitness, and service practical physical fitness. The training requirements have shifted from "standard oriented" to "adaptive, refined, and scenario oriented" [3].

B. CURRENT RESEARCH STATUS AT HOME AND ABROAD

Research on occupational physical training for foreign flight attendants places more emphasis on adapting to job scenarios and guiding safety abilities, such as designing specialized physical training content based on narrow cabin spaces, high altitude and low pressure scenarios [4], and making emergency response physical fitness standards the core condition for flight attendants to take up their positions [5]. However, related studies mostly focus on innovative training methods and have not constructed demand forecasting and curriculum adjustment models based on industry standard evolution, which is not highly compatible with the localization needs of flight attendant talent cultivation in China. Optimize the accuracy of prediction models by improving swarm intelligence algorithms [6]. In the field of physical training, some studies have applied predictive models to athlete physical training, vocational physical training, and other areas, such as predicting athlete specific physical training needs based on random forest (RF) models [7], and constructing a dynamic adjustment system for enterprise vocational physical training courses based on job requirements [8]. However, existing research has not yet taken the evolution of industry standards as the core direction, and there have been no reports on the application of it in predicting the demand for flight attendant professional physical training and dynamically adjusting courses. There is a lack of personalized and dynamic model design for flight attendant professional physical training. At present, no studies have integrated the evolution of civil aviation industry standards into the prediction of flight attendants' physical training demand and dynamic curriculum adjustment, which is the key gap of this study.

C. TECHNICAL ROADMAP

The technical route of this article follows the logic of "theoretical analysis standard deconstruction data collection model construction verification application strategy optimization", as follows:

1. Theoretical construction stage: Define core concepts through literature research, sort out relevant theories on the evolution of civil aviation industry standards, occupational physical training, and machine learning prediction, and analyze the impact mechanism of industry standard evolution on flight attendant occupational physical training.
2. Standard deconstruction stage: Sort out the industry standards related to physical fitness for civil aviation flight attendants from 1996 to 2024, divide the evolution stages, identify core dimensions and driving factors, and construct a quantitative indicator system for the evolution of industry standards.
3. Data collection stage: Using methods such as school enterprise research, data statistics, and literature review, multiple sources of flight attendant occupational physical training data were collected to construct a time-series dataset containing 38 characteristic variables.
4. Data preprocessing stage: Clean, deduplicate, handle missing values, handle outliers, normalize the raw data, use correlation analysis and variance analysis to complete feature screening, and determine the input features of the model.
5. Model construction stage: Improve the sparrow search algorithm, optimize the feature subset and hyperparameters of the random forest model, and construct the IMSSA-RF training demand prediction model; Based on the results of demand forecasting and the evolution of industry standards, construct a dynamic adjustment model for courses.
6. Model validation stage: Conduct comparative experiments between the IMSSA-RF model and traditional RF, LSTM, and ARIMA models to verify the prediction accuracy; Design an experimental group and a control group to conduct empirical research to verify the effectiveness of the course dynamic adjustment model.
7. Application optimization stage: Based on the model validation and empirical research results, this article proposes optimization strategies for the flight attendant physical fitness system and engineering technical training frameworks. It concludes by summarizing research findings, analyzing limitations, and outlining future research directions for the synergistic development of these high-demand industries.

II. THEORETICAL BASIS AND DEFINITION OF CORE CONCEPTS

A. DEFINITION OF CORE CONCEPTS

1) Evolution of Civil Aviation Industry Standards

Civil aviation industry standards refer to technical norms and codes of conduct issued by civil aviation management departments, industry associations, etc., which regulate the production and operation, service quality, personnel capabilities, and other aspects of the civil aviation industry. They have the characteristics of legality, standardization, dynamism, and leadership. The evolution of civil aviation industry standards refers to the continuous improvement, updating, and upgrading process of civil aviation industry standards in the time dimension, including the addition, revision, and abolition of standards, as well as dynamic changes in the indicator system, requirement level, and scope of application. Its core characteristics are the refinement of indicators, the enhancement of requirements, the concretization of scenarios, and the integration of capabilities. The driving factors for evolution include industry technology development, safety demand improvement, service quality upgrading, policy and regulatory adjustments, etc. The civil aviation industry standards studied in this article focus on core standards directly related to the physical fitness of flight attendants, including national/industry standards in the fields of physical examination, vocational skills, emergency response, service quality, etc. [9].

2) Flight Attendant Professional Physical Fitness

Occupational physical fitness refers to the total physical fitness that is suitable for specific occupational positions, ensuring the smooth progress of job work, improving job efficiency, and reducing occupational injury risks [10-12]. Flight attendant professional physical fitness refers to the comprehensive physical fitness required by flight attendants to adapt to the requirements of civil aviation cabin work positions, ensure cabin flight safety, and improve cabin service quality. Different from ordinary basic physical fitness, it has four characteristics: job scenario oriented, safety oriented, high-altitude adaptability, and service integration. This article divides the physical fitness of flight attendants into four dimensions: basic physical fitness, emergency physical fitness, high-altitude adaptation physical fitness, and service practical physical fitness. Among them, basic physical fitness is the foundation, emergency physical fitness and high-altitude adaptation physical fitness are the core of safety guarantee, and service practical physical fitness is the support for service quality.

B. RELEVANT THEORETICAL BASIS

Swarm intelligence optimization theory is a theoretical system that simulates the foraging, migration, and anti predation behaviors of natural biological populations, and constructs optimization algorithms to solve complex optimization problems. It has the characteristics of strong global search ability, fast convergence speed, and simple implementation [13]. Sparrow search algorithm, particle swarm optimization algorithm, genetic algorithm, etc. are typical swarm intelligence optimization algorithms. By improving and optimizing the algorithms, their optimization performance can be further enhanced, achieving efficient optimization of model feature selection and parameter configuration. The swarm intelligence optimization theory provides theoretical guidance for improving the sparrow search algorithm and optimizing the random forest model in this study, and is the core theoretical basis for improving the accuracy of prediction models.

C. IMPACT MECHANISM OF THE EVOLUTION OF CIVIL AVIATION INDUSTRY STANDARDS ON THE OCCUPATIONAL PHYSICAL TRAINING OF FLIGHT ATTENDANTS

The civil aviation industry standards have made clear and rigid provisions on the indicator system, standard requirements, and assessment methods of flight attendant professional physical fitness. The evolution of the standards directly changes the training objectives and assessment standards of flight attendant professional physical fitness, which is the core basis for flight attendant professional physical fitness training. One is the expansion of the indicator system. The evolution of standards has expanded the physical fitness indicators for flight attendants from a single basic physical fitness to a comprehensive indicator system that integrates basic, emergency, high-altitude adaptation, and practical service, requiring comprehensive coverage of training course content; Secondly, the requirements for meeting standards have been raised, and the evolution of standards has continuously increased the threshold for meeting various physical fitness indicators, such as weight-bearing turnaround running in cabin emergency response and endurance requirements in high-altitude environments, requiring an increase in training intensity and duration; The third is the refinement of assessment methods, and the evolution of standards has transformed physical fitness assessment from "unified assessment" to "graded assessment and scenario based assessment", requiring training courses to achieve hierarchical design and scenario based implementation [14].

Indirect correlation paths between basic information variables and physical training needs:

Airline fleet size: Expansion of fleet size → Increase in route density → Extension of monthly flight hours of flight attendants (correlation coefficient 0.73) → Improvement of demand for physical endurance and fatigue resistance; Meanwhile, the higher the proportion of wide-body aircraft, the greater the physical consumption of emergency disposal in the cabin (e.g., dual-channel evacuation, heavy object handling), and the more stringent the requirements for emergency physical fitness.

Route network coverage: The higher the proportion of long-distance routes → The longer the duration of high-altitude flight → The longer the exposure time to high-altitude low-pressure environment → Improvement of demand for high-altitude adaptive physical fitness (e.g., hypoxia tolerance, pressure regulation adaptation); The proportion of plateau routes and international long-distance routes is positively correlated with physical training intensity (correlation coefficient 0.68).

III. EVOLUTION ANALYSIS OF INDUSTRY STANDARDS RELATED TO PHYSICAL FITNESS FOR CIVIL AVIATION FLIGHT ATTENDANTS

A. INDUSTRY STANDARD SORTING AND EVOLUTION STAGE DIVISION

1) Industry Standard Sorting

Using the keywords of "civil aviation, flight attendants, flight attendants, occupational physical fitness, physical examination, occupational skills, emergency response", this study systematically sorted out the core industry standards directly related to flight attendant occupational physical fitness that were released/revised in China from 2019 to 2024 through the official website of the Civil Aviation Administration of China, the national standard full-text disclosure system, the industry association official website, China National Knowledge Infrastructure, and other platforms. The standards that were not directly related to flight attendant occupational physical fitness were excluded, and a total of 16 core standards were finally selected, including 3 national standards, 10 industry standards, and 3 management rules, covering five major areas including physical examination, occupational skills, emergency response, service quality, and physical examination certificates. The specific details are shown in Table 1 [15]. This study takes data from 15 colleges and 30 airlines during 2014–2024 as the research object, and a total of 495 annual panel data are obtained.

Systematically sort out all core standards from 1996 to 2024, add effective standards from 2014 to 2018 (e.g., CCAR-67FS-R2 revised in 2013, GB/T 32745-2016 "Quality of Air Passenger Transport Services" released in 2016), revise the original "core standards from 2019 to 2024" to "core standards from 1996 to 2024", and increase the total number from 16 to 22, ensuring that data from 2014 to 2018 are supported by corresponding standards of the same period.

2) Division of Evolution Stages

Based on the background, core content, and physical fitness requirements of the standards, combined with the development stages of the civil aviation industry, the evolution process of China's civil aviation flight attendant professional physical fitness related industry standards from 1996 to 2024 is divided into four stages, each stage has clear time nodes, core characteristics, and physical fitness requirements guidance, as follows:

1. Sprout period (1996-2007): With basic physical fitness standards as the core orientation, the number of standards is small and the content is simple, only clarifying the basic physical fitness and basic physical fitness indicators of flight attendants, such as height, weight, vision, basic endurance, etc. The physical fitness requirements are aimed at "meeting basic job requirements", without considering job scenarios and service needs. Representative standards are MH/T 2001-1996 and CCAR-67FS-R1 [16].

2. Growth period (2008-2017): With basic physical fitness and job physical fitness as the core orientation, the number of standards gradually increased and the content continued to enrich. For the first time, physical

fitness indicators were linked to vocational skills and cabin services, and physical fitness requirements for cabin emergency response and basic services were added. Physical fitness requirements shifted from "standard type" to "job adaptation type", represented by standards such as MH/T 3013-2008, MH/T 3021-2012, and GB/T 32745-2016.

3. Maturity period (2018-2021): With the construction of a comprehensive physical fitness system as the core orientation, the standard system tends to be improved, and a comprehensive indicator system combining basic physical fitness and job physical fitness has been established. The physical fitness requirements for emergency response and cabin services have been refined, and the physical fitness level has been included in the job ability evaluation system. The physical fitness requirements are developing towards "refinement and scenario based", represented by the standards MH/T 3013-2018, MH/T 3035-2021, CCAR-121-R5 [17]. Although there were no major disruptive revisions to the standards from 2014 to 2018, there were local indicator optimizations and requirement enhancements (e.g., the 2016 standard added "physical fitness adaptation requirements for special passenger services", and the 2018 standard refined "graded fitness standards for flight attendants of different levels"). These evolutionary characteristics have all been quantified into model input indicators to ensure the time consistency and logical coherence between data and standard evolution.

B. CORE DIMENSIONS AND CHARACTERISTIC LAWS OF INDUSTRY STANDARD EVOLUTION

By analyzing and comparing the contents of 16 core standards, combined with the connotation and composition of flight attendant professional physical fitness, four core dimensions of the evolution of industry standards related to civil aviation passenger professional physical fitness have been identified. These dimensions are interrelated and mutually supportive, forming a complete system of standard evolution. They are the core basis for constructing a quantitative indicator system for industry standard evolution, as follows:

1. Dimension of Physical Fitness Index Requirements: This is the core dimension of standard evolution, including the system composition of physical fitness indicators, achievement thresholds, and assessment methods. The evolution characteristics are manifested in the expansion of the indicator system from a single basic physical fitness to a four in one comprehensive physical fitness, the continuous increase of the standard threshold, and the transformation of the assessment method from unified assessment to graded assessment and scenario based assessment.

2. Job scenario adaptation dimension: This is the scenario oriented dimension of standard evolution, including three sub scenarios: cabin emergency scenario, cabin service scenario, and high-altitude environment scenario. The evolution characteristics are manifested in the continuous improvement of the fit between physical fitness requirements and job scenarios, and the design of special physical fitness indicators for different cabin scenarios to achieve the scenarization and concretization of physical fitness requirements.

3. Dimension of safety capability standards: This is the core guiding dimension of standard evolution, including emergency response physical fitness, high-altitude safety physical fitness, and occupational health physical fitness. The evolution characteristics are manifested in the continuous strengthening of physical fitness requirements related to safety capabilities, making emergency physical fitness standards a necessary condition for employment, adding high-altitude environment adaptation physical fitness and occupational health physical fitness requirements, highlighting the development concept of "safety first" in civil aviation [18].

4. Service Capability Adaptation Dimension: This is the quality oriented dimension of standard evolution, including three aspects: service practical fitness, service efficiency fitness, and special passenger service fitness. The evolution characteristics are manifested in the continuous refinement of physical fitness requirements related to service capabilities, incorporating physical fitness levels into the service quality evaluation system, requiring high compatibility between service practical physical fitness and service and

TABLE 1. Core Industry Standards Related to Cabin Crew Vocational Physical Fitness in China's Civil Aviation

Year	Standard Code	Standard Name	Issuing Authority	Key Physical Fitness Requirements
2019	MH/T 3028-2019	Civil Aviation Cabin Service Specifications	CAAC	Service-related physical fitness for equipment operation and special passenger assistance
2020	CCAR-121-R5	Air Carrier Certification Rules (Revised)	CAAC	Emergency physical fitness as a mandatory qualification
2021	MH/T 3035-2021	Emergency Response Capability Evaluation Specifications	CAAC	Assessment standards for evacuation, fire fighting, and water ditching
2022	GB/T 41401-2022	Professional Competence Requirements for Aviation Service Personnel	SAMR	High-altitude adaptive fitness; four-dimensional fitness system
2022	CCAR-67FS-R3	Physical Certification Rules (Re-revised)	CAAC	Stricter high-altitude adaptation and regular physical review
2023	MH/T 3013-2023	Professional Skill Requirements (Re-revised)	CAAC	Graded physical standards for junior, middle, and senior crew
2023	CAAC Doc. 46	Action Plan for Improving Civil Aviation Service Quality (2023–2027)	CAAC	Build a training system adaptive to evolving industry standards
2024	MH/T 3042-2024	Professional Competence Grading Evaluation Specifications	CAAC	Physical fitness linked to professional grade and promotion
2024	MH/T 3043-2024	Specifications for Cabin Crew Vocational Physical Fitness Training	CAAC	Official training standards: content, intensity, methods, assessment

passenger needs, and promoting the improvement of aviation service quality [19,20].

C. CONSTRUCTION OF QUANTITATIVE INDICATOR SYSTEM FOR THE EVOLUTION OF CIVIL AVIATION INDUSTRY STANDARDS

Adjust "airline fleet size" and "route network coverage" from "core predictive variables" to "scenario control variables", and add annotations in Table 2 (Quantitative Index System for the Evolution of Civil Aviation

Industry Standards): "As scenario control variables, they indirectly affect the physical training demand by influencing flight attendants' work intensity and job scenario complexity". Meanwhile, clarify in the abstract and research content: "Taking industry standard evolution indicators as core predictive variables and airline operation characteristics as scenario control variables" to avoid misunderstandings.

1) Principles for Constructing Indicator System

To ensure the scientificity, comprehensiveness, quantifiability, and operability of the quantitative indicator system for the evolution of civil aviation industry standards, the construction process follows the following five principles:

1. Principle of comprehensiveness: The indicator system should comprehensively cover the four core dimensions of standard evolution, including all core elements of physical fitness indicator requirements, job scenario adaptation, safety capability standards, and service capability adaptation, to avoid missing key evolution features.

2. Quantifiability principle: All indicators must be able to be quantified. For qualitative descriptions of standard content, they can be converted into quantitative indicators through expert scoring, content analysis, and other methods to ensure that the indicators can be used for model training and quantitative analysis.

3. Targeted principle: The indicator system should be tailored to the evolving characteristics of industry standards related to the physical fitness of civil aviation flight attendants, highlighting the job scenario, safety orientation, and high-altitude adaptability of flight attendant physical fitness, and avoiding similarity with the indicator system of other civil aviation industry standards.

2) Indicator System Construction Process

The method of combining literature analysis, expert interviews, and content coding is used to construct a quantitative indicator system for the evolution of civil aviation industry standards. The specific steps are as follows:

1. Preliminary indicator extraction: Based on the four core dimensions of standard evolution, 16 core standards were encoded and feature extracted, and 28 three-level indicators were preliminarily extracted to form the initial draft of the indicator system.

2. Expert Consultation: Select 30 experts (10 from the civil aviation industry, 10 from flight attendant talent development, 5 from machine learning, and 5 from physical training) to review the initial draft of the indicator system and solicit their opinions on the selection, modification, and supplementation of indicators.

3. Indicator screening and optimization: Based on expert review opinions and the principles of indicator system construction, duplicate, redundant, and difficult to quantify indicators are eliminated, and key missing indicators are supplemented. Finally, a quantitative indicator system for the evolution of civil aviation industry standards is determined, which includes 4 primary indicators, 12 secondary indicators, and 22 tertiary indicators.

3) Specific Content of Indicator System

The constructed quantitative index system for the evolution of civil aviation industry standards covers 4 primary indicators, 12 secondary indicators, and 22 tertiary indicators, clarifying the quantification methods, connotations, and weight ratios of each indicator, achieving comprehensive quantification of standard evolution, and providing core input indicators for the construction of subsequent training demand prediction models, as shown in Table 2.

IV. MULTI SOURCE DATA COLLECTION AND PREPROCESSING FOR FLIGHT ATTENDANT PROFESSIONAL PHYSICAL TRAINING

A. SELECTION OF RESEARCH SUBJECTS

To ensure the representativeness, comprehensiveness, and diversity of the research data, a stratified sampling method was used to select the research subjects, covering different regions, types, and scales of civil aviation colleges and airlines, taking into account the eastern, central, and western regions, covering different types of airlines such as full-service airlines, low-cost airlines, and local airlines, to ensure that the data can reflect the overall situation of physical training for flight attendants in China. The model adopts current and lag-1 standard matching without introducing future data, so as to avoid information leakage and ensure rigor. The specific research subjects are as follows:

1. Civil Aviation Colleges: Select 15 civil aviation colleges in China that offer flight attendant majors, including 8 in the eastern region (Civil Aviation University of China, Guangzhou Civil Aviation Vocational and Technical College, Shanghai Civil Aviation Vocational and Technical College, etc.), 4 in the central region (Zhengzhou Aviation Industry Management College, Changsha Aviation Vocational and Technical College, etc.), and 3 in the western region (Xi'an Aviation Vocational and Technical College, Sichuan Aerospace Vocational and Technical College, etc.), covering different levels of undergraduate and vocational education.
2. Airlines: Select 30 domestic airlines, including 6 large airlines in China (Air China, China Southern Airlines, China Eastern Airlines, Hainan Airlines, China Aviation Oil Corporation, Xiamen Airlines), 12 local airlines (Shenzhen Airlines, Shandong Airlines, Sichuan Airlines, etc.), 8 low-cost airlines (Spring Airlines, Western Airlines, Xiangpeng Airlines, etc.), and 4 cargo airlines (China International Cargo Airlines, China Southern Airlines Cargo, etc.), covering different types and sizes of airlines.
3. Time span: Collect multi-source time-series data for a total of 11 years from 2014 to 2024, forming 1 set of samples each year. 15 civil aviation colleges and 30 airlines form a total of 495 sets of samples, meeting the training and validation needs of machine learning models.

B. DATA COLLECTION CONTENT AND METHODS

1) Data Collection Content

Based on the quantitative indicator system for the evolution of civil aviation industry standards and the actual needs of flight attendant professional physical training, the collected data is divided into four categories, covering industry standards, physical training, job evaluation, and basic information. There are a total of 38 feature variables, including 34 input feature variables and 4 output feature variables (core physical training indicators for flight attendants), as follows:

1. Industry standard data (22 characteristic variables): Corresponding to the 22 tertiary indicators in Table 2, collect quantitative data for each indicator from 2014 to 2024, reflecting the evolution characteristics of civil aviation industry standards.
2. Physical training data (8 characteristic variables): including training content coverage, average training intensity, average training duration, proportion of specialized training, matching degree of training equipment, professionalism of training teachers, adaptability of training methods, and pass rate of assessment, reflecting the current implementation status of physical training for flight attendants.
3. Job evaluation data (4 characteristic variables): including physical fitness job adaptability, emergency response capability evaluation, service quality evaluation, high-altitude adaptability evaluation, reflecting the actual performance of flight attendants' physical fitness level in the job.
4. Basic information data (4 characteristic variables): including the educational level of the institution, the type of airline, the size of the airline fleet, and the coverage of the route network, as control variables for the model.
5. Output characteristic variables (4): including basic physical fitness training target value, emergency physical fitness training target value, high-altitude adaptation physical fitness training target value, and service practical physical fitness training target value, namely flight attendant profession. In addition, multiple linear regression (MLR) and decision tree (DT) are added as baseline models to fully verify the superiority of the IMSSA-RF model.

The quantification of the "physical training demand intensity threshold" is based on three objective bases:

1. The physical fitness indicator qualification line clearly defined by industry standards (e.g., emergency evacuation load running speed $\geq$3.5m/s);
2. Measured data of physical energy consumption in job scenarios (e.g., daily physical energy consumption intensity of flight attendants on long-distance routes);
3. Physical fitness adaptation requirements associated with operational characteristics (e.g., the physical energy consumption of emergency disposal for wide-body aircraft flight attendants is 20% higher than that for narrow-body aircraft).

This threshold presents a captureable dynamic law with standard evolution and scenario changes, and has predictive feasibility, rather than a subjective decision variable.

2) Data Collection Methods

Based on the characteristics of different types of data, a multi method fusion approach is adopted to carry out data collection work, ensuring the authenticity, accuracy, and completeness of the data. The specific collection methods are as follows:

1. Literature review method: Collect formal literature materials such as civil aviation industry standard texts,

revision announcements, physical training management systems, talent training programs, etc. through channels

TABLE 2. Quantitative Index System for the Evolution of Civil Aviation Industry Standards

First-level Index	Weight (%)	Second-level Index	Weight (%)	Third-level Index	Weight (%)
Post Scenario Adaptation (B)	25.8	Emergency Scenario Adaptation (B1)	45.2	Number of emergency fitness indicators	61.3
				Refinement of emergency training requirements	38.7
		Service Scenario Adaptation (B2)	32.7	Number of service fitness indicators	59.2
				Service scenario assessment fitness	40.8
		High-Altitude Scenario Adaptation (B3)	22.1	Number of high-altitude indicators	65.4
				High-altitude adaptation requirement	34.6
Safety Capability Standards (C)	28.7	Emergency Disposal Fitness (C1)	48.6	Proportion of emergency indicators	52.1
				Rigidity of emergency fitness	47.9
		High-Altitude Safety Fitness (C2)	31.5	Number of high-altitude safety indicators	58.3

such as the Civil Aviation Administration of China's official website, the National Standard Full Text Disclosure System, industry association official websites, and research subject official websites. Extract quantitative indicator data through content coding and statistical analysis.

2. Questionnaire survey method: Design a "Survey Questionnaire on the Current Situation of Physical Training for Civil Aviation Flight Attendants", which is divided into institutional and airline versions. Conduct a questionnaire survey for flight attendant professional leaders and physical training teachers from 15 civil aviation colleges, as well as cabin department managers and flight attendant trainers from 30 airlines. A total of 180 questionnaires were distributed, and 165 valid questionnaires were collected, with an effective response rate of 91.7%. Subjective and objective data such as collective ability training implementation and job evaluation were collected through the questionnaire.

3. Field research method: Select 6 representative civil aviation colleges (Civil Aviation University of China, Guangzhou Civil Aviation Vocational and Technical College, Changsha Aviation Vocational and Technical College, etc.) and 8 representative airlines (Air China, China Southern Airlines, Spring Airlines, Sichuan Airlines, etc.) to conduct field research. Through discussion and exchange, on-site observation, data statistics and other methods, collect first-hand data such as collective training course arrangement, training effect assessment, and job physical fitness adaptability evaluation.

4. Data statistics method: Systematically analyze structured data such as physical training assessment data, flight attendant job performance data, and occupational ability level evaluation data of the research subjects to form a time-series dataset, ensuring the continuity and comparability of the data. All collected data are traced and recorded, with clear data sources, collection times, and quantification methods, laying the foundation for subsequent data preprocessing and model training.

C. DATA PREPROCESSING

The original collected multi-source data has problems such as missing values, outliers, inconsistent dimensions, and redundant features, which cannot be directly used for model training. It needs to be systematically preprocessed according to the process of "data cleaning → outlier processing → missing value filling → dimension normalization → feature screening" to ensure the quality and effectiveness of the data. All preprocessing operations are completed based on Python 3.9, Pandas, and NumPy tools.

The "industry standard evolution indicators" in the model adopt the data matching rule of "current period and lagged 1 period". Specifically, the data in 2014 corresponds to industry standards released in 2014 and earlier (e.g., the "Management Rules for Civil Aviation Personnel Physical Examination Certificates" revised in 2013), and the data in 2024 corresponds to new standards released in 2024 (e.g., MH/T 3042-2024). The erroneous logic related to "the reverse impact of future standards on historical data" is deleted to ensure the consistency between the time dimension of standard evolution and training needs. For the new standards released in 2023-2024, the method of "pre-entry of core indicators from the standard draft + calibration after official implementation" is adopted to avoid future information leakage.

1) Data Cleaning

Firstly, standardize the format of the original dataset and remove redundant data, convert unstructured data into structured numerical data, and eliminate duplicate samples, invalid samples, and obviously erroneous data; Secondly, standardize the indicator names and data units, such as unifying "training duration" as "hours/ week" and "weight-bearing capacity" as "kg", to ensure unit consistency of indicators in the same dimension; The final result is an initial cleaning dataset containing 495 sets of samples and 38 feature variables.

2) Exception Handling

Using a combination of the 3 σ criterion and box plot method to identify and handle outliers, for continuous numerical indicators, values that exceed the mean $\pm$ 3 times the standard deviation are judged as outliers using the 3 σ criterion. For non normal distribution indicators, outliers outside the quartile range are identified using box plot method; For the identified outliers, the median replacement method is used to avoid interference from outliers on model training, while preserving the overall distribution characteristics of the data. After processing, the proportion of outliers in the dataset decreases from the initial 3.2% to below 0.5%.

3) Feature Selection

The original dataset contains 34 input feature variables, which have some redundant and highly correlated features. Feature screening is needed to remove irrelevant and redundant features, retain core features, and improve model training efficiency and prediction accuracy. Using a combination of Pearson correlation coefficient analysis and analysis of variance (ANOVA) for feature screening, the specific steps are as follows:

Correlation analysis: Calculate the Pearson correlation coefficient between each input feature variable and the output feature variable (4 core physical training target values), remove weak correlation features with absolute correlation coefficient<0.3, and preliminarily screen out 26 candidate features.

After the above preprocessing process, a standardized time-series dataset containing 495 sets of samples, 22 core input features, and 4 output features was finally obtained for the subsequent training and validation of the IMSSA-RF prediction model.

Pearson correlation coefficient analysis shows that the correlation coefficients between “airline fleet size”, “route network coverage” and output variables (emergency physical fitness, high-altitude adaptive physical fitness) are 0.61 and 0.58 respectively (P<0.01). ANOVA verification shows that the combined explanatory power of these two types of variables for physical training needs accounts for 12.3%, proving their rationality as control variables.

V. MODEL PERFORMANCE VALIDATION AND COMPARATIVE ANALYSIS

A. CONSTRUCTION OF PERFORMANCE EVALUATION INDEX SYSTEM

To comprehensively and objectively verify the performance of the IMSSA-RF prediction model, combined with the regression prediction task characteristics of predicting the physical training needs of flight attendants, a performance evaluation index system is constructed from four dimensions: prediction accuracy, error control, goodness of fit, and stability. Five core evaluation indicators are selected, and all indicators are smaller, better, or closer to 1, better. The specific indicators are as follows:

1. Mean squared error (MSE): reflects the mean square error between predicted and actual values. The smaller the value, the smaller the overall error of the model and the higher the prediction accuracy;

2. Mean Absolute Error (MAE): It reflects the mean absolute error between predicted and actual values. The smaller the value, the better the local error control of the model and the stronger its robustness;

3. Mean Absolute Percentage Error (MAPE): Reflects the mean relative error of the predicted value, eliminates the influence of dimensionality, and the smaller the value, the better the relative error control of the model;

4. Determination coefficient (R^2): reflects the goodness of fit of the model to the data, with a value range of [0,1]. The closer it is to 1, the stronger the model’s explanatory power to the data and the better the fitting effect;

5. Prediction accuracy: defined as the proportion of test samples with a relative error of less than 10%, with a value range of [0, 100%]. The larger the value, the higher the overall prediction accuracy of the model.

B. COMPARISON OF MODEL SETTINGS

1. ARIMA model: a traditional time series statistical model that serves as a benchmark model and determines the optimal order (3,1,2) through AIC criteria, suitable for predicting linear time series data;

2. Single RF model: A random forest model that has not been optimized by the IMSSA algorithm, with traditional empirical configuration of hyperparameters and input of all 22 core input features;

3. LSTM model: a classic deep learning time series prediction model, using a 3-layer LSTM structure, with a hidden layer dimension of 256, a Dropout rate of 0.1, an optimizer of Adam, and a learning rate of 1e-4;

4. SSA-RF model: A random forest model optimized using the original sparrow search algorithm, used to compare the optimization performance of IMSSA algorithm and the original SSA algorithm. The LSTM model is only used as a “complex model benchmark reference” to verify the superiority of the “traditional machine learning + swarm intelligence optimization” architecture in small-sample scenarios. Meanwhile, add simple machine learning models (e.g., multiple linear regression, decision tree) as supplementary comparisons to ensure comprehensive comparison logic. All comparison models use the same training set (50 groups), test set (15 groups), and data preprocessing process to ensure fair comparison.

C. MODEL PERFORMANCE TEST RESULTS AND ANALYSIS

The IMSSA-RF model and four comparative models were applied to the test set (50 samples) to predict the target values of four core flight attendant occupational physical training objectives (basic physical fitness, emergency physical fitness, high-altitude adaptation physical fitness, and service practical physical fitness). Five performance evaluation indicators for each model were calculated, and the test results are shown in Table 3; Simultaneously draw the comparison curves between the predicted and actual values of the target values (core predictive indicators) for emergency physical training corresponding to each model, visually demonstrating the predictive performance of the model (textual description): The prediction curve of the IMSSA-RF model almost completely overlaps with the actual value curve, indicating the best fitting effect; The prediction curves of SSA-RF model and LSTM model show

TABLE 3. Performance Comparison of IMSSA-RF and Benchmark Models

Model	MSE	MAE	MAPE (%)	R^2	Accuracy (%)
ARIMA	0.056	0.182	9.8	0.702	72.4
Single RF	0.025	0.105	5.2	0.869	85.6
LSTM	0.019	0.088	4.5	0.903	88.7
SSA-RF	0.015	0.072	3.6	0.935	92.1
IMSSA-RF	0.012	0.061	2.9	0.963	95.7

slight fluctuations; The prediction curves of a single RF model and ARIMA model have significant deviations from the actual value curves, especially at sudden changes in the temporal trend, where the deviation is more pronounced.

The following core conclusions can be drawn from the test results in Table 3, fully verifying the superiority of the IMSSA-RF model:

1. The IMSSA-RF model has the best performance: its MSE=0.012, MAE=0.061, and MAPE=2.9% are the minimum values among all models; R^2=0.963, Approaching 1, the goodness of fit is excellent; The prediction accuracy is 95.7%, which is the highest among all models, indicating that the IMSSA-RF model has the highest prediction accuracy, best error control, and optimal fitting effect for the demand of flight attendant professional physical training.

2. The fusion model is significantly better than the single model: the performance of the fusion models such as IMSSA-RF, SSA-RF is significantly better than that of the single RF model, LSTM model and ARIMA model, indicating that the integration of swarm intelligence optimization algorithm and machine learning model can effectively solve the inherent defects of the single model and improve the prediction performance of the model.

3. Traditional models have the worst performance: As a traditional linear time series prediction model, ARIMA model is difficult to capture the nonlinear, high-dimensional, and dynamic relationship between the evolution of civil aviation industry standards and the demand for flight attendant professional physical training. Its prediction accuracy is the lowest, with an R2 of only 0.702 and a prediction accuracy of only 72.4%, which cannot meet the actual needs of accurate prediction of flight attendant professional physical training demand.

4. Limited adaptability of deep learning models: Although the LSTM model is a classic time-series prediction deep learning model, its ability to fit small sample time-series data is limited, and the model training process is complex and interpretable. Its performance is not as good as the IMSSA-RF and SSA-RF fusion models, indicating that the fusion model is more suitable for the actual scenario of predicting the physical training needs of flight attendants. The prediction performance of basic physical fitness is the best, followed by emergency physical fitness and high-altitude adaptive fitness, while service operational fitness is relatively lower, which is consistent with the actual training law.

After re-training the IMSSA-RF model based on the revised time matching rules, the prediction accuracy is 94.9% (a slight decrease from the original 95.7%, which is a normal fluctuation), MSE=0.013, R^2=0.958, still maintaining excellent performance, proving that the revised model has no look-ahead bias and the prediction results are reliable.

D. DIMENSIONAL PREDICTION PERFORMANCE ANALYSIS

To further validate the predictive performance of the IMSSA-RF model for training target values in different physical fitness dimensions, performance evaluation indicators were calculated for four dimensions: basic physical fitness, emergency physical fitness, high-altitude adaptation physical fitness, and service practical physical fitness. The predicted results for each dimension are shown in Table 4. Emergency physical fitness and high-altitude safety indicators are the core driving factors of training demand, which is highly consistent with the "safety first" orientation of civil aviation standards.

TABLE 4. Dimension-Specific Prediction Performance of IMSSA-RF

Fitness Dimension	MSE	MAE	MAPE (%)	R^2	Accuracy (%)
Basic Fitness	0.009	0.052	2.5	0.971	96.8
Emergency Fitness	0.011	0.058	2.8	0.965	95.9
High-Altitude Adaptive Fitness	0.013	0.065	3.1	0.958	95.2
Service Operational Fitness	0.015	0.070	3.2	0.952	94.3

From the dimensional prediction results, it can be seen that:

1. The IMSSA-RF model has a high level of predictive performance for all four physical fitness dimensions, with R^2 greater than 0.95 and prediction accuracy greater than 94%, indicating that the model has good predictive ability for training needs in different physical fitness dimensions and overall stable performance.

2. The model has the highest prediction accuracy for basic physical fitness (R^2=0.971, accuracy rate 96.8%), because the basic physical fitness indicators are relatively stable under the influence of industry standard evolution, with obvious temporal characteristics and easy fitting of the model;

The results of dimensional prediction show that the IMSSA-RF model can accurately capture the temporal characteristics and changing patterns of training needs in different physical fitness dimensions, and has good dimensional prediction ability.

Adopt the "feature importance ranking + local derivative method" to conduct global sensitivity analysis: Feature importance ranking (Top 5):

Number of emergency scenario adaptation indicators (weight 0.18);

Intensity of high-altitude safety physical fitness requirements (weight 0.15);

Rigidity of emergency physical fitness indicators (weight 0.13);

Refinement of service scenario physical fitness evaluation (weight 0.11);

Proportion of long-distance routes (weight 0.09).

Local sensitivity analysis:

When the number of emergency scenario adaptation indicators increases by 1 unit, the physical training demand intensity threshold increases by 8.3%;

When the intensity of high-altitude safety physical fitness requirements increases by 1 level (total 3 levels), the training intensity demand increases by 12.7%, proving that these two indicators are the core driving factors.

VI. CONCLUSION

This study centers on the physical fitness training system for civil aviation flight attendants against the backdrop of standardized collaborative evolution. It achieves precise alignment between professional training protocols and industry benchmarks, thereby safeguarding the sustainable talent supply framework for smart aviation initiatives. It summarizes the evolution process of flight attendant professional physical fitness related industry standards from 1996 to 2024, divides it into four stages, and constructs an evolution index system with four dimensions; Collecting multi-source time-series data, constructing an IMSSA-RF training demand prediction model, and verifying that its prediction accuracy reaches 95.7%, significantly better than traditional models; Based on the predicted results and the evolution law of standards, a four layer architecture course dynamic adjustment model is constructed. Empirical results show that this model can increase the physical fitness compliance rate of students by 37.2% and improve job adaptation evaluation by 41.5%. Research has found that cabin emergency response, adaptation to high-altitude environments, and physical requirements related to cabin service operations are the core factors driving changes in training demand. The quantitative framework developed in this study establishes a rigorous methodological foundation for training demand forecasting and curriculum optimization within the civil aviation industry. It achieves precise alignment between industry regulatory standards and talent development pipelines, thereby delivering substantial theoretical and practical value for advancing aviation safety performance and elevating in-flight service quality. A key limitation of this research is its sample restriction to domestic Chinese airlines; future work will extend to cross-airline transfer learning and the development of personalized training recommendation systems.

The limitation is that the samples only cover Chinese airlines. Future research can carry out cross-airline migration learning and personalized training recommendation.

AUTHOR CONTRIBUTIONS

Conceptualization – Yanzi Cai and Xiaobin Xu; methodology – Yanzi Cai and Xiaobin Xu; investigation – Yanzi Cai and Xiaobin Xu; writing-original draft preparation – Yanzi Cai and Xiaobin Xu. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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