Research on Dynamic Adaptability Prediction of Civil Aviation Vocational College Major Group Based on Multimodal Data of Curriculum System and VMD Transformer

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ABSTRACT The digital and intelligent transformation of the civil aviation industry has driven a drastic change in the talent demand structure, necessitating a workforce capable of navigating smart airports, aviation logistics, maintenance, navigation and communication systems. As the core carrier of civil aviation technical and skilled talent cultivation, the dynamic adaptability of the curriculum system and industry job requirements directly determines the quality of talent cultivation in the civil aviation vocational professional group. The current construction of civil aviation vocational college professional groups faces problems such as lagging curriculum system updates, lack of quantitative basis for adaptability evaluation, and neglect of multi-source data coupling characteristics and dynamic temporal patterns in demand fore casting. Traditional single dimensional data statistics and linear prediction methods are difficult to accurately capture the dynamic changes in industry demand and the multimodal response characteristics of the curriculum system. Variational Mode Decomposition (VMD) can effectively decompose the multi-scale features of nonstationary temporal data, and the Transformer model can deeply explore the spatiotemporal correlations and complex coupling relationships of multimodal data through its self-attention mechanism. By integrating VMD and Transformer models, this article constructs a dynamic adaptability prediction model for civil aviation vocational majors based on multimodal curriculum data, effectively overcoming the limitations of traditional prediction methods in this technically evolving field.

INDEX TERMS civil aviation vocational education,vmd-transformer,multimodal data,dynamic adaptability,navigation systems

I. INTRODUCTION

A. RESEARCH BACKGROUND

THE civil aviation and manufacturing industries serve as national strategic pillars, where the commercial operation of C919 aircraft and the implementation of smart airport systems parallel the high-tech shift toward automated spinning and green processing. Both sectors are undergoing a deep transformation from traditional operations to a future defined by digitalization, intelligence, and ecological sustainability. The industry's job structure, skill requirements, and professional standards are undergoing comprehensive changes ("China Civil Aviation Development White Paper 2024"). As the main battlefield for cultivating technical and skilled talents in civil aviation, vocational education in civil aviation needs to resonate with the industry's demand for professional groups. As the core carrier of professional group construction, the dynamic adaptability of the curriculum system to industry job requirements has become a key indicator for measuring the quality of talent cultivation. In 2022, the Ministry of Education issued the "Guidelines for the Construction of Vocational Education Professional Groups (Higher Vocational Education)", which clearly stated that "the curriculum system of professional groups needs to be aligned with the skill requirements of industrial positions, establish a dynamic adjustment mechanism, and achieve precise adaptation to industrial development"; In 2023, the "Action Plan for High Quality Development of Civil Aviation Vocational Education (2023-2027)" further requires "deepening the integration of industry and education, school enterprise cooperation, building a professional group curriculum system that is suitable for the transformation of the civil aviation industry, and improving the job adaptability of talent cultivation".

B. RESEARCH STATUS

The construction of vocational education professional groups (clusters) in foreign countries started earlier, forming mature models such as Germany's "dual system", Australia's "TAFE", and the United States' "community colleges". Relevant research mainly focuses on the matching mechanism between professional groups and industry demand, such as constructing a professional group curriculum system through industry job capability analysis, and establishing a dynamic adjustment mechanism for professional groups based on changes in industry demand [1-3]; In terms of research methods, methods such as job competency matrix and quantitative analysis of industry demand are often used to achieve quantitative matching between professional groups and industry demand [4,5]. However, foreign research is mostly based on their own industrial structure and vocational education system, which differs from the characteristics and current development status of civil aviation vocational education in China, making it difficult to directly apply relevant results.

C. INNOVATION POINTS

The innovation of this article is mainly reflected in the following four aspects:

Innovation of Data System: For the first time, a multimodal data index system for the civil aviation vocational college professional group has been constructed, which includes five dimensions: industry demand, curriculum system, faculty, teaching resources, and training quality. The system integrates structured, semistructured, and unstructured multi-source data and 2018-2024 time-series data, covering all elements and processes adapted to the professional group, and solves the problem of lack of data support in existing research.

D. RESEARCH CONTENT AND TECHNICAL ROUTE

1) Research Content

The main research content of this article includes:

1. Theoretical basis and indicator system construction: Sort out the relevant theories of adaptability, multi modal data fusion, VMD, and Transformer for civil aviation vocational college majors, and analyze the feasibility of applying VMD Transformer models to dynamic adaptability prediction; Identify the core influencing factors of dynamic adaptation and construct a multimodal data indicator system.
2. Multimodal data collection and preprocessing: Conduct research on 8 civil aviation vocational colleges and 12 core civil aviation positions, and collect multimodal time-series data from 2018 to 2024; Preprocess the raw data by cleaning, normalizing, modal fusion, feature filtering, etc., and construct model training and testing datasets.
3. Construction and training of VMD Transformer prediction model: VMD is used to perform multi-scale decomposition on non-stationary temporal feature data to obtain stationary IMF components; Build a Transformer dynamic adaptability prediction model that integrates VMD, and fuse IMF components with multimodal static features as inputs; Optimize model parameters through grid search and cross validation, train the model using the training set, and validate its performance through the testing set.

2) Technical Roadmap

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

1. Literature research stage: Sort out the relevant research results on the construction of civil aviation vocational college professional groups, multimodal data fusion, VMD, and Transformer, clarify the research status and shortcomings, and construct the theoretical basis for the research.
2. Data collection and preprocessing stage: Using methods such as questionnaire surveys, school enterprise research, data statistics, and text mining to collect multimodal time-series data; Clean, deduplicate, and normalize the data, quantify the features of unstructured data, perform VMD multi-scale decomposition on time-series data, and divide the training and testing sets.
3. Model construction and training phase: Build a single Transformer, LSTM, ARIMA model, and VMD Transformer fusion model; Using grid search and 5-fold cross validation to optimize model parameters; Train the model using the training set, test the model performance using the testing set, and compare and select the optimal model.
4. Model analysis and strategy design stage: Use the optimal model for short-term and medium-term adaptability prediction; Identify core influencing factors through feature importance analysis; Based on the predicted results and the parallel digital trajectories of the civil aviation and manufacturing sectors, this study designs a dynamic optimization strategy for the curriculum systems of both aviation and engineering majors to align with the latest industry development trends. This approach ensures that the vocational training framework remains responsive to the technical demands of smart airport operations and automated production technologies.

II. THEORETICAL BASIS AND DEFINITION OF CORE CONCEPTS

A. DEFINITION OF CORE CONCEPTS

1) Dynamic Adaptability of Civil Aviation Vocational College Majors

The Civil Aviation Vocational Professional Group refers to a professional cluster composed of several related majors driven by a core major, such as the Airport Operations Professional Group, Aviation Maintenance Professional Group, Air Attendants Professional Group, etc., guided by the demand for core positions in the civil aviation industry chain. Dynamic adaptability refers to the degree to which the curriculum system of civil aviation vocational college majors matches the skill requirements, professional standards, and development trends of civil aviation industry positions in the time dimension. Its core connotation includes dimensional adaptability (matching the dimensions of curriculum system, faculty, resources, and job requirements) and temporal adaptability (matching the pace of curriculum system updates and changes in job skill requirements), with four major characteristics of dynamism, temporality, multidimensionality, and coupling. This article defines the dynamic adaptability of civil aviation vocational college majors as a comprehensive adaptability index, which is quantitatively represented by weighted summation of multidimensional indicators. The value range is [0,1], and the closer the value is to 1, the higher the adaptability [6-9].

B. CORE THEORETICAL BASIS FOR DYNAMIC ADAPTATION OF CIVIL AVIATION VOCATIONAL COLLEGE MAJORS

1) Theory of Industry Education Integration and Collaborative Development

The theory of integrated and coordinated development of industry and education emphasizes the deep integration and symbiotic relationship between vocational education and industrial development. The professional con-struction and curriculum system of vocational education need to resonate with the job demands, technological up-grades, and development trends of the industry. Industry provides demand orientation and practical platforms for vocational education, while vocational education provides talent support and technical services for the industry.

This theory provides a fundamental theoretical basis for defining the connotation and constructing an indicator system for the dynamic adaptability of the civil aviation vocational college professional group, and clarifies the core logic of the coordinated development of the professional group curriculum system and the demand of the civil aviation industry.

2) Job Capability Matching Theory

The theory of job competency matching holds that the core of talent cultivation is to achieve precise matching between the learner's ability structure and the job's ability demand structure. Job ability demand is the fundamental direction of talent cultivation, and the curriculum system is the core carrier for achieving ability matching. The civil aviation industry positions have the characteristics of strong skill specialization, fast update rate, and high team collaboration requirements. Their ability demand structure is constantly changing with the transformation of the industry. This theory provides a theoretical basis for the design and optimization of the civil aviation vocational college professional group curriculum system to meet the job ability requirements.

3) Multimodal Data Fusion Theory

Multimodal data fusion theory refers to the integration of multi-source data from different sources, types, and structures through certain algorithms, mining the inherent correlation features between data, and achieving comprehensive and accurate characterization of the research object [10]. This theory provides theoretical guidance for constructing a multimodal data index system for civil aviation vocational college professional groups, realizing the fusion processing and feature extraction of multi-source heterogeneous data, and ensuring that the data can comprehensively reflect the core features of dynamic adaptation of professional groups.

Multi-source Heterogeneous Data Fusion Theory: Refers to the integration of comprehensive data from different channels (industry enterprises, vocational colleges, regulatory authorities) with different storage formats and structural characteristics through specific algorithms. It includes structured data (e.g., statistical report data), semi-structured data (e.g., vocational standard documents, curriculum syllabi), and unstructured data (e.g., enterprise job feedback texts, teaching evaluation comments). The core goal is to mine inherent correlation features between data and achieve comprehensive and accurate characterization of the research object, which is different from "multimodal data" in machine learning (cross-sensory input such as video, audio, and text).

C. CORE THEORETICAL FOUNDATIONS OF VMD AND TRANSFORMER

1) Core Principles of Variational Mode Decomposition (VMD)

The core of VMD is to construct and solve variational problems, decomposing the original non-stationary signal f (t) into K stationary IMF components, each IMF component having a center frequency and satisfying: the sum of bandwidths of each IMF component is minimized; The sum of all IMF components is equal to the original signal. The specific solving process includes two steps: constructing variational problems and solving alternating direction multipliers (ADMM) 1. Construct a variational problem, obtain the analytical signals of each IMF component through Hilbert transform, introduce the center frequency to modulate the analytical signal to the fundamental frequency band, calculate the L^2 norm of the gradient to estimate the bandwidth of each IMF component;

2. Adopt the alternating direction multiplier method to iteratively solve the variational problem, continuously updating the IMF component $u_k(t)$ and the center frequency until convergence, and obtaining K stationary IMF components [11]. The key parameters of VMD include the number of decomposition modes K and the penalty factor α. K determines the number of decomposition scales, while α controls the smoothness of IMF components. Reasonable parameter selection can effectively improve the decomposition effect.

2) Core Principles of Transformer Model

The core of the Transformer model is the self-attention mechanism and encoder decoder structure, whose basic units include multi-head self-attention layers, feedforward neural network layers, layer normalization, and residual connections.

1. Self attention mechanism: By calculating the similarity between the query vector (Query), key vector (Key), and value vector (Value), the attention weight of each feature on the prediction result can be obtained, which can effectively

mine the long-term dependencies and dimensional coupling features of the data;

2. Multi head attention mechanism: The self-attention mechanism is divided into multiple heads, each head learns feature associations at different scales, and then concatenates the results to enhance the model's feature extraction ability;

3. Encoder decoder structure: The encoder is responsible for extracting features from the input data and obtaining feature vectors containing spatiotemporal correlation features; The decoder is responsible for generating predicted values for future time points based on the output of the encoder and historical prediction results [12,13]. In temporal prediction tasks, the complete structure of encoder decoder is usually adopted, with historical temporal data as the encoder input and future predicted values as the decoder output. The dynamic evolution law of temporal data is mined through self-attention mechanism.

3) Core Logic of VMD and Transformer Fusion

The core of the fusion of VMD and Transformer is to first decompose, then fuse, and then predict, fully leveraging the advantages of both to solve the prediction problem of non-stationary multimodal temporal data:

1. VMD, as a data preprocessing module, performs multi-scale decomposition on non-stationary demand time series data in the civil aviation industry to obtain a series of stationary IMF components, effectively reducing the non-stationarity and noise of the data and improving its quality;

2. Fuse the decomposed IMF components with multi-modal static features such as curriculum system and teaching staff to form a fusion feature set that includes multi-scale temporal features and multi-dimensional static features;

3. As the core prediction module, Transformer takes the fused feature set as input and uses self-attention mechanism to mine the spatiotemporal correlation, dimensional coupling, and long-term dependency features of the feature set, achieving accurate prediction of dynamic adaptability. The fusion of the two achieves effective processing of non-stationary data and deep mining of multimodal features, significantly improving the accuracy and stability of the prediction model.

4) Feasibility Analysis of Applying VMD Transformer Model to Dynamic Adaptability Prediction

The VMD Transformer model can be effectively applied to predict the dynamic adaptability of civil aviation vocational college majors, and its feasibility is mainly reflected in the following four aspects:

1. Core features of adapting to the data of civil aviation vocational college professional groups: Civil aviation vocational college professional group data has multimodal, non-stationary, temporal, and high-dimensional characteristics. VMD can effectively handle the multi-scale features of non-stationary temporal data, and Transformer can deeply explore the coupling characteristics and long-term dependencies of multimodal data. The fusion of the two and the high adaptability of data features can solve the processing bottleneck of traditional methods.

2. Able to accurately capture the evolution law of dynamic adaptation: The dynamic adaptability of civil aviation vocational college professional groups shows a dynamic evolution trend with the upgrading of civil aviation industry technology and the updating of job skills, with abrupt and phased characteristics. VMD can decompose the abrupt and trend characteristics of data, and Transformer can capture the long-term evolution law of adaptability, achieving accurate prediction of dynamic changes in adaptability.

3. Ability to achieve deep fusion of multimodal data: The dynamic adaptability of professional groups is influenced by the synergy of multimodal factors such as industry demand, curriculum system, faculty, resources, etc. There are complex coupling relationships between various factors. The self-attention mechanism of Transformer can explore the inherent correlations between different modalities and dimensions of data, achieving deep fusion and feature extraction of multimodal data [14].

III. CONSTRUCTION OF DYNAMIC ADAPTABILITY MULTIMODAL DATA INDEX SYSTEM FOR CIVIL AVIATION VOCATIONAL COLLEGE MAJOR GROUP

A. PRINCIPLES AND METHODS FOR BUILDING AN INDICATOR SYSTEM

1) Principles for Constructing Indicator System

To ensure the scientific, comprehensive, operable, and dynamic nature of the multimodal data index system for the dynamic adaptability of civil aviation vocational college majors, the construction process follows the following six principles:

1. Principle of comprehensiveness: The indicator system should comprehensively cover the core elements of dynamic adaptation of professional groups, including industry demand, curriculum system, teaching staff, teaching resources, training quality, etc. It should also cover structured, semi-structured, and unstructured multimodal data to avoid missing key influencing factors.

2. Principle of scientificity: The selection of indicators should be based on relevant theories such as industry education integration and job competency matching, combined with the development characteristics of the civil aviation industry and the educational laws of civil aviation vocational education. The definition of indicators should be clear and accurate, and the quantitative methods should be scientific and reasonable [15,16].

3. Principle of operability: Indicators should be able to be quantitatively collected through methods such as school enterprise research, data statistics, and text mining. For unstructured data, feasible feature quantification methods should be developed to ensure the availability and processability of the data.

4. Principle of dynamism: The indicator system should reflect temporal characteristics, selecting temporal data from 2018 to 2024, which can reflect the dynamic evolution of professional group adaptability over time and meet the needs of temporal prediction.

5. Targeted principle: The indicator system should be tailored to the characteristics of the civil aviation vocational education professional group, highlighting the fast technological updates, strong job specialization, and high safety requirements of the civil aviation industry, and avoiding similarity with the indicator system of other vocational education professional groups.

6. Hierarchical principle: The indicator system should be divided into different levels such as first level indicators, second level indicators, and third level indicators (feature variables), with clear hierarchy and rigorous logic, which facilitates subsequent multimodal data fusion, feature extraction, and model construction [17]. The indicator system should comprehensively cover the core elements of dynamic adaptation of professional groups... and cover structured, semi-structured, and unstructured multi-source heterogeneous data to avoid missing key influencing factors.

2) Method for Constructing Indicator System

This article adopts a combination of literature analysis, industry expert interviews, and on-site research by schools and enterprises to construct a dynamic adaptability multimodal data index system for civil aviation vocational college professional groups. The specific steps are as follows:

1. Literature analysis: Systematically review the research results related to the construction of civil aviation vocational education professional groups, the adaptability of vocational education professional groups, and multimodal data fusion. Collect the influencing factors and evaluation indicators of sports education integration teaching, and preliminarily construct an indicator system framework.

2. Industry expert interviews: Select 30 experts for indepth interviews, including 10 civil aviation industry enterprise experts (from airports, airlines, and civil aviation maintenance enterprises), 10 civil aviation vocational education experts, 5 vocational education quantitative analysis experts, and 5 machine learning experts. Solicit experts' opinions on the preliminary indicator system framework, and screen, modify, and supplement the indicators [18,19].

3. School enterprise field research: Select 8 civil aviation vocational colleges (covering the eastern, central, and western regions) and 12 civil aviation enterprises (including Air China, China Southern Airlines, China Eastern Airlines, Capital Airport, Shanghai Pudong Airport, etc.) to conduct field research. Based on the job requirements of civil aviation enterprises and the actual construction of professional groups in vocational colleges, further optimize the indicator system.

4. Indicator screening and determination: Based on expert interviews and school enterprise research opinions, combined with the principles of indicator system construction, preliminary indicators are screened, duplicate, redundant, and difficult to quantify indicators are deleted, key missing indicators are supplemented, and finally the dynamic adaptability multimodal data indicator system for civil aviation vocational college professional groups is determined [20].

B. CONSTRUCTION OF MULTIMODAL DATA INDICATOR SYSTEM

Based on the above principles and methods, this article constructs a dynamic adaptability multimodal data index system for the civil aviation vocational college professional group, which includes 5 primary indicators, 16 secondary indicators, and 42 tertiary indicators (feature variables). At the same time, the data types, quantification methods, and time spans of each feature variable are clarified, achieving full coverage of structured, semi-structured, unstructured multimodal data and 2018-2024 time-series data, providing standards for subsequent data collection and feature extraction. The specific indicator system is shown in Table 1.

Revised Quantification Method for A5 (Matching Degree between Vocational Standards and Jobs): Adopt a combined quantification method of "core skill semantic matching + enterprise expert rating calibra tion":

1. Text preprocessing and core information extraction: After word segmentation and stop-word removal of vocational standard documents and job manuals, use TF-IDF + industry dictionary matching to extract core skill-related content, excluding generic phrases such as safety warnings and management norms (accounting for about 35%), retaining only text fragments directly related to skill requirements.

2. Core skill semantic matching: Use the BERT model to calculate the semantic similarity of core text fragments (excluding literal similarity), focusing on capturing the semantic fit between "skill requirement descriptions" and "vocational standard clauses", with the similarity score ranging from [0,1].

3. Enterprise expert rating calibration: Invite 8 technical backbones from civil aviation enterprises (working experience $\geq$8 years) to score the semantic matching results from the perspective of practical job skill appli cation (1-5 points), which is normalized to [0,1] and accounts for 30% of the total weight.

4. Final score calculation: Comprehensive semantic matching degree (70% weight) and expert rating (30% weight) to obtain the final score of A5, with a value range of [0,1].

C. SELECTION AND OPTIMIZATION OF CHARACTERISTIC VARIABLES

The 42 three-level indicators constructed are the initial characteristic variables for the dynamic adaptability of civil aviation vocational college majors, including 37 temporal characteristic variables and 5 static character istic variables; There are 26 structured variables, 8 semi-structured variables, and 8 unstructured variables. In order to reduce the

TABLE 1. Multimodal Data Index System for Dynamic Adaptability of Civil Aviation Higher Vocational Professional Groups

First-Level Indicator	Weight (%)	Second-Level Indicator	Third-Level Indicator (Feature Variable)	Variable Code	Data Type	Quantification Method
Industry Demand Dimension (A)	28	Job Skill Demand	Core Job Skill Update Rate	A1	Structured-Time Series	Enterprise survey, ratio of annual updated skills to total skills
			Number of Quantified Job Skill Indicators	A2	Structured-Time Series	Enterprise competency matrix, number of quantified skill indicators
			Proportion of Emerging Job Skill Demands	A3	Structured-Time Series	Ratio of emerging job skill demands to total skill demands
		Vocational Standard Update	Civil Aviation Vocational Standard Update Frequency	A4	Structured-Time Series	Number of annual updates to vocational standards
			Matching Degree between Vocational Standards and Jobs	A5	Semi-Structured-Time Series	Text analysis, similarity score between vocational standards and job manuals
		Industry Development Trend	Application Rate of Digital Technologies in Civil Aviation	A6	Structured-Time Series	Proportion of digital equipment/technologies applied in enterprises
			Growth Rate of Talent Demand in Civil Aviation Industry	A7	Structured-Time Series	Annual growth rate of demand for technical and skilled talents in civil aviation
			Intensity of Enterprise Job Demand Feedback	A8	Unstructured-Time Series	Text mining, sentiment tendency and frequency of enterprise job feedback
Curriculum System Dimension (B)	25	Curriculum Design	Modularization Degree of Curriculum System	B1	Structured-Static	Expert scoring, proportion and connection degree of modular courses
			Matching Degree between Core Courses and Job Skills	B2	Semi-Structured-Time Series	Text analysis, similarity between curriculum syllabi and job skills
			Timeliness Rate of Emerging Course Offering	B3	Structured-Time Series	Time difference between the emergence of industry demand and the offering of emerging courses
			Proportion of Courses Integrating "Posts, Curriculum, Competitions, and Certifications"	B4	Structured-Time Series	Ratio of class hours of integrated courses to total class hours
		Curriculum Implementation	Adaptability of Teaching Methods	B5	Unstructured-Time Series	Text mining, adaptability score of teaching methods from teaching evaluations
			Curriculum Update Frequency	B6	Structured-Time Series	Number of annual updates to the curriculum system
		Curriculum Evaluation	Alignment between Curriculum Evaluation and Job Demands	B7	Semi-Structured-Time Series	Text analysis, matching degree between curriculum evaluation indicators and job demands
Teaching Staff Dimension (C)	18	Staff Structure	Proportion of "Double-Qualified" Teachers	C1	Structured-Time Series	Ratio of double-qualified teachers to total full-time teachers
			Proportion of Teachers with Civil Aviation Industry Experience	C2	Structured-Time Series	Proportion of teachers with working experience in civil aviation enterprises
			Qualification Rate of Teachers' Academic Degrees/Professional Titles	C3	Structured-Time Series	Proportion of teachers with master's degree or above / intermediate title or above
		Staff Competence	Participation Rate of Teachers in Industry Technical Training	C4	Structured-Time Series	Annual proportion of teachers participating in civil aviation industry technical training
			Teachers' Participation in School-Enterprise Cooperation Projects	C5	Structured-Time Series	Ratio of teachers participating in school-enterprise cooperation projects to total teachers
			Adaptability of Teachers' Teaching Competence to Job Demands	C6	Unstructured-Time Series	Text mining, evaluations of teachers' teaching competence from students and enterprises

computational complexity of the model and improve its prediction accuracy, it is necessary to screen the initial feature variables, remove redundant and irrelevant feature variables, and retain the core feature variables. This article uses a combination of analysis of variance (ANOVA) and mutual information method for feature screening. The specific steps are as follows:

1. Analysis of Variance: Calculate the F-value and P-value between each initial feature variable and the target variable (Dynamic Adaptability Composite Index), screen out feature variables with $P<0.05$, and eliminate redundant variables that are not significantly correlated with the target variable.

2. Mutual information method: Calculate the mutual information value between the selected feature variable and the target variable. The larger the mutual information value, the stronger the correlation between the feature variable and the target variable; Simultaneously calculate the mutual information values between feature variables and eliminate feature variables that are highly redundant (mutual information values>0.8).

3. Determination of core characteristic variables: Combining the results of analysis of variance and mutual information method, 35 core characteristic variables were ultimately retained, and 7 redundant variables (A2, C3, D3, E3, B5, C6, D4) were removed. The core characteristic variables cover all secondary indicators of the 5 primary indicators, ensuring the comprehensiveness and effectiveness of the features.

Explanation of core variable selection logic:

Theoretical basis: All variables are selected based on core theories such as industry-education integration and job competency matching, combined with the core connotation of dynamic adaptability of civil aviation vocational college professional groups, covering five key dimensions (industry demand, curriculum system, faculty, teaching resources, training quality) without logical redundancy.

Empirical support: Feature importance ranking shows that the cumulative importance of the top 10 core variables (including A1 Core Job Skill Update Rate, B2 Matching Degree between Core Courses and Job Skills, etc.) accounts for 68.7%, and the importance distribution of variables in each dimension is balanced (industry demand: 29.3%, curriculum system: 26.5%, faculty: 19.8%, teaching resources: 15.2%, training quality: 9.2%), proving the scientificity and rationality of the feature set.

D. CORRELATION ANALYSIS OF CHARACTERISTIC VARIABLES

In order to further analyze the relationship between core feature variables and avoid the influence of multi collinearity on model training, this paper uses Pearson correlation coefficient to conduct correlation analysis on 35 core feature variables, and calculates the correlation coefficient r between feature variables. The range of correlation coefficient values is [-1,1], and the closer | r | is to 1, the stronger the correlation between the two feature variables; |R |<0.6 indicates that there is no significant multicollinearity between the feature variables, making it suitable for model training. The correlation analysis results show that the absolute values of the correlation coefficients between the 35 core feature variables are all less than 0.55, indicating no significant multicollinearity and no further dimensionality reduction is required. They can be directly used as input feature variables for the VMD Transformer model to construct a dynamic adaptability prediction model for civil aviation vocational college majors. Collinearity detection and optimization:

Collinearity test: Variance Inflation Factor (VIF) and Tolerance are used to test 35 core variables. The VIF values of C1 (proportion of "Double-Qualified" Teachers) and C2 (proportion of Teachers with Civil Aviation Industry Experience) are 6.8 and 7.2 respectively (VIF>5), B2 (Matching Degree between Core Courses and Job Skills) and B7 (Alignment between Curriculum Evaluation and Job Demands) have a VIF of 5.6, and A6 (Application Rate of Digital Technologies in Civil Aviation) and A7 (Growth Rate of Talent Demand in Civil Aviation Industry) have a VIF of 5.3, indicating moderate collinearity.

Variable optimization: C1 and C2 are merged into a comprehensive variable "Teacher Industry Adaptability" through Principal Component Analysis (PCA), with a variance contribution rate of 82.3%; B2 and B7, A6 and A7 are similarly merged into "Curriculum-Job Matching Comprehensive Index" and "Industry Development Dynamic Index" respectively. After optimization, 31 core variables are retained, and retesting shows all variables have VIF<3 and Tolerance>0.33, completely eliminating collinearity.

IV. MULTI MODAL DATA ACQUISITION AND PREPROCESSING FOR CIVIL AVIATION VOCATIONAL COLLEGE MAJOR GROUP

A. SELECTION OF RESEARCH SUBJECTS

To ensure the representativeness, comprehensiveness, and diversity of the research data, this article uses stratified sampling to select research objects, covering different regions and types of civil aviation vocational colleges and civil aviation enterprises, taking into account the eastern, central, and western regions, and covering the core links of the civil aviation industry chain. The specific research subjects are as follows:

1. Civil Aviation Vocational Colleges: Select 8 civil aviation vocational colleges, including 4 in the eastern region (Beijing Civil Aviation Vocational and Technical College, Shanghai Civil Aviation Vocational and Technical College, Guangzhou Civil Aviation Vocational and Technical College, Jiangsu Aviation Vocational and Technical College), 2 in the central region (Zhengzhou Aviation Industry Management College, Changsha Aviation Vocational and Technical College), and 2 in the western region (Sichuan Aerospace Vocational and Technical College, Xi'an Aviation Vocational and Technical College), covering core professional groups such as airport operation, aviation maintenance, air crew, and civil aviation logistics.

2. Civil aviation enterprises: Select 12 civil aviation enterprises, including 3 airlines (Air China, China Southern Airlines, China Eastern Airlines), 4 airports (Capital Airport, Shanghai Pudong Airport, Guangzhou Baiyun Airport, Xi'an Xianyang Airport), 3 civil aviation maintenance enterprises (Ameco, China Eastern Airlines Technology, China Southern Airlines Maintenance), and 2 civil aviation logistics enterprises (China Civil Aviation Logistics, SF Express), covering core links of the civil aviation industry chain such as air transportation, airport operation, maintenance support, and logistics services.

3. Time span: Collect multimodal time-series data for a total of 7 years from 2018 to 2024, forming 1 set of samples each year. Eight vocational colleges form a total of 56 sets of samples, meeting the training requirements of machine learning models.

B. MULTIMODAL DATA ACQUISITION METHOD

Based on the types and quantification methods of various characteristic variables in the dynamic adaptability multimodal data index system of civil aviation vocational college majors, a "combination of multiple methods" approach is adopted for data collection to ensure the authenticity, accuracy, and completeness of the data. Design differentiated collection methods for different types of data, as follows:

1. Structured data collection: Using the method of school enterprise research and data statistics, survey questionnaires were distributed to civil aviation vocational colleges and enterprises, and statistical reports were collected to collect structured data such as job skill update rate, proportion of dual qualified teachers, matching degree of practical training equipment, and employment rate of graduates. A total of 280 survey questionnaires were distributed, and 268 valid questionnaires were collected, with an effective response rate of 95.7%.

2. Semi structured data collection: Using the method of text collection+structured parsing, semi-structured texts such as job manuals, occupational standard documents, vocational college curriculum outlines, teaching plans, etc. of civil aviation enterprises were collected. Through text parsing, field extraction, and other methods, they were converted into quantitative indicators, and more than 360 semi-structured texts were collected.

3. Unstructured data collection: Using text mining and questionnaire survey methods, unstructured texts such as job feedback from civil aviation enterprises, teaching evaluations from vocational colleges, student internship reports, and evaluations of enterprise training quality were collected. Text data was obtained through web crawlers, manual collection, and other methods, with a total of more than 5200 unstructured texts collected; At the same time, collect

subjective evaluations from enterprises and students through questionnaire surveys as a supplement to text mining.

All collected data are classified and labeled according to "college enterprise year" to form a unified multimodal dataset, laying the foundation for subsequent data preprocessing and model training.

C. MULTIMODAL DATA PREPROCESSING

The original collected multimodal data has problems such as missing values, outliers, inconsistent dimensions, and modal heterogeneity. Unstructured data has not been quantified, and time-series data has non-stationarity. Directly using it for model training will seriously affect the predictive performance of the model. Therefore, it is necessary to standardize and integrate preprocessing of raw data, including six steps: unstructured data quantification, data cleaning, missing value processing, outlier processing, data normalization, and VMD temporal feature decomposition. This article uses Python language combined with tools such as Pandas, Numpy, Scikit learn, jieba, TextRank to complete data preprocessing. The specific steps are as follows:

1) Unstructured/Semi Structured Data Quantification

For unstructured text data such as job feedback, teaching evaluation, and training quality evaluation, the method of "text preprocessing+feature extraction+quantitative scoring" is adopted to achieve quantification:

1. Text preprocessing: Using methods such as Chinese word segmentation, stop word removal, and part of speech tagging to clean unstructured text and remove invalid information;

2. Feature extraction: Using a combination of TF-IDF and TextRank, extract core feature words from the text and construct a feature lexicon;

3. Quantitative scoring: Based on the feature lexicon, sentiment analysis, similarity calculation and other methods are used to convert unstructured text into quantitative scores in the [0,1] interval. For semi-structured data such as course outlines and occupational standards, the text similarity calculation method is used to calculate their matching degree with job skill requirements, achieving quantification. The range of values after quantification is [0,1].

2) Data Cleaning

The main purpose of data cleaning is to eliminate duplicate data, invalid data, and annotated erroneous data from the original data, ensuring the uniqueness and validity of the data. Perform plagiarism check on 56 sets of sample data using Python code, and remove 2 sets of duplicate samples; Check the annotation information of the data and remove one group of samples with annotation errors; The rationality test was conducted on the quantitative results of unstructured data, and abnormal quantitative data was removed. Finally, 53 valid samples were obtained, including 38 groups (71.7%) in the training set and 15 groups (28.3%) in the testing set.

Sample expansion optimization: Based on the trend characteristics and periodic rules of the 2018-2024 time-series data, a "time-series generation expansion method" is adopted to generate 12 sets of virtual samples, focusing on supplementing data from the abnormal period of 2020-2022. The generation process refers to the statistical distribution of core feature variables (e.g., core job skill update rate, curriculum update frequency) to ensure consistency with the original data. After expansion, the training set sample size increases from 38 to 50 groups. The KS test verifies that the expanded samples have no significant distribution difference from the original samples ($p>0.05$), ensuring data validity.

3) Handling of Missing Values

For the missing values of a small number of non key indicators in the valid sample, a combination of "mean filling method+median filling method+K-nearest neighbor filling method" is used for processing: for feature variables with normal distribution, mean filling is used; For non normally distributed characteristic variables, median imputation is used; For temporal feature variables, the K-nearest neighbor ($K=3$) imputation method is used to fill in data from adjacent years. After processing, all sample data have no missing values, ensuring the integrity of the data.

4) Exception Handling

Outliers refer to extreme values that differ significantly from most data, mainly caused by data collection errors, statistical errors, and other reasons. This article uses a combination of the 3 σ principle and box plot method to identify outliers: for normally distributed characteristic variables, the 3 σ principle is used (outliers are those that exceed the mean $\pm$ 3 times the standard deviation); For non normally distributed characteristic variables, box plot method is used (outliers are those that exceed 1.5 times the interquartile range of the upper and lower quartiles). A total of 23 outliers were identified and processed using a combination of nearest neighbor replacement and interpolation methods to ensure the validity of the data.

5) Data Normalization

There are differences in the dimensions and range of values of different feature variables, such as the per capita training equipment value (10000 yuan/person) and the degree of course modularization ([0,1]). Directly using them for model training will result in feature variables with larger dimensions dominating, affecting the training effectiveness of the model. Therefore, it is necessary to normalize the data and map the value ranges of all feature variables uniformly to the [0,1] interval.

6) VMD Temporal Feature Decomposition

For the non-stationarity of 30 core temporal feature variables, VMD is used to perform multi-scale decomposition on each temporal feature variable to obtain the stationary

IMF component. The specific decomposition steps are as follows:

1. Parameter setting: Determine the optimal parameters of VMD through grid search method, with decomposition mode number K=6, penalty factor α=2000, convergence accuracy $\epsilon = 10^{-6}$;

2. Multiscale decomposition: Perform VMD decomposition on each non-stationary temporal feature variable to obtain 6 stationary IMF components, each corresponding to different time scale features (trend features, cycle features, mutation features, etc.);

3. Component screening: Calculate the correlation coefficient between each IMF component and the original temporal variable, remove invalid components with correlation coefficients<0.3, and ultimately retain 4-5 valid IMF components for each temporal feature variable, resulting in a total of 142 IMF component features. The decomposed IMF component features were fused with 5 static feature variables to form a fused feature set containing 147 features as input features for the VMD Transformer model, effectively solving the problem of non-stationarity in time-series data and improving the feature expression ability of the data.

VMD optimization strategy for abnormal period data (2020-2022):

Hierarchical decomposition: Prior to VMD decomposition, the time-series data is divided into "normal periods (2018-2019, 2023-2024)" and "abnormal periods (2020-2022)". The abnormal period data is separately subjected to trend extraction and noise filtering to isolate short-term fluctuations caused by external factors.

Anomaly correction: Calculate the deviation between the abnormal period data and the historical trend (2018-2019), and combine civil aviation industry recovery data (e.g., 2023 industry talent demand growth rate of 8.3%, digital technology application rate increase of 5.2%) to correct the decomposed IMF components, retaining long-term development trend features while eliminating epidemic-induced interference.

Component fusion: Re-fuse the corrected abnormal period IMF components with the normal period components to ensure the decomposed data reflects the true industry development trend.

V. CONSTRUCTION AND TRAINING OF DYNAMIC ADAPTABILITY PREDICTION MODEL FOR VMD TRANSFORMER CIVIL AVIATION VOCATIONAL PROFESSIONAL GROUP

A. OVERALL FRAMEWORK FOR MODEL CONSTRUCTION

The VMD Transformer dynamic adaptability prediction model for civil aviation vocational college majors constructed in this article takes the fusion feature set (147 features) as input and the dynamic adaptability comprehensive index ([0,1]) as output. It adopts a five layer architecture of "data preprocessing layer VMD decomposition layer feature fusion layer Transformer prediction layer output layer" to achieve accurate prediction of non-stationary multimodal time-series data.

Supplementary explanation for small-sample modeling feasibility: In the VMD-Transformer model used in this paper, the VMD layer has performed multi-scale decomposition and noise reduction on time-series data, effectively reducing data redundancy and noise interference. The self-attention mechanism of Transformer has high efficiency in capturing the coupling relationship of multi-source heterogeneous data. Combined with lightweight architecture optimization and sample expansion, small-sample modeling is feasible. Relevant practices are in line with the practical scenario where large-scale data acquisition is difficult in the field of vocational education, and the model performance has been verified to be stable and reliable through internal and external validation sets.

B. VARIATIONAL MODE DECOMPOSITION (VMD) LAYER DESIGN

The VMD layer serves as the core module for data preprocessing and feature decomposition of the model. Its core function is to perform multi-scale decomposition on non-stationary temporal feature data to obtain stationary IMF components, laying the foundation for subsequent feature fusion and prediction. This article is based on the design of VMD layer using Python language combined with SciPy library. The specific implementation steps are as follows:

1. Input: 30 core non-stationary temporal characteristic variables (2018-2024, 7 time steps);

2. Parameter initialization: Set the decomposition mode number K=6, penalty factor α=2000, convergence accuracy ε=10^{-6}, and maximum iteration number N=500;

3. Variational problem solving: iteratively decompose each temporal feature variable using the alternating direction multiplier method (ADMM), continuously update the IMF component and center frequency until the convergence condition is met;

4. Component screening: Calculate the correlation coefficient between each IMF component and the original variable, remove invalid components, and retain valid IMF components;

5. Output: 142 valid IMF component features (stationary time series features). The design of the VMD layer effectively reduces the non-stationarity and noise of the original time-series data, and the decomposed IMF components can more accurately reflect the multi-scale features of the data, improving the feature extraction ability of the model.

C. FEATURE FUSION LAYER DESIGN

The feature fusion layer serves as the connection module between the VMD decomposition layer and the Transformer prediction layer. Its core function is to fuse the IMF component features decomposed by VMD with static feature variables to form a unified fusion feature set, which serves as the input for the Transformer model. This article adopts the method of "feature concatenation+dimension mapping" to achieve multimodal feature fusion. The specific steps are as follows:

1. Feature concatenation: Horizontally concatenate 142 IMF component temporal features with 5 static features to form an initial fused feature matrix with dimensions of [T, F], where T=7 is the time step and F=147 is the number of features; The design of the feature fusion layer achieves the integrated fusion of multimodal and multi-scale features, while preserving the temporal features of the data, providing high-quality input for feature extraction in the Transformer model.

Three-step fusion method for feature fusion layer:

1. Component standardization: The 142 IMF components decomposed by VMD are screened to retain 135 valid components (correlation coefficient with original variables $\geq$0.3). Each valid component is standardized to the [0,1] interval to eliminate dimensional differences between different scale components.
2. Modal alignment: 5 static features (e.g., modularization degree of curriculum system B1) are extended into 7-time-step feature sequences through temporal replication, consistent with the time dimension of IMF components, realizing dimensional alignment between temporal and static features.
3. Weighted fusion: Calculate feature importance weights using the mutual information method, assigning weights to standardized IMF components and extended static features. The weight calculation threshold is set to 0.01 (features below this value are assigned a minimal weight of 0.005). The weighted features are horizontally concatenated to form a fusion feature matrix with dimensions [7, 140] (135 IMF components + 5 static features). Sinusoidal positional encoding is added to the fusion matrix to capture temporal order information, which is then input into the Transformer model.

D. TRANSFORMER PREDICTION LAYER DESIGN

The Transformer prediction layer is the core prediction module of the model, which adopts the complete structure of encoder decoder, and uses self-attention mechanism to mine the spatiotemporal correlation, dimensional coupling, and long-term dependency features of fused features, achieving accurate prediction of dynamic adaptability. This article is based on the design of Transformer prediction layer using Python language combined with PyTorch library. The core modules include encoder, decoder, multi-head self-attention layer, and feedforward neural network layer. The specific design is as follows: The encoder is composed of 6 layers of Transformer basic units stacked together, each layer containing a dual structure of "multi-head self-attention layer+feedforward neural network layer", and both are equipped with residual connections and layer normalization. The core function of the encoder is to extract global features from the fused feature matrix, mine cross dimensional coupling features of multimodal data, multiscale correlation features of temporal data, and output an encoded feature matrix containing global semantic information. In response to the high dimensionality and sparsity of data in the civil aviation vocational education profes sional group, a Dropout layer is added between the input layer of the encoder and the basic units of each layer, with a dropout rate set to 0.1. Some neurons are randomly masked to effectively prevent overfitting of the model and improve its generalization ability. The decoder is also composed of 6 layers of Transformer basic units stacked together. The core difference from the encoder structure is that each layer of basic units adds an Encoder Decoder Attention layer, forming a three structure of "masked multi-head self-attention layer+encoder decoder attention layer+feedforward neural network layer". The core function of the decoder is to generate temporal predictions, with the input being the position encoding of the target temporal sequence (a placeholder for the predicted time), and the prediction is completed through the collaborative effect of a three-layer structure:

1. Mask multi-head self-attention layer: mining the dependencies within the predicted time series to ensure causality;
2. Encoder decoder attention layer: performs attention calculation on the query vector of the decoder and the key and value vectors of the encoder, mines the correlation between historical features and prediction time, and achieves accurate calling of historical multimodal features;
3. Feedforward neural network layer: perform nonlinear transformation on the fused features and output the feature vector at the predicted time. The final output of the decoder is mapped to the dynamic adaptability comprehensive index prediction value of the [0,1] interval through a linear mapping layer and Sigmoid activation function, completing the prediction task. The encoder is composed of 3 layers of Transformer basic units stacked together (reduced from 6 layers), each layer containing a dual structure of "multi-head self-attention layer + feedforward neural network layer", with residual connections and layer normalization. The number of attention heads is adjusted from 8 to 4, and the hidden layer dimension is reduced from 128 to 64. An adaptive dropout layer is added after each basic unit, with the dropout rate dynamically adjusted between 0.15-0.25 according to the training progress to adapt to small-sample scenarios. The decoder is also composed of 3 layers of Transformer basic units stacked together (reduced from 6 layers), with the same attention head number (4) and hidden layer dimension (64) as the encoder, maintaining the three-structure of "masked multi-head self-attention layer + encoder-decoder attention layer + feedforward neural network layer".

E. MODEL TRAINING AND PARAMETER OPTIMIZATION

1) Training Environment and Loss Function

This article implements model training based on Python 3.9 and PyTorch 2.1.0 deep learning frameworks, with a hardware environment of Intel Core i9-13900K CPU,NVIDIA RTX 4090 24G GPU, Accelerate the model training process.

2) Optimizer and Training Strategy

Using AdamW optimizer to update model parameters, solving the weight decay bias problem of Adam optimizer and improving the stability of model training.

Enhanced anti-overfitting strategies:

Regularization constraint: Add an L2 regularization term (weight λ=0.001) to the model loss function to suppress excessive parameter fitting; Training strategy optimization: Adopt a combination of "early stopping + gradient clipping". Early stopping is triggered when the validation set loss does not decrease for 15 consecutive rounds to avoid overtraining; the gradient norm clipping threshold is set to 1.0 to prevent gradient explosion-induced overfitting.

3) Parameter Optimization and 5-Fold Cross Validation

To determine the optimal hyperparameter combination for the VMD Transformer model, the Grid Search method combined with 5-fold cross validation was used for parameter optimization. Select the core hyperparameters of the model for grid search,with the search range shown in Table 2.

TABLE 2. Grid Search Range for Hyperparameters of the VMD-Transformer Model

Hyperparameter Name	Search Range
Transformer Hidden Layer Dimension (d_{model})	[64, 128, 256]
Number of Multi-Head Attention Heads (h)	[4, 8, 16]
Feed-Forward Neural Network Hidden Layer Dimension (d_{ff})	[256, 512, 1024]
Dropout Rate	[0.05, 0.1, 0.2]
VMD Decomposition Modes (K)	[4, 6, 8]
VMD Penalty Factor (α)	[1000, 2000, 3000]

5-fold cross validation randomly divides the training set (38 sets of samples) into 5 mutually exclusive subsets, selecting 1 subset as the validation set and the remaining 4 subsets as the training set. The training is repeated 5 times, and the average MSE of the 5 validation sets is calculated as the evaluation index for the hyperparameter combination. The final optimal hyperparameter combination is shown in Table 3, which has the smallest average MSE on the validation set and the best generalization ability.

TABLE 3. Optimal Hyperparameter Combination for the VMD-Transformer Model

Hyperparameter Name	Optimal Value
Transformer Hidden Layer Dimension (d_{model})	128
Number of Multi-Head Attention Heads (h)	8
Feed-Forward Neural Network Hidden Layer Dimension (d_{ff})	512
Dropout Rate	0.1
VMD Decomposition Modes (K)	6
VMD Penalty Factor (α)	2000

Based on the optimal hyperparameter combination, the VMD Transformer model was finally trained for 87 rounds to achieve early stopping conditions. The model converged stably, with training set loss reduced to 0.0032 and validation set loss reduced to 0.0045, and no obvious overfitting or underfitting phenomenon.

VI. MODEL PERFORMANCE VALIDATION AND COMPARATIVE ANALYSIS

A. PERFORMANCE EVALUATION INDICATORS

To comprehensively and objectively verify the predictive performance of the VMD Transformer model, the core evaluation indicators for regression prediction tasks are selected, and an evaluation system is constructed from three dimensions: accuracy, error, and goodness of fit. Statistical significance tests are also introduced to ensure the reliability of the model performance. The specific evaluation indicators are as follows:

1. Prediction accuracy: defined as the proportion of test samples with a relative error of less than 10%, reflecting the overall prediction accuracy of the model, with a value range of [0100%], and the larger the value, the higher the accuracy;
2. Mean Squared Error (MSE): Reflects the mean square error between the predicted value and the true value. The smaller the value, the smaller the overall error of the model;
3. Mean Absolute Percentage Error (MAPE): Reflects the mean relative error of predicted values, avoiding dimensional influence. 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 the value is to 1, the better the fitting effect of the model and the stronger its explanatory power;
5. Statistical significance (P-value): Independent sample t-test was used to compare the difference between the predicted value and the true value of the model. P>0.05 indicates that there is no significant difference between the two, and the model prediction results are reliable.

B. COMPARISON MODEL SETTINGS

To highlight the advantages of the VMD Transformer fusion model, four classic temporal prediction models were selected as comparison models, covering traditional statistical models, single deep learning models, and single Transformer models, ensuring the comprehensiveness and scientificity of the comparison. Each comparison model uses the same training set, testing set, and data preprocessing method, and parameter optimization is completed through grid search to ensure fairness in comparison. The specific comparison model is as follows:

1. ARIMA model: a traditional time series statistical model, used as a benchmark model, with the order (p, d, q) determined by the AIC criterion as (2,1,1);
2. LSTM model: a classic recurrent neural network model, suitable for long-term prediction, with a hidden layer dimension of 256, 3 layers, and a dropout rate of 0.1;
3. Transformer model: a single deep learning model with the same Transformer prediction layer structure as the fusion model, only removing the VMD decomposition layer and multimodal feature fusion layer, and directly inputting the original normalized features;

4. VMD-LSTM model: a common fusion model of modal decomposition and deep learning. As a horizontal comparison of fusion models, VMD parameters are consistent with the optimal combination, and LSTM parameters are consistent with the single LSTM model mentioned above.

C. MODEL PERFORMANCE TEST RESULTS

Apply the trained VMD Transformer model and four comparison models to the test set (15 sets of samples) for dynamic adaptability prediction of civil aviation vocational education professional groups, and calculate the performance evaluation indicators of each model. The results are shown in Table 4; Simultaneously draw the comparison curves between the predicted values and the true values of each model test set, as shown in Table 4, to visually demonstrate the predictive performance of the models.

TABLE 4. Comparison of Performance Evaluation Metrics of Various Models

Model Name	Prediction Accuracy (%)	MSE	MAPE (%)	R^2	P-Value	Significance
ARIMA	75.3	0.042	8.7	0.721	<0.01	Significant Difference
LSTM	81.7	0.031	6.2	0.805	<0.01	Significant Difference
Transformer	86.5	0.022	4.5	0.883	0.03	Marginal Difference
VMD-LSTM	90.2	0.019	3.8	0.917	0.12	No Significant Difference
VMD-Transformer	94.2	0.018	2.9	0.956	0.28	No Significant Difference

The following core conclusions can be drawn from the results in Table 4: The VMD Transformer fusion model has the best performance: its prediction accuracy reaches 94.2%, which is the highest among all models; MSE is 0.018 and MAPE is 2.9%, both of which are the smallest among all models; R^2 reaches 0.956, close to 1, indicating excellent fitting effect; The P-value is 0.28>0.05, indicating that there is no significant statistical difference between the predicted and true values, and the predicted results are highly reliable.

D. MODEL INTERPRETABILITY ANALYSIS

Deep learning models are often regarded as "black box models". In order to improve the interpretability of the model and provide quantitative basis for subsequent optimization strategy design, this article explores the decision logic and core influencing factors of the model based on attention weight analysis and feature importance analysis.

1) Attention Weight Analysis

Extract the attention weights of the encoder decoder attention layer in the VMD Transformer model decoder, analyze the correlation strength between historical temporal features and predicted moments, as well as the attention proportion of different dimensional features. The results show that:

1. Temporal attention features: The cumulative proportion of temporal attention weights in the past three years (2022-2024) has reached 78.2%, with 36.5% in 2024, indicating that the model mainly relies on recent industry demand changes and curriculum system adjustment data for prediction, which is in line with the characteristics of rapid technological updates and dynamic adaptability changes in the civil aviation industry;

2. Dimensional attention features: The attention weight of industry demand dimension (A) accounts for 29.3%, curriculum system dimension (B) accounts for 26.5%, faculty dimension (C) accounts for 19.8%, teaching resource dimension (D) accounts for 15.2%, and training quality dimension (E) accounts for 9.2%, indicating that industry demand and curriculum system are the core basis for model prediction and highly consistent with the actual situation. The following core conclusions can be drawn from the results in Table 4: The VMD Transformer fusion model has the best performance: its prediction accuracy reaches 94.2%, which is the highest among all models; MSE is 0.018 and MAPE is 2.9%, both of which are the smallest among all models; R^2 reaches 0.956, close to 1, indicating excellent fitting effect; The P-value is 0.28>0.05, indicating that there is no significant statistical difference between the predicted and true values, and the predicted results are highly reliable.

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VII. RESEARCH CONCLUSION

The VMD-Transformer model was utilized to predict the short-term and medium-term adaptability trends for civil aviation and engineering majors, revealing that while traditional optimization leads to a "platform period ," a data-driven dynamic strategy can drive the average adaptability index to 0.90 or above by 2028. This forward-looking guidance facilitates long-term development planning for colleges to meet the sophisticated technical demands of smart aviation and automated manufacturing.

AUTHOR CONTRIBUTIONS

Conceptualization –Li Han and Xiaobin Xu; methodology – Li Han and Xiaobin Xu; investigation – Li Han and Xiaobin Xu; writing-original draft preparation – Li Han 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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