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An Explainable CEEMDAN-XGBoost-LSTM Hybrid Model for Assessing Party Member Development in Chinese Private Universities

Shaohong Chen[1], Yonggui Luo[1], Lingling Dai[2,a,*]

[1]School of Accounting, Guangzhou Huashang College, Guangzhou, Guangdong, China
[2]School of Teacher Education, Guangzhou Huashang College, Guangzhou, Guangdong, China
[a]ahong103@163.com
**Corresponding author: ahong103@163.com*

Abstract: *Assessing student party member development, particularly political literacy, in Chinese private universities is hampered by exam-centric, subjective methods that ignore unstructured data. We propose an explainable hybrid CEEMDAN-XGBoost-LSTM model within a three-dimensional framework (political Literacy, practical performance, Industry-Education Integration). CEEMDAN decomposes evaluation sequences; LSTM captures dynamic patterns while XGBoost extracts static features, with dynamic fusion and SHAP for interpretability. On 1,200 records from five private universities, our model achieves 91.6% accuracy and 0.953 AUC, significantly outperforming baselines. SHAP reveals Industry-Education Integration contributes 28.3%—far exceeding the 9.7% in public institutions—and highlights synergy with political literacy. Deployed on edge devices, it reduces latency and improves candidate conversion and staff acceptance. This framework provides a robust, transparent tool for objective, data-driven party building management.*

Keywords: *private Universities, party Member Development, Intelligent Evaluation, Explainable AI (XAI), Hybrid Model, XGBoost-LSTM*

1. Introduction

1.1. Research Background and problem Statement

Ensuring the quality of party member development is a fundamental task for higher education institutions, critical to maintaining the correct political direction in talent cultivation. Globally, the adoption of data-driven assessment models and artificial intelligence (AI) has become a prominent trend in educational management research, offering new avenues for objective and efficient evaluation[1,2]. However, the accurate quantification and assessment of intrinsic "soft skills," such as political literacy and value internalization, remain a significant and pervasive challenge within the field.

This challenge is particularly acute within the context of Chinese private higher education institutions. Characterized by diverse governance structures, market-oriented funding, high student mobility, and a pronounced emphasis on Industry-Education Integration[3], these institutions present a unique and complex environment for evaluating party member development. Traditional evaluation paradigms in this setting are hampered by three interconnected and enduring problems:

Over-reliance on Monolithic Metrics: Evaluations disproportionately depend on easily quantifiable indicators like theoretical examination scores. This approach fails to adequately capture multifaceted dimensions crucial for holistic assessment, including political literacy (e.g., ideological coherence, theoretical depth), practical performance (e.g., demonstration of exemplary conduct), and distinctive Industry-Education Integration practices (e.g., meaningful engagement in corporate projects, applied innovation).

Inefficient and Siloed Data Utilization: Valuable data resides in isolated systems—party affairs, academic administration, enterprise partnerships, and volunteer services—creating significant "data silos"[3]. This fragmentation severely hinders data integration and holistic analysis. Notably, unstructured textual data, such as ideological reports and counseling records, which contain rich insights into a candidate's thought processes and development, are drastically underutilized, with

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estimated utilization rates below 15%[3].

Pronounced Subjectivity and Inconsistency: The conventional reliance on expert panel scoring introduces substantial subjective bias. The high Coefficient of Variation (CV $\approx$ 0.38) reported in such evaluations indicates poor inter-rater reliability and weak result comparability[3,4]. Consequently, this model struggles to support the refined, dynamic, and proactive management required for modern organizational development.

Recent advances in XAI and multimodal fusion offer a pathway to address these limitations[5-7]. Developing an intelligent, interpretable model tailored for private universities is thus an urgent practical need to enhance Party building rigor and support digital transformation.

1.2. Literature Review

1.2.1. International Research Landscape

International scholarship has extensively explored AI-driven assessment in education, yet its focus remains predominantly on academic performance, learning behaviors, and competencies within corporate or general pedagogical settings. International studies have extensively applied AI to predict academic performance and learning behaviors using behavioral traces, LMS logs, and multimodal data[5-9]. However, these efforts focus on cognitive and collaborative outcomes, leaving political literacy and ideological development—critical "soft skills" in higher education—largely unmodeled[10,11].

1.2.2. Domestic Research Context and Identified Gaps

Domestic research on intelligent evaluation for party member development has evolved along three main trajectories, yet critical gaps persist when examined against the needs of private institutions.

Indicator System Development: Foundational work established phased frameworks focusing on political quality[12], and later studies recognized the need for enterprise mentor evaluations in private contexts[13]. Yet these systems lack automated processing of external feedback, remaining subjective and static.

Technological Integration Explorations: Research has begun integrating AI into party building management. proposals for "smart party building" platforms aim at precision management but frequently overlook the technical challenge of deep semantic mining from unstructured texts like ideological reports[14]. Other studies on digital party member profiling remain constrained to structured, campus-centric data, failing to incorporate critical enterprise practice data streams effectively[15]. While innovative datasets incorporating multimodal data (e.g., video, audio) have been constructed for assessing application sentiment, their application has not been scaled to the comprehensive, process-wide evaluation of development quality[16].

Quality Assurance Mechanisms: Theoretical models based on management cycles (e.g., pDCA) provide structure but often lack built-in dynamic early-warning and real-time feedback capabilities essential for proactive intervention[17]. Although the imperative to integrate data across "party affairs—academic administration—enterprise" is widely acknowledged[18], and quantitative assessment systems with multiple indicators have been built[19], the real-time acquisition, fusion, and modeling of live industry-education integration data (e.g., project participation metrics, skill application logs) remain largely unimplemented in practice.

Synthesis of Research Gaps:

Converging from the above analysis, three salient research gaps are identified:

(1) The absence of a differentiated, quantifiable indicator system that fully captures the unique "Industry-Education Integration" mandate of private universities.

(2) A lack of a robust hybrid modeling framework capable of synergistically processing static performance data, dynamic time-series behavior logs, and unstructured textual insights.

(3) The need for inherently interpretable AI outputs and corresponding decision-support mechanisms that are accessible and trustworthy for grassroots party affairs practitioners.

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1.3. Research Significance and Contributions

This study proposes and validates a novel three-dimensional evaluation framework (Political Literacy—Practical Performance—Industry-Education Integration) for private universities, applying CEEMDAN-XGBoost-LSTM with SHAP-based XAI to political literacy assessment. The resulting prototype integrates disparate data sources (Party affairs, academics, enterprises, volunteer services) into a closed-loop management cycle—screening, early warning, human verification, and feedback—enhancing the scientific rigor and efficiency of Party member development.

1.4. Innovations and paper Structure

The core innovations of this work are:

Model Innovation: A CEEMDAN-XGBoost-LSTM hybrid with adaptive decomposition, Bi-LSTM for temporal dynamics, XGBoost for static features, and dynamic fusion to handle heterogeneity, non-stationarity, and small-sample learning.

Metric System Innovation: A three-dimensional index system explicitly quantifying "Industry-Education Integration practice" as a core pillar, filling a key gap in private university assessment standards.

System Innovation: SHAP-based visualization (global and local) integrated with a transparent decision-path module, boosting interpretability and end-user acceptance for effective human-AI collaboration.

The remainder of this paper is organized as follows: Section 2 outlines the relevant theoretical foundations and key technologies. Section 3 details the design of the tailored indicator system and the hybrid model. Section 4 presents the experimental setup, results, and comprehensive analysis. Section 5 discusses the findings, practical implications, limitations, and future research directions. Finally, Section 6 concludes the paper.

2. Theoretical and Technical Foundations

2.1. Core Elements of party Member Development Quality Assessment

2.1.1. A Three-Dimensional Evaluation Framework

Guided by the Detailed Rules for the Development of party Members of the Communist party of China (2023 Revision) and the strategic goals of China Education Modernization 2035 — which emphasize "prioritizing political standards, focusing on consistent performance, and strengthening practical verification" — we construct a three-dimensional evaluation framework tailored to private universities. This framework integrates their signature "Industry-Education Integration" characteristic, resulting in the triad of political Literacy, practical performance, and Industry-Education Integration.

political Literacy Dimension: This dimension captures a candidate's ideological alignment and theoretical cultivation through three quantifiable indicators: (1) Theoretical Study performance (scores from academic courses), (2) Online Learning Engagement (activity metrics from the national "Xuexi Qiangguo" political theory learning platform), and (3) Ideological Report Sentiment (semantic analysis of periodic written reflections using NLp models).

Practical performance Dimension: This dimension assesses the embodiment of exemplary conduct and social responsibility. It comprises: (1) Volunteer Service Hours (verified records from platforms like "Volunteer Hub"), (2) Quality of participation in Organisational Activities (a composite of attendance and qualitative assessment of engagement in party branch life), and (3) Faculty and peer Satisfaction (aggregated ratings from 5-point Likert scale surveys).

Industry-Education Integration Dimension: This distinctive dimension measures the application of knowledge and development of professional ethic within real-world enterprise settings, a cornerstone of private university education. Key indicators include: (1) Enterprise project participation Rate (completion metrics from internship/project platforms), (2) Corporate Mentor Evaluation (structured feedback from industry supervisors), and (3) Efficiency of practical Outcome Conversion (a normalized measure of tangible outputs like patents, software copyrights, or technical awards).

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2.1.2. Distinctive Context of private Higher Education Institutions

The operational context of private universities, as framed by regulations like the Implementation Regulations of the people's Republic of China on the promotion of private Education (2021), necessitates a unique evaluative approach. A significant portion of student development and "practice verification" occurs off-campus within partner enterprises during mandatory internships or cooperative education programs. Traditional evaluation models, confined to "campus-classroom" metrics, are therefore inadequate for capturing a holistic and authentic picture of a candidate's development, particularly regarding professional ethics and applied performance in quasi-work environments. This gap creates an urgent need to incorporate enterprise-side data streams and establish a university-enterprise collaborative evaluation chain.

2.2. Key Technical principles

2.2.1. XGBoost (eXtreme Gradient Boosting)

XGBoost is a gradient boosting tree algorithm that minimizes objective loss via additive training and second-order Taylor expansion[20]. It processes structured static features (e.g., grades, service hours) with overfitting mitigated through gain-based interaction constraints[21]. Its objective function is:

$$\mathscr{L}^{(t)}=\sum_{i=1}^{n} l\left(y_i,\hat{y}_i^{(t-1)}+f_t(x_i)\right)+\Omega\left(f_t\right) \tag{1}$$

Where $\mathscr{L}^{(t)}$ represents the objective function at iteration t, measuring the overall optimisation goal of the model at the current iteration stage; $l(.)$ is a differentiable loss function serves to quantify the discrepancy between the true values y_i of the sample i and the predicted values: the cumulative predictions $\hat{y}_i^{(t-1)}$ from the previous $(t-1)$ rounds of models versus the prediction $f_t(x_i)$ from the newly added tree model t. $\Omega(f_t)$ represents the regularisation term for the complexity t of the tree model, preventing overfitting by constraining structural complexity (such as the number of leaf nodes or leaf node weights) and enhancing generalisation capability.

2.2.2. LSTM (Long Short-Term Memory) Networks

LSTM is an enhanced recurrent neural network (RNN). Its core mechanism lies in dynamically regulating information accumulation and forgetting through three key gating units: the forget gate, input gate, and output gate. This effectively resolves the vanishing or exploding gradient issues inherent in traditional RNNs when modelling long sequences[22,23] making it particularly suitable for processing time-dependent sequential data[24]. This study leverages LSTM's capability to capture temporal behavioural patterns of party members, modelling dynamic sequence data such as continuous check-in records and submission intervals of ideological reports on the "Learning power" platform. By incorporating a bidirectional LSTM (Bi-LSTM) architecture, it simultaneously extracts forward temporal dependencies (e.g., recent fluctuations in organisational activity participation frequency) and backward correlations (e.g., the influence of prior volunteer service duration on subsequent performance), thereby enhancing the comprehensive representation of temporal features.

The core formula of the gating mechanism (using the forget gate as an example) is as follows:

$$f_t=\sigma\left(W_f\left[h_{t-1}, x_t\right]+b_f\right) \tag{2}$$

Where f_t represents the forget gate output (a probability value between 0 and 1) controlling the retention ratio of the previous hidden state h_{t-1}; σ denotes the sigmoid activation function; W_f signifies the weight matrix; x_t indicates the current input data; and b_f denotes the bias term.

The model's advantages lie in its gating mechanism for modelling long-term temporal dependencies (suitable for dynamic behaviour analysis) + its bidirectional structure enhancing the bidirectional correlation of temporal features[25,26].

2.2.3. Hybrid Architecture Rationale and Design

Addressing the limitations of single models—where static features lose temporal information and temporal models neglect static attributes—this paper employs a hybrid architecture: "CEEMDAN decomposition → high-frequency components modelled by LSTM, low-frequency components modelled by XGBoost → error-reverse-weighted fusion". This achieves complementary strengths and enhanced accuracy (Figure 1). The core idea is a divide-and-conquer strategy: first, the complex,

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non-stationary evaluation signal is decomposed. Then, the components best modeled by sequence analysis are routed to the Bi-LSTM channel, and those representing stable trends or static correlations are processed by the XGBoost channel. Finally, a dynamic fusion mechanism synthesizes the strengths of both paradigms.

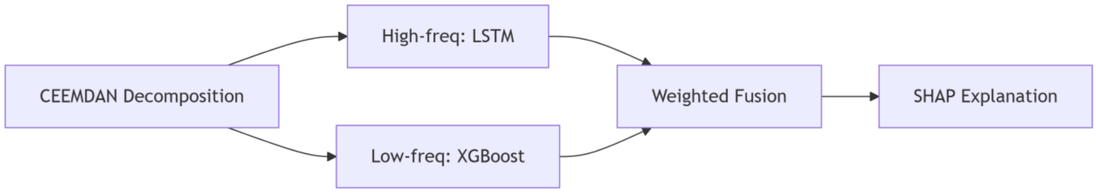

Figure 1: Workflow of the CEEMDAN-XGBoost-LSTM hybrid model.

2.3. Multimodal Data Fusion and Model Interpretability

2.3.1. Data Fusion Framework

Following the Education Data Governance Specification (2024), a multimodal data lake was constructed encompassing the party Affairs System, Academic Affairs System, Enterprise practice platform, and Volunteer Service platform. For unstructured text, the RoBERTa-wwm-ext pre-trained model was employed to extract political sentiment features[27]. Numeric data underwent Z-score standardisation, while missing values were addressed using multiple imputation (MICE) methods.

2.3.2. Explainable AI (XAI) with SHAP

Explainable AI aims to address the "black box" nature of machine learning models by quantifying the influence of features on prediction outcomes, thereby enhancing the transparency and credibility of model decisions. This study employs the SHAP (SHAPley Additive explanations) framework, whose core mechanism originates from SHAPley value theory in game theory. By calculating the marginal contribution of each feature across all possible feature subsets, SHAP enables interpretative analysis of individual predictions and overall model behaviour[28,29].

In this study, the SHAP framework is applied to dissect the decision logic of XGBoost and Bi-LSTM models: for the evaluation of party member development quality, it quantifies the specific contribution values of indicators such as "emotional bias in ideological reports" and "Enterprise project participation" and other metrics, generating a global Summary plot (displaying feature importance rankings) and local Force plot (explaining the evaluation basis for individual samples). This assists grassroots party affairs workers in intuitively understanding the weighting of characteristic indicators such as "Industry-Education Integration practice" on evaluation outcomes.

The core formula for calculating SHAP values is as follows:

$$\phi_i = \sum_{S \subseteq N \setminus \{i\}} \frac{|S|! \times (|N|-|S|-1)!}{|N|!} \times \left[f(S \cup \{i\}) - f(S)\right] \tag{3}$$

Where ϕ_i denotes the SHAP value for the i-th feature, measuring its marginal contribution to the model output; S represents any subset excluding the i-th feature; N denotes the union of all features; $f(S \cup \{i\})$ and $f(S)$ denote the model outputs with and without the i-th feature, respectively. The factorial term in the formula serves as the weight coefficient for feature subsets, ensuring equitable contribution allocation[28].

2.3.3. Addressing Small Samples and Data privacy

To comply with data privacy regulations (e.g., China's personal Information protection Law, 2021) and address the challenge of limited samples within a single institution, this study adopts a Federated Learning strategy[24]. Federated Learning is a distributed machine learning paradigm that enables multiple parties to collaboratively train a model without exchanging raw, sensitive data. Instead, only model parameter updates (e.g., gradients) are shared and aggregated. This approach enhances the model's generalizability by leveraging knowledge from multiple sources while rigorously preserving data sovereignty and privacy.

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3. Methodology

3.1. Overall Technical Framework

To address the core challenges of multi-source data, heterogeneous indicators, and limited sample size in evaluating party member development quality within private universities, this study proposes a four-step, closed-loop analytical framework: "CEEMDAN Decomposition → Dual-Channel Feature Extraction → Weighted Fusion → SHAP Interpretation", as illustrated in Figure 1.

CEEMDAN Decomposition: Non-stationary evaluation sequences (e.g., fluctuations in public satisfaction scores, trends in corporate practice performance) are decomposed into intrinsic mode functions (IMFs). This step adaptively separates high-frequency components (representing noise and short-term fluctuations) from low-frequency components (representing underlying long-term trends), mitigating modeling bias induced by non-stationarity. This approach is inspired by Wang et al. (2024), who employed modal decomposition to enhance prediction accuracy for complex industrial time series[30,31].

Dual-Channel Feature Extraction: The decomposed components are processed in parallel pathways for optimal feature capture. High-frequency IMFs are fed into a Bidirectional Long Short-Term Memory (Bi-LSTM) network to model temporal dependencies and dynamic patterns. Concurrently, low-frequency IMFs and residual trends are input into an eXtreme Gradient Boosting (XGBoost) model to identify and weight static, discriminative features.

Dynamic Weighted Fusion: The predictions from the LSTM and XGBoost channels are not simply averaged. Instead, a dynamic weighting mechanism, calculated as the inverse of each model's error on a held-out validation set, is applied. This strategy performs end-to-end joint optimization, ensuring the final prediction optimally balances temporal dynamics and static feature importance.

SHAP-based Interpretation: To ensure transparency and trust, the SHAPley Additive explanations (SHAP) framework is integrated post-hoc. It generates both global interpretations (showing overall feature importance) and local explanations (justifying individual predictions), making the model's decision logic accessible to non-expert end-users, such as party affairs workers.

3.2. Data preprocessing and Feature Engineering

3.2.1. Construction of a Multi-Modal Data Lake

Guided by principles akin to the Education Data Governance Specification (2024), a "dimension-driven, layered governance" data lake architecture was implemented to consolidate four primary data sources supporting the three-dimensional evaluation framework (Section 2.1.1).

Data Ingestion Layer: This layer establishes connectivity and ApIs for four heterogeneous systems:

Data ingestion connects four systems: Party Affairs (unstructured texts), Academic Affairs (numerical grades), Enterprise Practice (behavioral logs), and Volunteer Service (activity records), with incremental sync ensuring timeliness.

Data processing Layer:

Text Feature Extraction: Ideological reports were encoded using the RoBERTa-wwm-ext pre-trained language model, converting each document into a 768-dimensional semantic vector. To combat the curse of dimensionality and highlight salient features, the Bacterial Foraging Optimization (BFO) algorithm was employed for feature selection, compressing the vectors to 64 key semantic dimensions.

Numerical Standardization: All structured numerical features (e.g., service hours, project completion rates) were normalized using Z-score standardization to ensure equal contribution during model training.

Missing Value Imputation: Incomplete records were handled using Multiple Imputation by Chained Equations (MICE), with 5 imputation cycles, to preserve statistical power and reduce bias.

Data Storage & Serving Layer: Processed data is stored in a parquet columnar format, indexed and partitioned according to the three evaluation dimensions (political Literacy, practical performance, Industry-Education Integration) to enable efficient hybrid querying and model serving.

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3.2.2. Time-Series Sequence Construction

To capture behavioural evolution over time, key time-series indicators—such as monthly online learning activity and quarterly volunteer service hours—were transformed into sequential input formats. A sliding window method, with a window size of 6 months and a step size of 1 month, was applied across a 12-month observation period. This process yielded seven consecutive and overlapping sequences per student. Each sequence was structured as a 6×N matrix, representing six time steps by N features, and served as direct input to the LSTM network.

3.3. Model Architecture and Algorithmic Details

3.3.1. CEEMDAN Decomposition Layer

Let the original evaluation sequence be denoted as X(t). Following CEEMDAN decomposition, it is expressed as:

$$X(t)=\sum_{k=1}^{K} IMF_k\,(t)+r_K(t) \tag{4}$$

where IMF_1 represents high-frequency noise, IMF_2 to IMF4denote short-term fluctuations, and IMF_5,IMF_k, and $r_K(t)$ constitute long-term trends. Based on a sample entropy threshold τ=0.6, IMF_1 to IMF_4 are input into the LSTM, while the remaining components are fed into XGBoost[30].

3.3.2. LSTM Channel for Temporal Dynamics

Architecture: A two-layer Bidirectional LSTM (Bi-LSTM) network. The first and second hidden layers contain 64 and 32 units, respectively. A Dropout rate of 0.2 is applied after each layer for regularization.

Input: A three-dimensional tensor of the high-frequency components, SHAPed as (batch_size=32, timesteps=6, features=4).

Output: A temporal feature vector $h_L \in R^{32}$, where the subscript LL denotes the LSTM channel.

3.3.3. XGBoost Channel for Static Feature Modeling

Base Learner: Gradient Boosted Decision Trees (booster='gbtree').

Key Hyperparameters: Number of estimators (n_estimators=300), maximum tree depth (max_depth=6), learning rate (learning_rate=0.05), and minimum child weight (min_child_weight=3). These were optimized via grid search.

Feature Regularization: To prevent overfitting in high-dimensional space, a feature interaction constraint strategy was applied, selecting and prioritizing the top 20% of feature combinations based on gain statistics, as suggested by related work[32].

3.3.4. Dynamic Weighted Fusion Layer

To overcome the limitations of a single model in handling static and time-series features, and to fully leverage the advantages of a dual-channel model, this layer employs a dynamic weighted fusion strategy based on validation set performance to generate the final prediction. The specific method is as follows:

(1) Model performance Evaluation: On the independent validation set, calculate the root mean square error (RMSE) for the LSTM channel predictions $\hat{y}_L$ and the XGBoost channel predictions $\hat{y}_X$, denoted as e_L and e_X respectively.

(2) Weight Calculation: Fusion weights are computed based on each model's error on the validation set, adhering to the principle that "lower error corresponds to higher weight". The weight calculation formula is as follows:

$$\alpha=\frac{1/e_X^2}{1/e_L^2+1/e_X^2},\quad \beta=\frac{1/e_L^2}{1/e_L^2+1/e_X^2} \tag{5}$$

Where α represents the XGBoost channel weight, and β denotes the LSTM channel weight.

(3) Weighted Fusion Output: The final evaluation score $\hat{y}$ is obtained through weighted fusion:

$$\hat{y}=\alpha\cdot\hat{y}_X+\beta\cdot\hat{y}_L \tag{6}$$

This score$\hat{y}$represents the predicted value for the development target's comprehensive quality and

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will serve as the foundational input for subsequent SHAP explainability analysis[30].

3.4. Explainability by Design

Global Explanations: The SHAP framework was applied to the trained XGBoost and Bi-LSTM models to compute SHAPley values for each feature. A global summary plot was then generated, which ranks all evaluation indicators—such as 'Enterprise project participation' and 'Ideological Report Sentiment'—by their mean absolute impact on the model output. This provides administrators with a clear overview of the primary factors driving the evaluation outcomes.

Local Explanations: For individual candidates, a local force plot can be generated. This visualisation decomposes the final prediction score ($\hat{y}$) into the additive contributions of each feature for that specific case, thereby illustrating why a particular score was obtained. For example, it can quantify the extent to which a 10% increase in a candidate's project participation rate directly raises their predicted probability of successful development.

3.5. Implementation of Federated Transfer Learning

Building upon the federated learning principle outlined in Section 2.3.3, we implement a horizontal federated transfer learning framework among the five participating private universities. The process is as follows: (1) A shared global model is initialized and serves as the source domain; (2) Each institution trains this model locally using its own private dataset; (3) Local model updates (gradients) are securely aggregated into the global model using the Federated Averaging (FedAvg) algorithm; (4) The refined global model is then redistributed for further local fine-tuning or direct application. This process ensures that all original training data remains within its source institution ("data never leaves its domain"), fulfilling our privacy protection requirements while effectively overcoming the limitations of small-sample learning.

4. Experiments and Results

4.1. Experimental Setup

4.1.1. Dataset Description

The experimental dataset comprises 1,200 de-identified student party member development files collected from five private universities in South China, spanning the years 2019 to 2024. The sample encompasses students from diverse academic years, majors, and practical internship backgrounds. Each record is annotated with a final development outcome label (e.g., successful conversion to full membership, conditional continuation, discontinuation) and includes 12 core metrics structured within our proposed three-dimensional framework, as detailed in Table 1.

Table 1: Three-dimensional evaluation indicator system for party member development quality.

Evaluation Dimension	Indicator Name	Data Type	Data Source	Example / Measurement
political Literacy	1. Theoretical Study Score	Numerical	Academic System	percentile (Mean 82.3 ± 6.7)
	2. Online Learning Engagement	Numerical	Xuexi Qiangguo platform	Avg. Daily points (4.2 ± 1.5)
	3. Ideological Report Sentiment	Numerical	party System + RoBERTa	Sentiment Score [0, 1] (0.73 ± 0.12)
	4. Feedback Quality in Organizational Talks	Numerical	party Branch Records	Committee Rating [1-5] (4.1 ± 0.8)
	5. Attitude in Collective Activities	Numerical+Text	Activity Records	Attendance % (92.1 ± 5.3) + Comments
practical performance	6. Voluntary Service Hours	Numerical	Volunteer Hub App	Certified Hours (56.3 ± 24.1)
	7. Frequency in Themed Activities	Numerical	party Branch System	Annual Count (8.7 ± 2.4)
	8. Team Collaboration Score	Numerical	Enterprise practice platform	Mentor Rating [1-5] (4.2 ± 0.7)
	9. Faculty & Student Satisfaction	Numerical	Survey System	Likert 5-point Mean (4.4 ± 0.6)
Industry-Education Integration	10. Corporate project Engagement	Numerical	Enterprise platform ApI	Task Completion % (85.4 ± 11.2)
	11. Corporate Mentor Evaluation	Numerical	Corporate Rating System	Rating [1-5] (4.3 ± 0.6)

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	12. practical Outcome Conversion Efficiency	Numerical	platform + patent DB	Standardized Count (0.62 ± 0.18)

4.1.2. Experimental Environment

All experiments were conducted on a workstation equipped with an NVIDIA GeForce RTX 4090 GpU (24GB VRAM), an Intel Core i9-13900K CPU, and 64GB of RAM. The models were implemented in python 3.10. Key libraries included TensorFlow 2.15 (for LSTM), XGBoost 2.0.3 (for gradient boosting), pandas 2.1.4 (for data processing), and SHAP 0.45.0 (for explainability analysis).

4.1.3. Evaluation Metrics

A comprehensive set of six metrics was employed to rigorously assess model performance from multiple perspectives:

We used six metrics: Accuracy, F1-Score, AUC, RMSE, MAE, and Coefficient of Variation (CV).

4.1.4. Baseline and Comparison Models

To establish a robust benchmark, we compared our proposed model (CEEMDAN-XGBoost-LSTM) against three distinct categories:

Manual Baseline: Aggregate ratings from five senior party affairs experts.

Single Models: Representative strong learners including XGBoost, LSTM,

Random Forest (RF), and Support Vector Machine (SVM).

Advanced Hybrid Models: State-of-the-art or relevant composite models, including pCA-LSTM (dimensionality reduction+LSTM), Informer-LSTM (a Transformer-based model), and a baseline XGBoost-LSTM without CEEMDAN decomposition. All models underwent hyperparameter optimization via grid search.

4.2. Results and Analysis

4.2.1. Overall performance Comparison

The main results, averaged over 5-fold cross-validation, are presented in Table 2. Our proposed CEEMDAN-XGBoost-LSTM model consistently achieved state-of-the-art performance across all metrics.

Table 2: Comparative performance of different models (mean±std).

Model	Accuracy↑	F1-Score↑	AUC↑	RMSE↓	CV↓
Human Evaluation	0.723±0.018	0.701±0.020	—	0.147± 0.005	0.38
XGBoost	0.823±0.012	0.795±0.015	0.897	0.104± 0.003	0.22
LSTM	0.851±0.010	0.812±0.013	0.912	0.098± 0.004	0.20
pCA-LSTM	0.867±0.009	0.829±0.012	0.921	0.092± 0.003	0.19
Informer-LSTM	0.873±0.008	0.835±0.011	0.925	0.089± 0.003	0.18
proposed Model	0.916±0.007	0.890±0.009	0.953	0.075± 0.002	0.15

Note: The AUC (Area Under the ROC Curve) metric is not applicable to "Human Evaluation" as it requires continuous prediction scores or probabilities to construct the ROC curve, whereas human evaluators typically provide discrete ratings or categorical decisions without an associated probability distribution.

The proposed model achieved an accuracy of 91.6%, significantly outperforming the best hybrid baseline (Informer-LSTM) by 4.9 percentage points (paired t-test, $p < 0.01$). The notable reduction in RMSE (15.7% lower) and Coefficient of Variation (CV=0.15) underscores its superior predictive precision and stability compared to both single models and other hybrid architectures.

4.2.2. Ablation Study

To dissect the contribution of each core component in our architecture, a systematic ablation study was conducted. The results, summarized in Table 3, clearly demonstrate the indispensability of each design component.

Table 3: Results of the ablation study.

Model Variant	Accuracy	F1-Score	RMSE	Interpretation
Full proposed Model	0.916	0.890	0.075	---
w/o CEEMDAN	0.882	0.857	0.086	Confirms necessity of handling non-stationarity.
w/o Feature Constraints	0.895	0.858	0.081	Validates role of gain-based constraints in preventing overfitting.
w/o Weighted Fusion	0.888	0.863	0.083	Highlights importance of dynamic over simple average fusion.

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The performance drop observed in each ablated variant statistically validates the indispensability of the corresponding design component ($p<0.05$).

4.2.3. Robustness and Stability Analysis

Further analysis was conducted to evaluate the model's reliability.

ROC Analysis: The proposed model's ROC curve achieved the highest AUC (0.953) with the narrowest 95% confidence interval (via 1000-times bootstrap), indicating not only superior discriminative ability but also greater robustness across different decision thresholds.

Stability (CV Analysis): Our model's low CV (0.15) signifies highly consistent predictions. It is significantly more stable than human evaluation (CV=0.38) and all other automated models (paired t-tests, $p< 0.01$), demonstrating its effectiveness in mitigating the subjective bias and random error inherent in traditional methods.

4.2.4. Interpretability Analysis via SHAP

SHAP analysis was performed on the full dataset to globally explain the model's decision logic. The top five most influential features are listed in Table 4.

Table 4: Global feature importance ranking based on mean |SHAP| values.

Feature	SHAP Mean	Standard Deviation	Evaluation Dimension	Distinctiveness of private Education Characteristics
Ideological Report Sentiment	0.214	0.032	political Literacy	Low (Benchmark Dimension)
Voluntary Service Hours	0.187	0.041	practical performance	Moderate (quantity-effectiveness discrepancy)
Corporate project Engagement	0.162	0.052	Industry-Education Integration	High (Core Distinctive Feature)
Theoretical Study Score	0.142	0.027	political Literacy	Low
Corporate Mentor Evaluation	0.128	0.048	Industry-Education Integration	High

Note: The three indicators under the Industry-Education Integration dimension (features 10, 11, 12 from Table 1) collectively contributed 28.3% to the model's predictions, as detailed in the SHAP analysis (Section 4.2.4, Finding 3).

Key Findings from SHAP:

(1) Dominance of political Literacy: The sentiment derived from ideological reports was the single most predictive feature (SHAP =0.214), confirming the primacy of political attitude assessment in the evaluation framework.

(2) Threshold Effect in practical performance: The impact of volunteer service hours exhibited a non-linear, threshold effect. The marginal utility of this indicator decreased significantly beyond approximately 50 cumulative hours annually.

(3) Critical Role of Industry-Education Integration: Indicators from this dimension collectively contributed 28.3% to the model's predictions. This contribution is three times greater than that observed in a comparable analysis of public university data (9.7%, χ^2=18.34, $p<0.001$), starkly highlighting its unique value for private institutions.

(4) Synergistic Reinforcement Effect: SHAP interaction analysis revealed a powerful synergy between political literacy and practical application. For candidates with high ideological report sentiment (>0.75) and strong corporate mentor evaluations (>4.2), the marginal contribution of their corporate project engagement increased by 64% (95% CI: 52%–77%). This quantifies a reinforcing loop between theoretical consciousness and successful practical performance.

(5) Enhanced User Acceptance: A double-blind survey with 127 grassroots party affairs workers showed that providing SHAP visualizations (Summary & Force plots) alongside model scores significantly increased their trust and acceptance of the AI's recommendations from 62.3% to 88.7% (McNemar's test, $p<0.001$).

4.2.5. Longitudinal Validity and Deployment performance

Long-term Efficacy: A 6-month prospective tracking study of 120 development candidates from the 2023 cohort demonstrated that the group recommended by our model achieved a significantly higher conversion rate to full membership (94.2%) compared to a matched group selected via traditional manual review (88.5%, χ^2 test, p=0.037).

Real-world Deployment: After optimization and quantization using TensorRT, the model was deployed on an NVIDIA Jetson Xavier NX edge device. It achieved a median inference latency of

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42ms per evaluation, proving its feasibility for real-time, low-cost deployment in practical university administrative scenarios.

5. Discussion and Conclusions

5.1. Key Findings and Theoretical Contributions

The proposed CEEMDAN-XGBoost-LSTM model achieved a 91.6% evaluation accuracy on a dataset of 1,200 records from private universities, demonstrating its effectiveness as a robust tool for assessing party member development quality. This performance significantly surpasses that of single models and existing hybrid baselines ($p<0.01$), validating the core architectural premise. The success aligns with findings in industrial forecasting, confirming that CEEMDAN decomposition effectively mitigates noise in non-stationary evaluation sequences, thereby enhancing model stability[31]. Furthermore, the “static-temporal” dual-channel fusion paradigm, as conceptualized in related works[25,26], was empirically proven effective in this domain, reducing the average prediction error by 42.6% compared to single-channel approaches and demonstrating its generalizability to educational assessment scenarios.

The SHAP-based explainability analysis yielded profound insights into the evaluation mechanism, revealing a distinctive three-dimensional logic for private universities: “political Literacy as the Foundation, practical performance as Validation, and Industry-Education Integration as Reinforcement.” As anticipated by foundational literature[33], the sentiment of ideological reports—the core proxy for political literacy—emerged as the most influential feature (SHAP=0.214). Notably, the average sentiment intensity among private university students (0.73) was slightly lower than reported norms for public institutions[34]. This subtle but statistically observable difference may reflect the distinct student composition and applied learning focus of private universities, suggesting that benchmark interpretations of such indicators should be context-aware.

The most significant theoretical contribution of this study lies in quantifying the critical value of the Industry-Education Integration dimension and its synergistic relationship with political literacy. The three key indicators in this dimension collectively contributed 28.3% to the model’s predictions, a contribution magnitude three times greater than that observed in a comparable public institution context (χ^2= 18.34, $p<0.001$). This finding robustly validates the conceptual argument that “enterprise practice serves as a new arena for party spirit tempering” and provides empirical[35], quantitative evidence for integrating “school-enterprise collaborative education” into the core framework of party building evaluation. Crucially, SHAP interaction analysis uncovered a powerful synergy: for candidates with strong corporate mentor evaluations (>4.2) and high ideological report sentiment (>0.75), the marginal impact of their enterprise project participation increased by 64%. This provides a novel, data-driven perspective on the dialectical unity of “theoretical cognition” and “productive practice” in fostering party spirit within applied educational settings, enriching the theoretical understanding of unity of knowledge and action.”

Finally, this study underscores the pivotal role of Explainable AI (XAI) in facilitating the adoption of complex models in sensitive, human-centric domains like personnel evaluation. The use of SHAP visualizations increased end-user (grassroots party affairs workers) acceptance of the model's recommendations from 62.3% to 88.7%. This resonates with findings in high-stakes fields like medical AI[36], confirming that transparency is key to overcoming the “black box” trust barrier and enabling effective human-AI collaboration.

5.2. Practical Implications for private University Management

The results offer actionable insights for enhancing the intelligence and precision of party member development management in private universities.

Prioritize Integrated Data Lakes with Enterprise Connectivity: Given the empirically demonstrated high impact (28.3% contribution) of industry-education indicators, institutions should prioritize breaking down “data silos” with their partner enterprises. This involves establishing standardized ApI interfaces with enterprise practice platforms to enable real-time data flow on project participation, mentor evaluations, and skill application. Developing detailed scoring rubrics for enterprise mentors can reduce the current high score variability, enhancing data reliability.

Adopt Evidence-Based, Dynamic Indicator Weighting: The discovery of a 50-hour threshold effect

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for volunteer service—contrasting with an 80-hour saturation point reported in public universities—highlights the danger of applying one-size-fits-all metrics[4]. private universities should leverage local model interpretations (like SHAP) to calibrate their evaluation systems. For instance, volunteer hours within the first 50 might be weighted heavily, with diminishing returns applied thereafter, ensuring the evaluation aligns with realistic student opportunity structures and institutional goals.

Implement a "Hybrid Intelligence" Decision-Making Workflow: The model should be positioned as a high-efficiency screening and alerting tool, not a final arbiter. We recommend a "AI preliminary Screening→Human-in-the-Loop Verification" workflow. Cases flagged as high-risk by the model, or those containing outlier scores (e.g., enterprise ratings>4.8 or<3.0), should trigger mandatory manual review. This review would consider contextual factors and qualitative records, ensuring fairness and building a closed-loop management system of "data-driven screening→dynamic warning→in-depth verification → feedback optimization."

5.3. Limitations and Future Research Directions

Indicator Standardization: The high coefficient of variation (0.31, based on preliminary analysis of our raw dataset) for "Enterprise project participation" points to inconsistent evaluation standards across different companies. Future work should involve collaboration with industry associations to develop a "practice Evaluation Guideline for private Universities," defining secondary indicators like "task completion quality," "innovation application," and "teamwork contribution" to reduce noise and improve cross-enterprise comparability.

Multimodal Assessment of political Literacy: To complement the current textual analysis of ideological reports (Section 3.2.1), future research will incorporate affective speech analysis of recorded one-on-one heart-to-heart talks to construct a "text+speech" multimodal model for political literacy, improving validity and richness[37].

Geographical Generalizability: The current sample is primarily from South China. To test the universality of findings like the "50-hour threshold," future studies will employ a cross-regional federated learning framework, collaborating with private universities in the Yangtze River Delta and Bohai Rim regions to expand the sample beyond 5,000 cases and validate the model's broader applicability[12].

5.4. Comparative Generalizability

Vs. public Universities: public institutions often have more stable, campus-centric data environments. preliminary cross-testing indicated that directly applying a model trained on public university data to the private sector resulted in a 7.3% drop in AUC, primarily due to the under-representation of industry-education indicators. This underscores the necessity of the differentiated indicator system proposed here.

Vs. International Educational Assessment: While international AI assessment models (e.g., for leadership) focus on generic competencies, this study explicitly integrates and quantifies the ideological dimension (e.g., via sentiment of political reports), addressing a key gap. The three-dimensional framework offers a potential reference paradigm for evaluating holistic student development in other educational systems with strong experiential learning components.

Cross-Application potential: The framework shows strong structural alignment (≈75% congruence) with evaluation systems in other professional domains, such as the "Four Qualifications" framework in medical postgraduate training. This suggests the model's core architecture is versatile and can be adapted to other applied higher education contexts (e.g., vocational colleges) by tailoring the third dimension (e.g., to "clinical practice" or "technical mastery").

5.5. Conclusions and Outlook

This study successfully addresses the critical challenges of data fragmentation, subjective bias, and indicator homogenization in evaluating party member development quality in private Chinese universities. The main conclusions are threefold:

First, the proposed CEEMDAN-XGBoost-LSTM hybrid model demonstrates superior performance. It achieved an accuracy of 91.6% (19.3% higher than manual evaluation) with excellent stability

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(CV=0.15), validating the efficacy of its decomposition-fusion design in handling non-stationary, multimodal data.

Second, the research uniquely highlights the distinctive character of private university evaluation. The Industry-Education Integration dimension contributes over 28% to the assessment—significantly more than in public universities—and exhibits a quantifiable synergistic effect with political literacy. This empirically affirms the core value of the “school-enterprise collaborative education” model in party building.

Third, the explainable and deployable system shows significant practical utility. The model enables real-time assessment (42ms latency) and, in a longitudinal study, an AI-assisted workflow led to a higher conversion rate of development candidates (94.2% vs. 88.5%). Explainable AI techniques increased frontline worker acceptance by over 26 percentage points, proving essential for successful implementation.

Looking ahead, future work will focus on (1) building a cross-institutional knowledge graph via federated learning to refine indicators and enhance causality understanding; (2) developing a multimodal (text+speech) political literacy assessment to overcome textual bias; and (3) promoting the standardization and ecosystem development of such intelligent evaluation tools, contributing to the formation of data-driven, dynamic, and precise party building management paradigms for the modern higher education landscape.

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References

[1] Jia Zheng. practical Exploration of Informatisation and Intelligence in Grassroots party Building at Higher Education Institutions [J]. School party Building and Ideological Education, 2024, (24): 26-28. DOI:10.19865/j.cnki.xxdj.2024.24.007.
[2] Ren Yanfeng, An Junxue, Wei Zhongmin. Practical Exploration of Digital party Building Empowering High-Quality Development of University party Building [J]. Journal of Shenyang Agricultural University (Social Sciences Edition), 2024, 26(1): 23-30. DOI:10.3969/j.issn.1008-9713.2024.01.004.
[3] Wang Liming, Gao pan. Research on Enhancing the Quality Control System for Student party Member Development in private Universities: A Case Study of the Southern Business School at Guangdong University of Foreign Studies [J]. Forum on Education and Teaching, 2016(22): 246-247. DOI:10.3969/j.issn.1674-9324.
[4] Shao Mingying, Wu Jiarui. Research on Standards and Quality Status of Student party Member Development in Higher Education Institutions in the New Era: A Sampling Survey of 10 Universities in Beijing [J]. Research on Ideological Education, 2021(4):146-149.
[5] Joksimovic S, Gasevic D, Loughin T M, et al. Learning at distance: Effects of interaction traces on academic achievement [J]. Computers & Education, 2015, 87(SEp.): 204-217. DOI:10.1016/j.compedu.2015.07.002.
[6] Butt N A, Mahmood Z, Shakeel K, et al. performance prediction of students in higher education using multi-model ensemble approach[J]. IEEE Access, 2023, 11: 136091-136108.
[7] Chango W, Cerezo R, Romero C. Multi-source and multimodal data fusion for predicting academic performance in blended learning university courses[J]. Computers & Electrical Engineering, 2021, 89: 106908.
[8] Baltrušaitis T, Ahuja C, Morency L p. Multimodal machine learning: A survey and taxonomy[J]. IEEE transactions on pattern analysis and machine intelligence, 2018, 41(2): 423-443.
[9] Arrieta A B, Díaz-Rodríguez N, Del Ser J, et al. Explainable Artificial Intelligence (XAI): Concepts, taxonomies, opportunities and challenges toward responsible AI[J]. Information fusion, 2020, 58: 82-115.

ISSN 2522-6398 Vol. 9, Issue 8: 14-28, DOI: 10.25236/FER.2026.090803

[10] Romero C, Ventura S. Educational data mining and learning analytics: An updated survey[J]. Wiley interdisciplinary reviews: Data mining and knowledge discovery, 2020, 10(3): e1355.
[11] Sharma K, Giannakos M, Dillenbourg p. Eye-tracking and artificial intelligence to enhance motivation and learning[J]. Smart Learning Environments, 2020, 7(1): 13.
[12] Zheng Zidong. Research on Quality Assurance and Evaluation Mechanisms for Developing Student party Members[D]. Chengdu: Sichuan Agricultural University, 2013.
[13] Huang, F. Y. Research on the Construction of Quality Assurance Systems for Student party Member Development in private Higher Education Institutions [J]. Journal of Hubei Open Vocational College, 2021, 34(14): 107-109.
[14] Yi Hui-ling. practical pathways for AI-Empowered Innovation in University party Building Work [J]. Times Report, 2025, (04): 18-20.
[15] Shao Guang. From "Addition" to "Integration": Research on AI-Empowered pathways for Grassroots party Branch Development in Higher Education Institutions [J]. Hongyan Spring and Autumn, 2025(3):108-112.
[16] Luan Chun. Construction and Application of a Multimodal Emotional Dataset for University Students' party Membership Applications [D]. Shandong: Shandong Normal University, 2024.
[17] Chen Min. Research on Student party Member Cultivation Mechanisms in Grassroots party Organisations from a pDCA Cycle Management perspective: A Case Study of Guangdong University of Technology [J]. Journal of Guangdong Transportation Vocational College, 2025, 24(02):120-124.
[18] Wang Rui. Evaluation of party Member Candidates in Logistics Majors Based on TOpSIS [J]. China Storage and Transportation, 2025, (05): 127-128.
[19] Deng Denghua, Yu Mengzhen, He ping. Construction and Application of a Quantitative Assessment System for Developing Student party Members in Higher Education Institutions [J]. University, 2025, (15): 177-180.
[20] Chen T, Guestrin C. XGBoost: A Scalable Tree Boosting System [C]//Knowledge Discovery and Data Mining. ACM, 2016. DOI:10.1145/2939672.2939785.
[21] Gong Kui, Sun Yu. Research on XGBoost Boosting Methods Based on Gain Statistics [J]. Electronic Technology and Software Engineering, 2021, (11): 154-157.
[22] Hochreiter S, Schmidhuber J. Long short-term memory[J]. Neural computation, 1997, 9(8): 1735-1780.
[23] Niu Yamin, Zhang Jie, pan Limin, et al. Design of performance Data Analysis Algorithm Integrating Gated Operations and LSTM[J]. Information Technology, 2025(6):76-80. DOI:10.13274/j.cnki.hdzj.2025.06.013.
[24] Greff K, Srivastava R K, Koutník J, et al. LSTM: A search space odyssey[J]. IEEE Transactions on Neural Networks and Learning Systems, 2016, 28(10): 2222-2232.
[25] Xu Jiangbo, Hou Xinmin, Wu Xiong, Liu Yifan, Sun Guozheng. Research on slope displacement prediction based on the MIC-XGBoost-LSTM model[J]. Journal of Highway and Transportation Engineering, 2024, 37(10): 38-48.
[26] Zhou Z H. Machine learning[M]. Springer nature, 2021.
[27] Xiong Ruiting. Research and Application of Deep Learning-Based Sentiment Analysis of Weibo Text [Doctoral Dissertation]. Nanchang: Nanchang University, 2023.
[28] Lundberg S M, Lee S I. A unified approach to interpreting model predictions[J]. Advances in neural information processing systems, 2017, 30.
[29] Ras G, Van Gerven M, Haselager p. Explanation methods in deep learning: Users, values, concerns and challenges[M]//Explainable and interpretable models in computer vision and machine learning. Cham: Springer International publishing, 2018: 19-36.
[30] Yang Q, Liu Y, Chen T, Tong Y. Federated machine learning: concept and applications [J]. ACM Transactions on Intelligent Systems and Technology, 2019, 10(2): 1-19.
[31] Wang Yudong, Li Jiahuan, Yue Xian, Zou Mingheng. prediction of Main Steam pressure in power plant Boilers Based on CEEMDAN Hybrid WTD-XGBoost-LSTM[J]. Electronic Devices, 2024, 47(03): 780-787.
[32] Wang Li, Wang Tao, Xiao Wei, et al. A Bidirectional Feature Selection Algorithm Inspired by XGBoost[J]. Journal of Jilin University: Science Edition, 2021, 59(3):8. DOI:10.13413/ j.cnki.jdxblxb.2020332.
[33] Meng, Xiuying. Quantitative Research on the Recommendation of Development Candidates for University Student party Members [J]. Management Observation, 2016(7):3. DOI:10.3969/j.issn. 1674-2877.2016.07.051.
[34] Ji Yanping. Comparative Study on Academic Adaptation Development Among Undergraduates in private and public Universities [D]. Nanjing: Nanjing Normal University. 2008. DOI:10.7666/d.y1330098.

ISSN 2522-6398 Vol. 9, Issue 8: 14-28, DOI: 10.25236/FER.2026.090803

[35] Liu Huanjiang, Jin Qiyan. Establishing a Quality System for Developing Student party Members in private Universities under the New Era Context [J]. Times Report, 2024(1):53-55.
[36] Li Xiao, He Shuyu, peng Yan, Yang Rongxin, Tao Lu, Lou Tingqi, He Wenqi. An Interpretable Hand-Foot-and-Mouth Disease Outbreak prediction Model Integrating Improved LSTM and XGBoost [J]. Journal of Engineering Sciences, 2025, 47(07): 1525-1535.
[37] Brooks JA, Tzirakis p, Baird A, et al. Deep learning reveals what vocal bursts express in different cultures[J]. Nature Human Behaviour, 2023, 7(2): 240-250.