

# AI-Driven Diagnostic and Intervention Mechanism for Foreign Language Learning

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**Abstract:** This paper focuses on foreign language learning scenarios and constructs an integrated AI-driven diagnostic and intervention mechanism. By establishing a multi-dimensional diagnostic indicator system and integrating technologies such as Natural Language Processing, speech recognition, and machine learning, a complete diagnostic process from data collection to competency profile generation is realized. On this basis, a library of personalized intervention strategies and recommendation algorithms are designed, and a dynamic adjustment mechanism is constructed to form a closed loop of "diagnosis-intervention-evaluation". This mechanism aims to break through the limitations of traditional diagnosis, such as poor timeliness and insufficient personalization, to achieve accurate diagnosis and personalized intervention in foreign language learning, thereby improving learning efficiency and learning experience. This research provides a theoretical framework and practical path for the development of intelligent foreign language learning systems, and has positive significance for promoting the in-depth integration of Artificial Intelligence and foreign language education.

**Keywords:** Artificial Intelligence; Foreign Language Learning; Diagnostic Mechanism; Intervention Mechanism; Challenges and Countermeasures

## 1. Introduction

With the rapid development of Artificial Intelligence technology and the in-depth advancement of educational digital transformation, the field of foreign language education is ushering in unprecedented opportunities for reform. The acceleration of globalization has put forward higher requirements for talents' foreign language competence, and traditional foreign language teaching models are facing severe challenges in terms of personalization, precision, and efficiency. Current foreign language learning diagnosis mainly relies on teachers' experience-based judgments or standardized tests, which have inherent limitations such as long diagnostic cycles, single dimensions, and delayed feedback, making it difficult to meet learners' personalized needs. Teachers are burdened with heavy workloads and struggle to conduct real-time, comprehensive status assessments and precise interventions for each learner. This "one-size-fits-all" teaching model leads to low learning efficiency, poor learning experience, and may even dampen learning motivation. How to use technical means to achieve accurate diagnosis and personalized support for foreign language learning [1], has become a key issue urgently needing to be solved in the field of educational informatization.

The rapid development of Artificial Intelligence technology has provided new technical support for foreign language learning diagnosis and intervention [2]. The AI-driven foreign language learning model can construct personalized diagnostic models based on learners' full-process learning data, generate customized intervention plans, and realize closed-loop management of diagnosis, intervention, evaluation, and optimization [3]. This study integrates Artificial Intelligence technology with foreign language learning theories to construct a systematic framework of diagnostic and intervention mechanisms. Through systematic mechanism design, it provides theoretical support and practical guidance for the development of intelligent foreign language learning systems. The research results help improve the accuracy of foreign language learning diagnosis and the personalization of interventions, reduce teachers' workload, optimize learning experience, promote the in-depth integration of Artificial Intelligence and foreign language education, and provide useful exploration for the innovation of foreign language teaching models in the new era.

## **2. AI-Driven Diagnostic Mechanism for Foreign Language Learning**

Traditional diagnostic methods rely on teachers' subjective judgments or standardized tests, which have limitations such as long diagnostic cycles, single dimensions, and delayed feedback. The AI-driven diagnostic mechanism, through various technical means, can achieve real-time, accurate, and personalized assessment of learning status, providing data support and decision-making basis for subsequent intervention links.

### ***2.1 Construction of a Multi-Dimensional Diagnostic Indicator System***

Modern foreign language learning theories emphasize that learning effects are comprehensively influenced by multiple factors such as language competence, cognitive level, learning behavior, and emotional state. Therefore, it is necessary to establish a multi-dimensional and multi-level evaluation framework. Among them, the language competence dimension is the core of diagnosis, covering indicators such as listening comprehension, oral expression, reading comprehension, writing competence, and translation competence; the cognitive level dimension focuses on the systematic mastery of linguistic knowledge, including indicators such as vocabulary size, grammatical rules, and pragmatic knowledge; the learning behavior dimension conducts analysis by recording learning process data [4], including indicators such as learning duration, learning frequency, learning path, practice completion rate, error rate, and repeated learning behavior; the emotional state dimension is inferred indirectly through multi-source data, including indicators such as learning motivation intensity, anxiety level, self-confidence level, and learning satisfaction. These four dimensions are interrelated and complementary, together forming a complete foreign language learning diagnostic indicator system.

### ***2.2 Multi-Modal Data Collection and Processing***

Multi-modal data includes various types such as learning platform logs, speech input, text input, video recordings, and sensor data, with each data source carrying diagnostic information of different dimensions. However, multi-modal data differs significantly in format, frequency, and quality. How to effectively collect, clean, and fuse these heterogeneous data is a key link in building a reliable diagnostic system. For speech data, noise reduction processing is required to eliminate environmental noise [5]; for text data, raw text needs to be converted into structured features; for behavioral data, data cleaning is necessary to remove outliers; multi-modal data fusion is a technical challenge that requires establishing a unified data representation method to map data from different sources and formats to the same feature space. It is also essential to establish a data quality control mechanism, including anomaly detection, missing value handling, and data standardization, to ensure that the data input into the diagnostic model is consistent and reliable.

### ***2.3 Diagnostic Model Construction and Competency Profile Generation***

The diagnostic model needs to select an appropriate algorithm architecture based on specific diagnostic tasks, ensuring both model performance and considering requirements for computational efficiency and interpretability. A competency profile is a comprehensive presentation form of diagnostic results. By integrating multi-dimensional diagnostic data, a learner's competency state profile is constructed to provide a decision-making basis for personalized intervention [6]. The construction of diagnostic models can adopt various machine learning methods: supervised learning is suitable for diagnostic tasks with labeled data, unsupervised learning can be used to discover group characteristics or abnormal behavior patterns of learners, and semi-supervised learning can combine a small amount of labeled data with a large amount of unlabeled data for training. A competency profile is a comprehensive presentation of diagnostic results, which integrates multi-dimensional diagnostic data such as language competence, cognitive level, learning behavior, and emotional state to construct a learner's competency profile. The competency profile includes elements such as competency level description, knowledge mastery, learning behavior characteristics, and emotional state assessment.

### ***2.4 Interpretability of Diagnostic Results***

In foreign language learning diagnosis scenarios, interpretability is crucial because learners and teachers need to understand the logic behind the diagnostic results. If the diagnostic results lack interpretability, even if the accuracy is high, it is difficult to gain user trust, let alone guide practical teaching improvement. Interpretability involves not only technical aspects but also result presentation

methods and user interaction design. Improving interpretability can be achieved from multiple levels. At the model selection level, priority should be given to models with strong interpretability, such as decision trees, rule-based systems, and linear models. For complex models, eXplainable Artificial Intelligence (XAI) technologies can be used for post-processing interpretation. At the result presentation level, technical explanations need to be converted into user-understandable language, and visual explanations can intuitively show the diagnostic process through charts, heatmaps, and decision path diagrams. At the user interaction level, an interactive diagnostic report interface should be designed to allow users to click to view detailed explanations and trace the diagnostic process.

### **3. Personalized Intervention Mechanism Based on Diagnosis**

Traditional interventions often adopt a "one-size-fits-all" approach, which is difficult to adapt to individual differences among learners. The AI-driven intervention mechanism emphasizes the closed-loop linkage between diagnosis and intervention, that is, dynamically adjusting intervention strategies based on diagnostic results to achieve true personalized learning support.

#### ***3.1 Construction of an Intervention Strategy Library***

The AI-driven intervention mechanism needs to establish a diversified strategy system covering different intervention objectives, methods, and intensities. The construction of the strategy library is based on educational psychology theories, learning science research, and practical experience to ensure the scientificity and effectiveness of the strategies. At the same time, the strategy library needs to be scalable, able to continuously optimize and expand based on feedback from practical applications, forming a dynamically updated strategy ecosystem. In terms of specific strategy design, it can be constructed from two dimensions: intervention objectives and intervention methods. From the perspective of intervention objectives, it can be divided into knowledge remediation, competency improvement, behavior adjustment, and emotional support. From the perspective of intervention methods, it can be divided into content intervention, path intervention, feedback intervention, and social intervention. The maintenance and update of the strategy library is a continuous process that requires establishing a strategy effect evaluation mechanism to verify the effectiveness of strategies through practical application data, eliminating ineffective strategies, optimizing effective ones, and continuously enriching the content of the strategy library.

#### ***3.2 Personalized Recommendation Algorithms***

Artificial Intelligence recommendation algorithms can achieve accurate and efficient strategy recommendation by calculating similarity, predicting preferences, and optimizing objectives based on learners' competency profiles, learning histories, and behavior patterns. The selection of recommendation algorithms directly affects recommendation quality and needs to be comprehensively considered based on factors such as recommendation scenarios, data characteristics, and performance requirements. Common recommendation algorithms include content-based recommendation, collaborative filtering, knowledge-based recommendation, and hybrid recommendation. Content-based recommendation matches learners' diagnostic results with strategy content characteristics, resulting in highly interpretable recommendations; collaborative filtering uses collective intelligence for recommendations, enabling the discovery of potential associations and the recommendation of novel strategies, but faces the cold start problem; knowledge-based recommendation uses domain knowledge for reasoning, allowing the system to infer appropriate strategies based on diagnostic results; hybrid recommendation combines the advantages of multiple recommendation methods to improve recommendation accuracy and diversity.

#### ***3.3 Dynamic Intervention Adjustment Mechanism***

The dynamic intervention adjustment mechanism emphasizes the closed-loop linkage of real-time monitoring, effect evaluation, and strategy optimization, forming a continuous cycle of "diagnosis-intervention-evaluation-adjustment". This mechanism can adapt to learners' dynamic changes, adjust intervention strategies in a timely manner, and ensure the continuous effectiveness of interventions. Real-time monitoring achieves adaptive optimization of intervention strategies through continuous data collection and status assessment. When changes in learners' status are detected, the effectiveness of the current intervention strategy is re-evaluated, and the intervention plan is adjusted

based on the latest diagnostic results; evaluation needs to adopt methods such as pre-test and post-test comparison, control group experiments, and time series analysis to ensure the reliability of evaluation results; strategy optimization uses algorithms such as reinforcement learning and multi-armed bandits to explore optimal strategies through continuous trial and error. Ultimately, the goal of the dynamic intervention adjustment mechanism is to achieve the accuracy, timeliness, and continuity of interventions, truly realizing personalized learning support that teaches students in accordance with their aptitude and dynamically adapts to their needs.

#### **4. Challenges and Countermeasures in Constructing the Intervention Mechanism**

Although Artificial Intelligence technology is gradually becoming the dominant force in foreign language teaching [7], there are still many challenges in the actual construction and application process. These challenges involve multiple levels such as data, technology, and application, and require systematic analysis and effective response to provide reference for the practical implementation of the mechanism.

##### **4.1 Data Challenges and Responses**

Data is the foundation of the AI-driven intervention mechanism, and practical applications face multiple challenges in data collection, processing, and management. Multi-modal data comes from diverse sources, has heterogeneous formats, and varies in quality; data annotation is costly and time-consuming, and annotation quality directly affects model performance; data privacy and security issues are increasingly prominent. In addition, problems such as data sparsity and cold start also restrict the application effect of the intervention mechanism. These data challenges need to be comprehensively addressed from technical, management, and ethical dimensions.

To address data quality challenges, it is necessary to establish a sound data quality control system. In the data collection stage, standardized data collection protocols should be adopted to unify data formats and collection frequencies, reducing data heterogeneity; in the data preprocessing stage, strict data cleaning processes should be implemented, including anomaly detection, missing value handling, and data standardization. To address data annotation challenges, technologies such as semi-supervised learning and active learning can be used to reduce annotation dependence. Semi-supervised learning uses a small amount of labeled data and a large amount of unlabeled data for training to improve model performance; active learning allows the model to actively select the most valuable samples for annotation, improving annotation efficiency. To address data privacy challenges, it is necessary to comply with data protection regulations and establish strict data management systems [8]. To address data sparsity and cold start problems, technologies such as transfer learning and meta-learning can be adopted.

##### **4.2 Technical Challenges and Breakthroughs**

There is a contradiction between the accuracy and interpretability of diagnostic models: complex models have high accuracy but poor interpretability, making it difficult to gain user trust. Different languages have significant differences in linguistic features and cultural backgrounds, requiring models to have good generalization ability. High real-time requirements pose challenges to computing resources and algorithm efficiency. Multi-modal data fusion technology is immature, and mechanisms for information complementarity and conflict resolution need to be improved. These technical challenges need to be addressed through algorithm innovation, model optimization, and computing architecture upgrading.

Improving model interpretability is a key direction for technical breakthroughs. At the model selection level, models with strong interpretability should be prioritized. Local interpretable methods explain individual prediction results by perturbing input data and observing output changes; global interpretable methods explain overall model behavior through feature importance analysis and activation maximization. To address cross-linguistic and cross-cultural adaptability challenges, technologies such as multilingual pre-training and cross-linguistic transfer learning can be adopted. To address real-time challenges, it is necessary to optimize algorithms and computing architectures. At the algorithm level, lightweight models can be used to reduce computational complexity; model compression technologies can be employed to reduce model size while maintaining performance. At the computing architecture level, technologies such as edge computing and distributed computing can

be adopted to distribute computing tasks to edge devices or the cloud, improving response speed. To address multi-modal data fusion challenges, more advanced multi-modal learning architectures should be explored.

#### **4.3 Application Challenges and Integration**

Technology ultimately needs to be applied in practice to generate value, but the application of the intervention mechanism in actual teaching scenarios faces many integration challenges. User acceptance is a key factor: if users distrust, do not understand, or refuse to accept the system, no matter how advanced the technology is, it will be difficult to play a role; integrating with existing teaching systems is difficult, requiring the seamless embedding of AI systems; ethical and fairness issues are increasingly prominent, including algorithmic bias, data discrimination, and the digital divide [9]. These application challenges need to be comprehensively addressed from user-centric, system integration, and ethical standard perspectives.

To improve user acceptance, a user-centric design approach should be adopted to fully investigate the needs, pain points, and expectations of teachers and students, ensuring that system functions meet actual teaching requirements; clear operation guidelines and feedback mechanisms should be provided to lower the threshold for use; sufficient interpretability should be offered to help users understand the system's decision-making logic and enhance trust. To address the integration with teaching systems, coordination is needed in various aspects such as curriculum design, teaching processes, and evaluation systems. AI systems should be aligned with curriculum objectives, teaching content, and teaching progress to ensure that intervention content is consistent with curriculum requirements. To address ethical and fairness issues, an ethical review mechanism should be established to regularly detect algorithmic bias; fair machine learning technologies should be adopted to introduce fairness constraints in model training, ensure data representativeness, and avoid model bias caused by the lack of data from certain groups. Continuous iterative optimization in practical applications is necessary to ultimately achieve the in-depth integration of technology and education.

### **5. Conclusions**

This research uses Artificial Intelligence technology to achieve accurate diagnosis and personalized intervention in foreign language learning, breaking through the limitations of traditional teaching models and improving learning efficiency and learning experience. However, the practical application of this mechanism still faces multiple challenges in data, technology, and application, which need to be continuously verified and improved in practice. Future research should further focus on improving model generalization ability and interpretability, optimizing human-machine collaboration models, and addressing ethical and fairness issues, so as to promote the in-depth integration of Artificial Intelligence and foreign language education and truly realize the vision of personalized learning that teaches students in accordance with their aptitude. The ultimate value of technology lies in serving educational practice, and it is hoped that the results of this research can provide useful reference for the development and application of intelligent foreign language learning systems.

### **Acknowledgements**

This work is supported by the China National Light Industry Council Education Committee project (QGJY2025027) and the "Textile Light" China National Textile and Apparel Council Higher Education Teaching Reform project titled "Research and Practice on the Development of First-Class Foreign Language Majors in Light Industry and Textile Universities from the Perspective of Digital Intelligence Empowerment".

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