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Leveraging Natural Language Processing (NLP) and machine learning in task-based language teaching: enhancing Chinese language acquisition with AI-driven feedback systems

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Abstract. This study explores the innovative application of intelligent technology in the task-based Chinese teaching method, focusing on the effectiveness of real-time guidance of speech recognition and intelligent analysis technology on learners' pronunciation, grammar, and vocabulary. In the experiment, 100 Chinese second language learners were divided into intelligent assistant groups and traditional teaching groups for comparative observation. According to the data, the task completion efficiency of the intelligent group increased by 20%, and the language proficiency evaluation index increased by an average of 30%. More than 80% of learners reported that the instant feedback mechanism effectively improved their confidence and participation in learning. The research proves that intelligent technology can build dynamic learning paths and optimize language acquisition efficiency through personalized training modules. Although the system has technical bottlenecks in the dimension of understanding cultural context, the experimental results provide empirical support for the deep integration of intelligent technology and language teaching, and lay the technical foundation for further research and development of a culturally sensitive intelligent teaching system.

Keywords: natural language processing, machine learning, task-based language teaching, Chinese language acquisition, AI-driven feedback

1. Introduction

This research focuses on technological innovation in the field of Chinese second language acquisition and explores the integration path of intelligent technology and task-based teaching mode. The unique tone system and writing system of Chinese language learning pose significant challenges to non-native language learners, and traditional teaching methods have technical limitations in terms of immediate feedback and personalized guidance. The task-based teaching mode can improve learners' practical application ability through contextualized language training, but its effectiveness needs to be improved by technology. Intelligent speech recognition and semantic analysis technology bring a breakthrough to the teaching feedback mechanism, which can analyze learners' pronunciation characteristics and grammatical structures in real time and form personalized training programs. Comparative experiments were designed to observe the effect of the intelligent assistant system on task performance efficiency, and the actual effect of intelligent technology on optimizing the language training process was verified using the language ability assessment matrix and learner feedback data [1]. The experimental data show that the teaching model integrated with intelligent technology has significant advantages in improving language production accuracy and learning motivation, and provides a technical reference framework for constructing a new Chinese teaching model.

2. Literature review

2.1. Task-based language teaching and its impact on language acquisition

The task-based language teaching model has been verified by teaching practice due to its effect on improving language application skills. This model guides learners to use the target language in real-life contexts by designing life-oriented tasks, such as ordering food in restaurants and asking for directions in traffic [2]. This immersive training mechanism effectively promotes language internalization and fluency, and allows learners to gradually master complex communication strategies. Although this model has achieved remarkable results in the traditional classroom, there is still room to explore the innovation of its integration with technological tools. With the introduction of intelligent voice interaction and semantic analysis technology, a dynamic language training system can be built to optimize the learning path through the instant feedback mechanism. This technology integration system can not only retain the core advantages of task-based teaching, but also break the time and space restrictions of traditional classrooms and inject intelligent development momentum into language teaching [3].

2.2. AI in education: applications and challenges

The innovative application of intelligent technology in education is opening up a new avenue for language teaching. Speech recognition technology and intelligent feedback systems have demonstrated their technical potential in language classrooms, and natural language processing technology has attracted considerable attention due to its ability to analyze language structure. This technology can achieve basic functions such as grammatical structure analysis and emotional feature capture, and provide accurate data support for language ability assessment. The intelligent teaching platform significantly improves the efficiency of language practice through its real-time correction mechanism and personalized training program [4]. However, it should be noted that there are still technical bottlenecks in understanding cultural context in the existing system, and breakthroughs are still needed in handling language variants and intercultural communication. Focusing on the complex language system of Chinese, this study explores how to deeply integrate intelligent technology into the task-based teaching mode, and through the construction of a dynamic language training system, breaks the limitations of traditional teaching in terms of immediate feedback and hierarchical guidance, and provides technical solutions for the innovation of Chinese as a second language teaching [5].

2.3. Machine learning for language learning: a review of previous studies

This study focuses on the application innovation of machine learning technology in educational scenarios, and focuses on its dynamic feedback mechanism in the field of language learning. This technology establishes a personalized training model by tracking learner behavioral characteristics and language output rules. In the field of language acquisition, machine learning can effectively exploit the internal correlation of massive learning data and optimize the design of teaching tasks accordingly [6]. The technical program covers core modules such as grammar bias recognition and pronunciation feature analysis, and forms personalized training programs by accurately locating learning difficulties. Experimental data show that this intelligent adaptation mechanism can significantly improve learners' training engagement and language production accuracy [7]. This study further explores how to integrate machine learning technology into the task-based language teaching mode, especially in the key links such as Chinese tone formation and Chinese character acquisition, to build an intelligent teaching system with the ability of self-optimization, and provide technical solutions for the effective mastery of complex language elements.

3. Experimental methodology

3.1. Participants and learning environment

The study selected 100 Chinese second language learners as experimental subjects, covering different language levels. The control group and the experimental group were trained through a random grouping mechanism. The control group used the traditional task-based teaching mode, while the experimental group used the teaching platform integrating intelligent analysis technology [8]. Both groups were designed to simulate real-life communication scenes, and the training tasks included interview exercises, a cultural knowledge competition, a video dialogue, and other modules. The intelligent platform provides real-time guidance and feedback on grammar, pronunciation, vocabulary, and other dimensions based on the learner's characteristics [9].

3.2. AI integration in the task-based learning platform

The intelligent teaching platform adopted by the experimental group integrates natural language analysis technology, covering core modules such as speech feature recognition, grammar error correction, and contextual feedback. The system incorporates a multimodal intelligent analysis engine to analyze language structure characteristics through deep learning models to continuously monitor learners' ability development trajectory [10]. The platform dynamically optimizes training programs and intelligently recommends advanced tasks based on learners' real-time performance. The real-time error correction mechanism helps learners synchronously correct errors during the language production process, thus forming a spiral of improvement.

3.3. Data collection and evaluation metrics

The research data collection period was 10 weeks, and learning behavior data was collected using a blended teaching method combining online and offline learning. The evaluation dimension includes three basic indices: topicality of tasks, accuracy of language elements (standard grammar vocabulary) and clarity of articulation (based on the speech evaluation system). At the later stage of the study, the learners' evaluation of the intelligent feedback system was obtained by means of a questionnaire survey and an in-depth interview [11]. By the comparative analysis between the control group and the experimental group, the real synergistic effect of intelligent technology on the task-based teaching mode is verified.

4. Experimental process

4.1. Task design and implementation

During the experimental period, both groups received the same amount of training tasks each week, but the experimental group simultaneously received feedback from the intelligent system while performing the task. The task difficulty is designed by week, and more challenging training modules are added each week, focusing on strengthening the ability to apply language in real-life communication scenarios. For example, the interview task requires learners to simulate real-time conversation scenes with native Chinese speakers and comprehensive structured language output [12]. The intelligent platform instantly analyzes the dialogue content and generates 3D improvements regarding pronunciation calibration, vocabulary optimization, and sentence model adjustment. At the end of the same training, the control group had to wait for centralized correction from the teacher, and the feedback cycle was significantly delayed. This delayed feedback mechanism results in the lack of immediacy of linguistic correction, which may impact the timely correction effect of error patterns [13].

4.2. AI feedback system in action

The intelligent feedback system operates all the way after the task begins, and each language output from the learner triggers the analysis program in real time. The system generates error correction schemes through technical modules such as pronunciation feature comparison, syntactic structure analysis, and context adjustment detection. For example, when a learner has a deviation in intonation, the system immediately marks the incorrect syllable and provides the standard pronunciation waveform. The feedback content is dynamically adjusted based on the learner's skill development curve to create a personalized training path. This supportive teaching allows learners to modify their language production strategies in real time.

4.3. Learner engagement and interaction with the AI system

The participation index was assessed based on the task completion rate and the satisfaction questionnaire. The data showed that the experimental group's learning enthusiasm was significantly improved, and the instant interaction provided by intelligent feedback effectively boosted their training enthusiasm. The built-in adaptive difficulty mechanism can automatically match the learner's skill threshold and avoid dynamic attenuation caused by repeated training [14]. Interview data showed that the experimental group generally appreciated the timeliness of intelligent feedback and the autonomous regulation of the training pace, and believed that this method could effectively maintain learning concentration.

5. Results and discussion

5.1. Language proficiency improvement

Experimental data showed that the improvement in language ability of the intelligent assistant group was significantly greater than that of the control group. In terms of task speed, the average time for the experimental group was reduced by 20%. As shown in Table 1, the average duration for the experimental group was 18 minutes, while that of the control group was 22 minutes. This increase in efficiency is due to the immediate guidance mechanism of intelligent feedback, which allows learners to quickly modify their language strategies. Language ability assessment indicators show that the overall improvement of the experimental group in the three dimensions of grammar, pronunciation, and vocabulary reached 30% (Table 2). This improvement is directly related to the system's error correction function, allowing learners to immediately reinforce the correct model in the language production process.

Table 1. Task completion time

Group	Average Task Completion Time (minutes)	Improvement (%)
AI-assisted	18	20
Control	22	0

5.2. Learner satisfaction and feedback

The satisfaction survey showed that 85% of learners in the experimental group recognized the educational value of the intelligent feedback system, while the control group's satisfaction was only 60%. Interview data showed that the experimental group generally believed that the real-time error correction mechanism could improve confidence in training, while the delayed feedback in the control group could lead to errors being solidified. This difference highlights the technical advantages of intelligent technology in maintaining learning motivation.

Table 2. Language proficiency and learner satisfaction

Group	Language Proficiency Improvement (%)	Learner Satisfaction (%)
AI-assisted	30	85
Control	0	60

5.3. Limitations and future directions

While the integration of AI into Task-Based Language Teaching (TBLT) has shown positive results, there are some technical limitations that need to be addressed for further improvement. One primary issue is the system's difficulty in analyzing cultural context. The current AI model struggles with recognizing language variants and cultural nuances within the Chinese language, particularly in regional dialects. Since Chinese varies significantly across regions, with different expressions and colloquial terms, the system sometimes fails to accurately interpret these variations. Future research could focus on incorporating cultural knowledge maps into the AI system, allowing it to better understand and adapt to these language differences. Additionally, the complexity of the Chinese tone system presents a challenge for pronunciation evaluation. As Chinese is a tonal language, the correct pronunciation depends heavily on tone, which is often difficult for AI systems to assess accurately in real-time. To improve this, future work should explore the development of more specialized algorithms that can account for tonal variations and refine pronunciation error detection. This could include creating a more robust database that focuses on tonal speech patterns, allowing the system to better understand and correct pronunciation errors.

6. Conclusion

This research verifies the innovative value of integrating intelligent technology and task-based language teaching model. Experimental data show that the real-time feedback system integrated with natural language processing technology can significantly improve the efficiency of Chinese language training, and the experimental group can accelerate the task speed dimension by 20% and the comprehensive index of language ability by 30%. The instantaneous error correction mechanism of 85% feedback effectively improves learners' learning confidence, which confirms the teaching effectiveness of intelligent technology. However, the research also reveals the technical bottleneck, and the accuracy of the system is limited in cultural context analysis and Chinese tone recognition, which indicates the key direction of technical optimization in the future. In the future, it is necessary to deepen the construction of the cultural knowledge map and develop a special tonal language algorithm module to improve the analysis ability of complex language elements. This technological path provides an operational solution for the digital transformation of traditional language teaching, and its methodological framework has demonstrative significance for the research and development of intelligent educational tools.

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