



Development of an Intelligent Chinese Teaching Platform for Lifelong Learning.

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SUMMARY: *Most traditional Chinese language teaching platforms are still based on fixed curricula and standardised progress plans; thus, they fail to meet the personalised demands of lifelong learners. Therefore, there will be problems with learning content and ability mismatches, as well as overly rapid or slow progress. Therefore, in this paper, an adaptive Chinese language learning platform has been constructed by combining a deep learning-based personalised recommendation system with natural language processing technology to address the above problems. The platform collects data and observes the behavior of learners to construct a personalised learning model, changes the learning path and content dynamically, and recommends relevant learning resources. Speech recognition and synthesis technologies are employed to provide a voice-interactive mode, and at the same time, errors in pronunciation and grammar are immediately corrected. In addition, reinforcement learning algorithms are used by the platform to automatically adjust the difficulty and type of tasks based on the learner's real-time performance to address the problem of mismatch between learning content and progress. Based on the experimental results, after three months, the test group achieved a fluency score exceeding 3.9 and reduced the number of pauses in oral expression to less than 10; thus, personalised learning was improved. The platform provides good, flexible learning support for lifelong learners; it has practical value and helps promote the development of intelligent language education.*

KEYWORDS: *Lifelong Learning, Chinese Language Teaching, Personalized Learning Recommendation System, Natural Language Processing, Speech Interaction*

1 Introduction

With the progress of globalisation and the rapid development of technology, many people have been required to learn new things throughout their lives in recent years [1, 2]. As the most widely spoken language in the world, the number of learners of Chinese is also growing [3, 4]. Most of the current Chinese teaching platforms lack personalised services for different individuals. The learning content and progress are relatively fixed, and they cannot be adjusted flexibly according to the different learning backgrounds and needs of the learners [5, 6]. This single teaching method has reduced the effectiveness of learning, and it is harder to keep students' interest and learning efficiency in life-long learning [7, 8]. Therefore, how to

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build an effective and personalised Chinese learning platform is now an urgent problem that needs to be solved [9, 10].

To improve the efficiency and effectiveness of Chinese learning, a number of studies have been conducted by scholars and institutions in China and abroad on the development and application of intelligent teaching platforms [11, 12]. Personalised learning-path recommendations based on big data analysis, the application of speech recognition technology in oral teaching, and adaptive learning systems have been proposed and applied in language learning [13, 14], for example. Based on the above studies, data-driven personalised learning and intelligent feedback systems have significantly boosted the learning motivation and efficiency of students [15, 16]. Although the above ways have increased the learning experience to some extent, due to their limited response to personalised needs and the limited scope of technological application, the existing platforms still fail to meet the personalised needs and continuous learning requirements of lifelong learners in Chinese as comprehensively as they should [17, 18].

In recent years, some studies have started to apply new technologies, such as deep learning, natural language processing and speech recognition, to explore more intelligent ways to teach language [19, 20]. Deep learning-based personalised recommendation systems can adjust learning paths dynamically according to the learner's past learning and progress to enhance the relevance and efficiency of learning [21, 22]. Natural Language Processing technology can help achieve real-time voice interaction for better practice of oral expression by learners [23, 24]. Existing studies have shown that intelligent platforms integrating the above technologies have achieved good results in other language learning by improving students' expression and oral communication skills. Most of the previous studies have concentrated on learning a few foreign languages, and there is a lack of systematic research and practical applications in the design of intelligent platforms for Chinese language learning. The two current problems are personalisation and flexibility for lifelong learners [25, 26].

Therefore, this paper aims to explore and develop an intelligent Chinese language teaching platform for lifelong learning, and based on deep learning and natural language processing technologies, address the deficiencies of current platforms in personalisation and flexibility. First, study the learning behaviour and needs of the learners, build a personalised recommendation system based on deep learning, and add speech recognition and generation technology to enable oral communication and real-time feedback. Next, a reinforcement learning algorithm will be used to optimise learning strategies and improve the efficiency of task completion and academic results for learners. Experiments have shown that the proposed intelligent platform can significantly improve students' language expression abilities and learning efficiency; thus, intelligent Chinese language teaching platforms show promise for lifelong learning.

2 Development of an Intelligent Platform for Chinese Teaching

2.1 Personalized Recommendation System for Lifelong Learning

First, based on the learners' historical learning data, task completion status and learning behaviour, a deep learning-based personalised recommendation system will be built in this study. The system has accumulated data on the learners' learning history, study time, task completion status and interaction with others, etc., to form a learning profile for each student.

Construction of a Learner Profile is the first step in this personalised recommendation

system. First of all, the basic learner information, such as age, background in learning, language ability, and learning data, including the time of each log-in, types of tasks performed, etc., will be collected. Next, a CNN will be used to extract features from the learners' behaviour patterns. CNNs have a multi-level network structure and can extract behaviour characteristics of learners at different times of learning to identify which tasks help in learning and which do not. Feature extraction produces a behaviour feature vector for each learner to build an individualised learning profile.

Build a learner profile, and then use this profile to monitor and assess the learning progress and knowledge acquisition of learners in the system dynamically. That is to say, this way will determine how accurate and how quickly different types of exercises (e.g., grammar practice, listening comprehension, reading comprehension) are completed by students on the platform. Based on the above data, the system evaluates how well a student has mastered each part of the knowledge and determines if there are any problems or deficiencies in learning. For example, if a student has repeatedly failed to master a particular grammar section, the system can recognise this problem and automatically offer a solution provided by the model. To ensure the accuracy and relevance of the recommended content, deep learning algorithms are also employed by the platform to analyze historical data of learners and calculate the correlation between each knowledge point and how well it fits with the learner's needs for that knowledge point. Figure 1 is as follows:

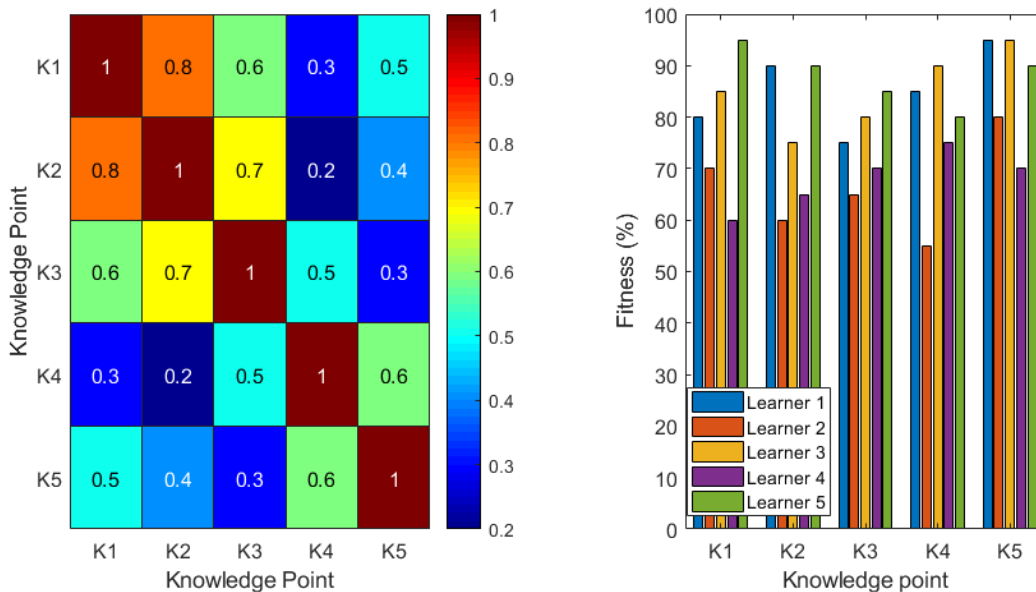


Figure 1: Correlation and Fitness

The left panel of Figure 1 is a correlation diagram that shows how all the knowledge points in the system are related; thus, it can be known whether certain knowledge points are linked to one another, which ones should be learned in a group, and what dependency relationship exists among them. K1 and K2 are positively correlated at a rate of 0.8, thus they are highly correlated. Study these two knowledge points together. K3 and K4 are less correlated (0.3), so they may be less connected in terms of knowledge. Based on the above content, modify the learning recommendations and avoid over-association. The right panel lists the suitability of five learners for five knowledge points. Learner 4 has a relatively low suitability (e.g., 60%) for several knowledge points, such as K1 and K5. Learner 3 has a relatively good fit (e.g., 85% and 90%) for most of the knowledge points, so the platform can suggest suitable learning tasks for them.

Build a learner profile and analyse the learning process, then use a combination of collaborative filtering and content recommendation algorithms to recommend suitable learning materials intelligently. Collaborative filtering algorithms recommend items that have been selected by other learners. Calculate the similarity among learners, and then find other learners who have a similar learning style, progress, etc. Based on the learning paths of these similar learners, we can then guide them to complete and perform good learning tasks. For example, if a learner successfully moves to intermediate grammar after finishing the elementary grammar tasks, and these tasks have also been completed at a high level by other learners, the system can recommend that learner take the same learning task path.

2.2 Fragmented Learning Support for Voice Interaction

Speech recognition technology will be used by the platform to acquire the learners' spoken data in real time and then compare this with a standard pronunciation reference for assessment of accuracy, fluency, etc. Google Speech-to-Text can be used in this platform to provide high-precision transcription and support many accents and speaking speeds for accurate evaluation. It is a speech-to-text system that provides real-time feedback on the pronunciation accuracy and fluency of learners' speech, thus correcting errors promptly. The system adapts to the user's different voices to provide individualised guidance and calculates pronunciation error rates (e.g., pitch, consonants and vowels) for a general evaluation of pronunciation quality.

Based on the results of speech recognition, it will inform the user of pronunciation errors. For example, if a learner has a tone or syllable error in their pronunciation, the platform will immediately notify the learner via a pop-up window and play a voice model of the correct pronunciation. A deep learning speech analysis model will be used by the platform to enhance the accuracy and usefulness of the feedback, identify problems in the learner's syllables, intonation, pronunciation, etc., and provide suitable exercise recommendations. Speaking education needs to teach fluency as well. Especially in the assessment of oral expression, the speech recognition system can record pauses and speed changes in speech, etc., to calculate a fluency score. When learners are too quiet or speak at an unusual speed during oral production, the system will alert them. Promptly and specifically, this feedback can help students correct their problems with speaking at the same time. Fluency scores are as follows: Table 1.

Table 1: Fluency Scores

Learner ID	Learning Stage	Fluency Score	Number of Pauses	Speech Rate (characters/minute)	Feedback Suggestion
1	Beginner	3.8/5	12	120	Increase speech rate, reduce pauses
1	Intermediate	4.2/5	9	140	Maintain fluency, reduce pauses
2	Beginner	2.9/5	20	100	Increase speech rate, reduce pauses
3	Beginner	3.2/5	18	110	Increase speech rate, reduce pauses
3	Intermediate	3.7/5	14	130	Increase speech rate, reduce pauses
4	Intermediate	4.0/5	10	135	Maintain fluency, reduce pauses

Table 1 shows the main performance indicators of the learners in oral English. Learner 001 has achieved a fluency score of 3.8/5 at the beginner level, speaks at a rate of 120 words per minute, and has 12 pauses. The platform recommended increasing the speed of speech and reducing pauses because of the slow speaking speed and frequent pauses that had reduced oral fluency. At this time, his level of fluency was 4.2/5, and both the speed of speaking and pauses had been improved. The system said, "Maintain fluency and reduce pauses", and this time the oral English level had improved significantly. Learner 003's performance at the beginner level is a fluency score of 3.2/5, a speaking rate of 110 words per minute, and 18 pauses. The platform had advised him to speak more rapidly and use fewer pauses; at this stage, his fluency reached 3.7 out of 5, and both the speed and the number of pauses had risen. The platform instructed "speed up speaking and reduce pauses", and thus gradually enhanced the user's ability to speak in English.

The platform's speech generation technology mainly offers standard Chinese pronunciation examples to help learners practice and correct their own pronunciation. To ensure the quality of the pronunciation, the Baidu Chinese TTS (Text-to-Speech) interface in the platform will be used to generate natural-sounding, clear and accurate Chinese speech for the demonstration. A regular reading and recitation are used for the teaching materials. A TTS system on the platform generates corresponding standard Chinese pronunciations of vocabulary, phrases and sentences based on user input. TTS technology not only produces the sound of words, but also generates appropriate intonation and speaking speed for learners to learn the intonation and speed patterns of Chinese. For example, polyphonic characters or complicated vocabulary in text can have different pronunciations depending on the context; at that time, the TTS system can be employed to guide students' learning. The system can also change the speed at which learners speak according to their own learning conditions [27, 28]. TTS technology offers learners a model for imitation and improves their listening ability at the same time. By repeatedly listening to standard pronunciation, they can improve their understanding of Chinese pronunciation, phonetic features and rhythm, as well as their accent, intonation and speaking speed gradually.

Speech recognition and generation technology are combined to form a closed-loop system of oral learning for this platform. Speech recognition technology will evaluate learners' oral expressions in real time, and in conjunction with TTS technology, provide standard pronunciation examples for an immediate-feedback mechanism. For instance, if a learner makes a pronunciation error, the system will provide speech-recognition feedback and Text-to-Speech (TTS) playback of the correct pronunciation, asking them to repeat it. Interactively correct the students' mistakes in pronunciation. As the oral training deepens, the platform can automatically adjust the learning content according to the pronunciation status and type of errors, and recommend more suitable practice tasks. For beginners, the platform can recommend more focused pronunciation exercises in the initial period of speech study to avoid giving too difficult tasks [29, 30]. Integrate speech recognition and generation technology in the platform to adjust oral tasks for different learners; thus, the learning materials will be challenging but not too difficult and provide an individualized learning experience.

2.3 Reinforcement Learning-Driven Adaptive Path

A reinforcement learning algorithm will be applied in this study's Chinese learning platform to dynamically optimise learning strategies for enhanced learning efficiency and continuous learner interest. Reinforcement learning is now being used to adjust the difficulty of learning tasks in real time and also to motivate learners to achieve their learning goals through a

reward mechanism; thus, learning paths and task recommendations can be optimised. The following are the steps for implementation and the method.

The platform is a Q-learning algorithm for learning optimisation. Q-learning is a model-free reinforcement learning algorithm that learns a policy through rewards and feedback by observing the actions of a learner. Each learning activity (such as completing a task or answering a question) on the platform is considered a "state", and each state is linked to a set of possible "actions" (i.e., learning tasks or recommended learning content). Q-learning is a way that, by repeatedly sampling rewards from a particular state and action to update the expected value of that state-action pair, will find the best sequence of decisions. The status of this platform will be learner knowledge mastery, learning progress, learning time, task completion, etc. Real-time data collection by the platform's data acquisition module continuously provides new information for the Q-learning algorithm. All the statuses indicate the learner's study results at that time. In each state, the platform offers various learning tasks or content recommendations as possible "actions". The above are examples of the learning contents. Difficulty of the tasks is adjusted dynamically according to the learner's performance. The quality of each action in terms of how well the task is completed or the accuracy of the result will be used by Q-learning for learning. The update rule for the Q value in Q-learning is as follows:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_a Q(s_{t+1}, a) - Q(s_t, a_t) \right] \quad (1)$$

In formula (1), s_t represents the current state; a_t represents the current action; r_t is the immediate reward for the current action; γ is the discount factor; and α is the learning rate. By continuously updating the Q value, the algorithm can gradually optimize the task recommendation strategy to ensure that learners receive the most appropriate learning content for their current level.

Q-learning is used to provide different levels of learning problems at different times based on learners' progress and performance. The main sources of feedback during learning are the learner's completion of a task and how accurately that task is performed. Each time a learner finishes an activity, the system records that it has been completed, failed or skipped. Based on the task completion status, Q-learning determines whether a task is beneficial for a learner. If a student performs well in a task repeatedly, the system will increase the difficulty of that task according to their Q-value and offer them more advanced tasks. If a student cannot finish the exercise, it will automatically reduce the level and offer them some simpler exercises again. A high-quality learner's work should have a relatively high accuracy rate. Analyze how accurately learners perform in various exercises on the platform and adapt the recommendations accordingly.

The Platform has a reward system to motivate and engage students more. According to the time taken and the accuracy of the task, points and virtual rewards will be given to the learners. Points are related to the difficulty of the task, and a higher-difficulty task will be given more points. Complete it successfully, and a new section or a more difficult problem will be unlocked. Therefore, this way will keep people motivated and work. See Table 2 for the details.

Table 2: Reward Mechanism

Learner ID	Task Name	Completion Time (minutes)	Accuracy (%)	Reward Points	Unlocked Task
1	Beginner Grammar Task	30	85	50	Intermediate Grammar Task
1	Intermediate Grammar Task	45	90	75	Advanced Grammar Task
2	Beginner Grammar Task	35	78	40	Intermediate Grammar Task
3	Beginner Grammar Task	28	92	60	Intermediate Grammar Task
4	Advanced Grammar Task	60	80	100	Completed

Table 2 shows the results of the learners in the various grammar tasks. Learner ID 1 first completed the beginner grammar task, took 30 minutes to do so, achieved an accuracy of 85%, was awarded 50 points, and unlocked the intermediate grammar task. Then, this learner completed the intermediate grammar task in 45 minutes with an accuracy of 90%, obtained 75 points, and unlocked the advanced grammar task. Learners gain experience by solving problems, gradually increase the difficulty of the problems, and thus learn new knowledge step by step.

2.4 Optimizing Cross-stage Learning Paths

The Bayesian Optimization Model will be used to set learning goals and provide customised recommendations on the platform. Bayesian optimisation is a probability-based global optimisation method that can handle many problems in the real world with many parameters and noisy data. Bayesian optimisation can be used on the platform to adjust the pace of learning dynamically and ensure that it is not too easy or too difficult.

The platform is an optimisation problem for the learning path, and its parameters to be optimised are task difficulty, type and sequence. Bayesian optimisation adjusts the learning path in the following ways: First, the platform gathers learner feedback data (e.g., task completion, learning time, accuracy) and builds a probabilistic model of the learner's current state. The above shows what students know and where they have difficulty. The Goal Function is employed to judge learning results. Input task characteristics (such as difficulty and type of content), output learning results (such as accuracy and time taken), and then calculate the efficiency score in real time. The Acquisition Function in Bayesian Optimisation decides which task and how difficult to solve. The platform will select problems for exploration and exploitation: new problems can be added to expand learners' knowledge by exploration, and existing knowledge will be continuously extended otherwise. The two should be adjusted flexibly so that they meet all learners' different needs for studying. As shown in Figure 2, the changes in the objective and acquisition functions can help learners adjust to their progress in learning.

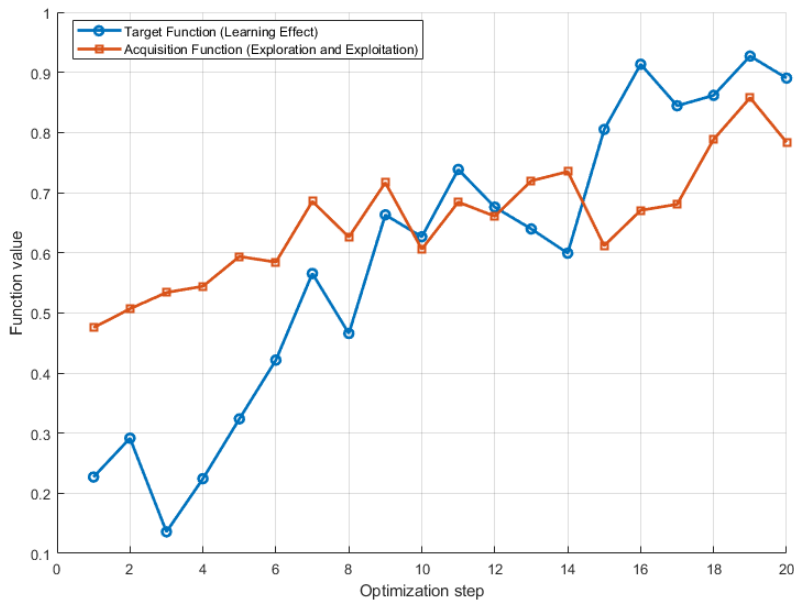


Figure 2: Changes in the Objective Function and Acquisition Function during Bayesian Optimization

Figure 2 shows how the objective function and acquisition function change in the course of Bayesian optimisation. To boost the students' academic performance in school. As shown in the figure, the value of the objective function gradually increases with each step of optimisation, and the Bayesian optimisation system is improving the learner's learning results in sequence by selecting learning tasks. At first, the objective function value is small; thus, the learner's learning results are not good. It is because at the beginning of optimisation, the platform has received limited learning feedback, the learner's knowledge mastery is relatively low, and thus the effect of optimisation has not yet been fully realised. With each round of optimisation, the system will gradually improve the learning result through carefully selected tasks and content. The acquisition function determines the trade-off between exploration and exploitation in Bayesian optimisation. In the beginning of optimisation, the system is in an "exploration" phase; that is, it has been trying new tasks and content to expand the learner's knowledge base and has thus obtained a high acquisition function value. With the progress of optimisation, the value of the acquisition function is gradually close to 0.8; therefore, the system will focus more on "using" existing knowledge to help learners strengthen their foundation and deepen their understanding.

The Adjustments to the learning path are based on the feedback mechanism of the Bayesian optimisation model. After completing a learning task, the platform will collect the learner's feedback data (such as whether the task was completed, accuracy rate and learning time) and update the learner status model. Based on the above data, the Bayesian optimisation model will determine the difficulty of the next learning task and set different tasks for each learner. For learners who are learning quickly, the system will give them harder problems; for those who are learning more slowly, the problems will be reduced accordingly.

Thus, the platform will continuously adjust the learning path to ensure that learners are always in an ideal learning condition. To help recommend a personalized learning path for students, the system will compare the attributes of various exercises (such as difficulty level, knowledge points, etc.) with the current level of these students' knowledge to select suitable exercises. Convert each task into a multi-dimensional feature vector that contains information about the difficulty, type and expected learning time of the task. The Design of each task

meets the learning objectives and has been standardised by task attribute modelling. At the same time, a capability model of the learner will be constructed based on their past data. Periodically update the model to improve the accuracy of the recommended content in training. Based on the dynamic adjustment mechanism of Bayesian optimisation, the platform can recommend tasks that are more suitable for the learner's current ability by considering learning history and long-term goals to help achieve optimal learning results for the learner.

Adaptive Learning Paths in the Platform offer customised learning experiences based on real-time monitoring of learners' progress and feedback. The following modules will be added to enhance the learner experience: after finishing a module, the system will record the student's progress and adapt the difficulty of the next module accordingly. If the learner does well, the platform will increase the difficulty of the task so as to prevent the learning content from being too simple and thus causing a loss of interest in learning. If the learner does poorly, the platform will lower the difficulty of the task to help the learner better grasp the basic content. The platform will give immediate feedback on all learning tasks and provide detailed information about how accurate the learner was, how long it took to complete the task, etc. Feedback helps learners know how well they have learned and what to improve next in their studies; thus, it can help them improve their learning efficiency. At each level of the platform, some tasks need to be completed by the learner to motivate them to continue learning. Set short-term and long-term goals for the learners, help them set a clear learning direction, and prevent them from losing motivation because of tasks that are either too difficult or too easy.

3 Experimental Evaluation

3.1 Improve Oral Skills

Fluency scores for the test group learners at the start, middle and end of the assessment are shown in bar charts to determine whether the platform has improved learners' oral fluency. A small number of lifelong learners (five in this case) will be selected to take part in the experiment. Integrated Speech Recognition Technology will be used to evaluate learners' spoken expression. Fluency scores of all learners at the beginning, middle and end of the assessment are presented here.

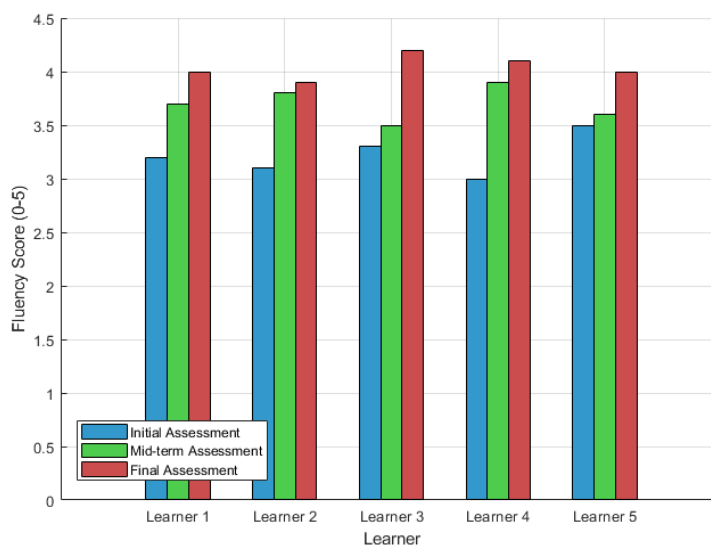


Figure 3: Fluency Scores of Test Group Learners at Different Times

Figure 3 shows the five learners in the test group on the horizontal axis and each learner's fluency score on the vertical axis. As shown above, the fluency scores of all learners have risen to some extent after the initial test and before the final test. Therefore, the platform's personalised learning path and voice feedback have helped improve the oral fluency of the learners. Learner 3's score increased from 3.3 to 4.2, and it was quite high. Learner 2's score is now 3.9 (up from 3.1). Although this improvement is relatively small, it is still helpful for the learners on the platform. Three months later, the learners' fluency scores have exceeded 3.9.

3.2 Analysis of Learners' Oral Performance

To assess whether the platform has improved the speaking skills (such as pauses and speaking speed) of the learners, five learners with different levels of speaking ability were selected and included in the entire three-month learning program. Set up and initialise the platform, make sure that all functions work normally, and enable personalised recommendations, speech recognition, speech generation and reinforcement learning. It will store all of the learners' study data in this platform, such as speech input, pauses and speaking speed. A speech-recognition system will monitor when students stop speaking or speak too quickly. Provide feedback on learning content and difficulty to help learners improve their speaking skills gradually through the platform.

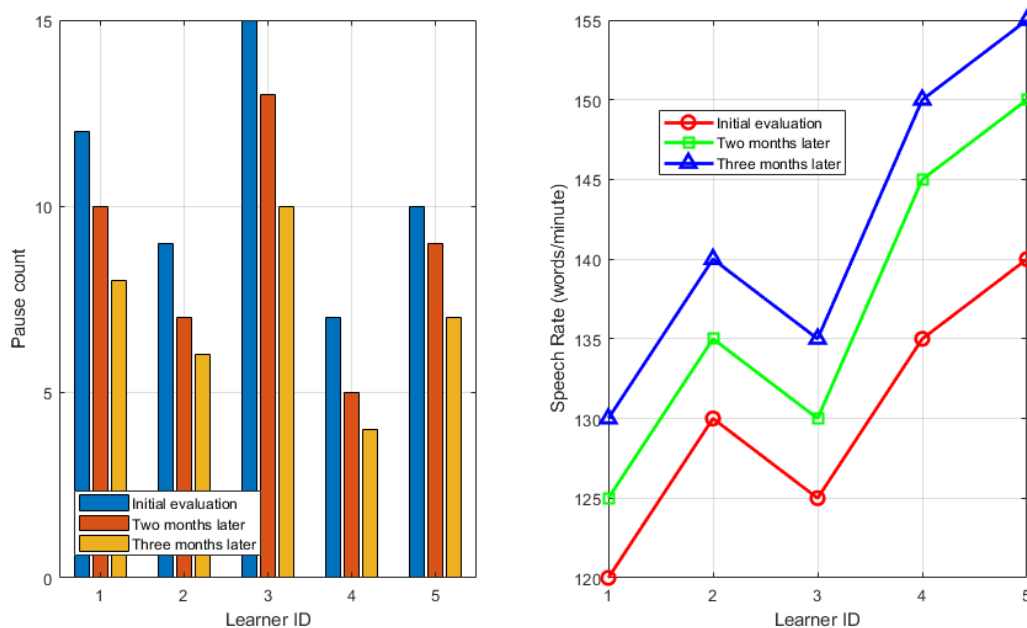


Figure 4: Analysis of Learners' Oral Performance

The five learners in the test group are shown on the X-axis of the left graph in Figure 4, and the number of pauses that occurred during the learners' oral expressions is represented by the Y-axis. The number of pauses in the learners' work is relatively large at the beginning. For example, Learner 1 stopped speaking 12 times and has some fluency problems in their spoken English. Two months later, the number of pauses has generally decreased in the mid-term assessment. Learner 1's pauses drop to 10, and Learner 5's pauses decrease from 10 to 9. In the final assessment three months later, the number of pauses for all learners decreased substantially, and particularly for Learner 4 and Learner 2, whose pauses dropped significantly; thus, their oral fluency had improved considerably. The right graph also shows five learners on the X-axis. The Y-axis is the speed of speaking by the learners, in words per

minute. In the initial assessment, all the learners speak relatively slowly; for example, Learner 1 speaks at about 120 words per minute and Learner 5 speaks at about 140 words per minute, and there are some pauses and disfluencies in their speech. During the mid-term assessment two months later, the speaking speed of the learners has generally increased: Learner 1 has risen from 120 words per minute to 125 words per minute, and Learner 5 has risen from 140 words per minute to 150 words per minute. Generally speaking, the learners' speaking speed is increasing. By the final assessment three months later, the learners' speaking speed had also increased to a certain extent, particularly for Learners 4 and 5, who had reached speeds of 150 words per minute and 155 words per minute, respectively, and this was higher than their initial assessment speeds.

3.3 Changes in Task Completion Time and Task Difficulty

Assess how effectively the intelligent platform has improved learners' task-completion speed and increased the difficulty of the tasks gradually. To determine if the platform can shorten the learners' task completion time effectively and increase the difficulty of the task appropriately to promote learners' progress. Determine how effectively the intelligent platform helps students complete tasks more efficiently and progressively increase the difficulty of the tasks. Verify whether the platform can help shorten learners' task completion time and appropriately increase task difficulty to motivate learners to continue studying.

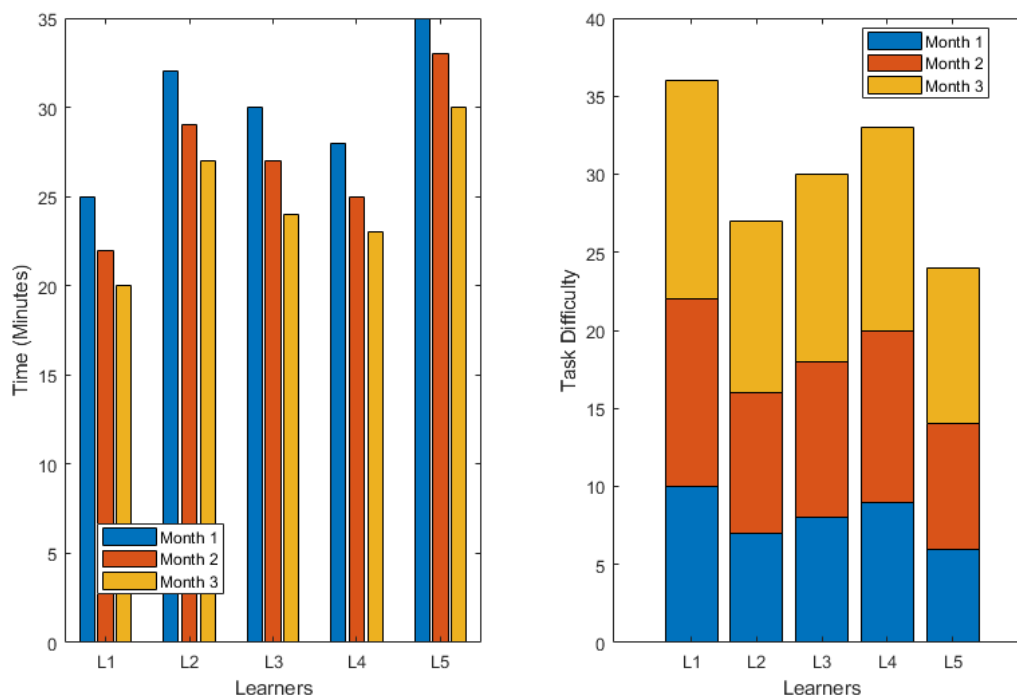


Figure 5: Task Completion Time and Task Difficulty Changes

The five learners on the horizontal axis of the left panel in Figure 5 are shown. The left-hand side is the time taken by each student for that day to finish the work. Learner 1's task-completion time has been declining steadily over the past three months (25 minutes, 22 minutes, 20 minutes); that is to say, their efficiency in studying has improved. Learner 2's task-completion time in the second and third months is relatively stable: 29 minutes and 27 minutes, respectively. This learner is one of the slower progressors among all the other learners. The learners on the horizontal axis of the right panel are the same as before (L1, L2,

L3, L4, L5). The vertical axis is the difficulty of the tasks completed each month, and it is given as the number of tasks. Learner 1's task difficulty has been gradually increasing over the past three months (10-12-14), and although they have been learning well, they are now ready for more difficult tasks. Learner 4's task difficulty is relatively low and gradually increases (7-9-11). Compared with the other learners, this learner may need more time to adjust to the higher-difficulty tasks.

3.4 Recommendation Accuracy

Evaluate the accuracy of personalised recommendation systems for all learners and at various times. Collect and analyze data at various times to see if the recommendation system's fit for learners' needs has improved over time. At every stage for all learners, calculate how accurate the system's personalised recommendations are compared to their actual requirements.

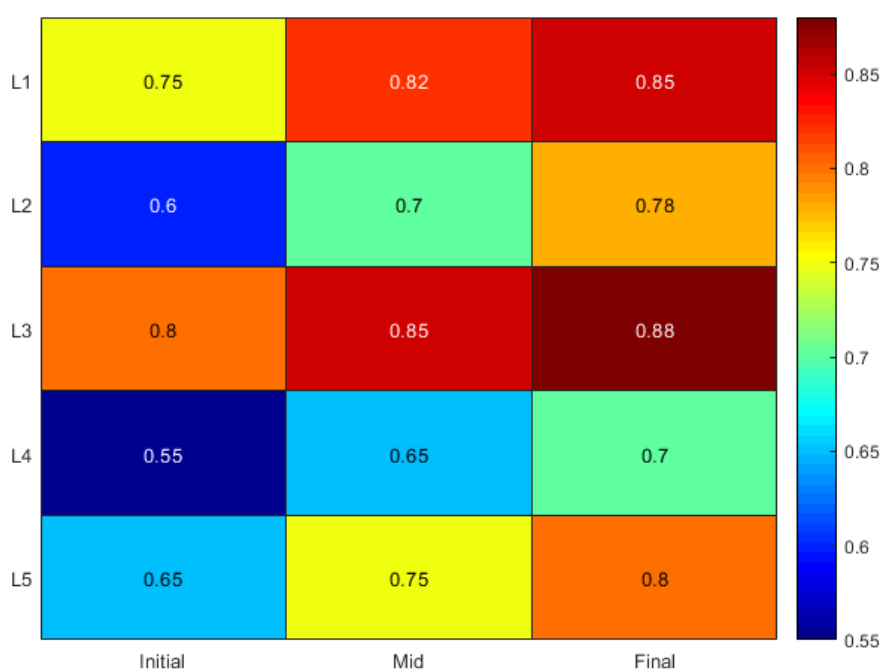


Figure 6: Recommendation Accuracy

Figure 6 is the three time points on the horizontal axis. The vertical axis is the five learners. Learner 1's recommendation accuracy at the beginning, middle and end of the process is 0.75, 0.82 and 0.85. Gradually better recommendation accuracy over time indicates that the platform's recommendation system is continually adjusting recommendations according to how far along the learner is, thus increasing accuracy. Learner 2's recommendation accuracy is 0.60 at the beginning, 0.70 in the middle, and 0.78 finally. Although the overall accuracy was relatively low, it showed a gradual increase over time and could be seen that the relevance of the recommended content to learners gradually improved as the platform developed. Learner 3 has achieved an accuracy of 0.80 at the start, risen to 0.85 in the middle, and finally reached 0.88. It has relatively high accuracy and stability; therefore, we believe that the recommendations of the platform are both relevant and precise, and they have reached a relatively stable state in recent years. The first accuracy of learner 4 is 0.55, the second is 0.65, and the last is 0.70. The accuracy of the recommendation is relatively low; although there has been some progress, there are still many deficiencies to be fixed. It may be that the learner's demands for recommended content have changed

substantially since they started using the platform, or that the platform has failed to meet these personalised demands fully. Learner 5's first accuracy is 0.65, its middle accuracy is 0.75, and finally 0.80. Although the accuracy of the recommendations has been improving gradually, it is still generally quite low and needs to be increased further.

3.5 User Satisfaction

The goals of this study are to evaluate learners' satisfaction with the functions of the intelligent Chinese learning platform in all areas, such as the recommendation system, ease of use, learning content, feedback mechanisms and interaction capabilities. Collect learners' satisfaction ratings to better understand the strengths and weaknesses of the platform, provide data support for subsequent optimisation work, etc.

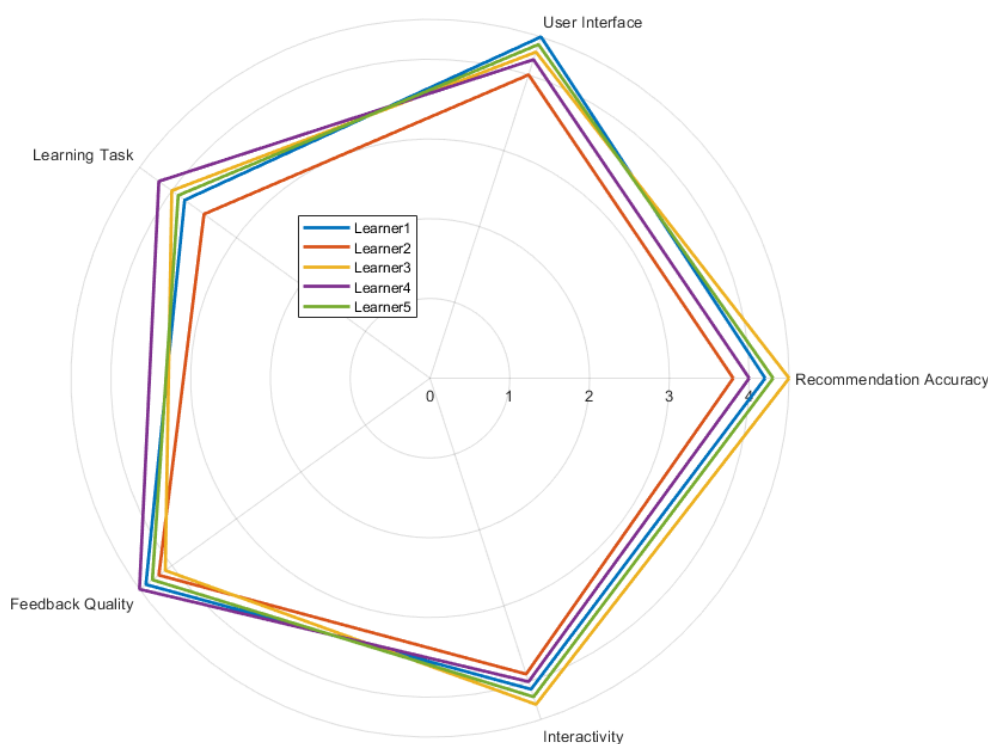


Figure 7: Satisfaction Ratings

Figure 7 shows the satisfaction ratings of five learners in different dimensions of the platform's functions. Learner 1 scored both the quality of feedback (4.4) and the accuracy of recommendations (4.2) as relatively high, thus being relatively satisfied with the platform's feedback and recommendation system. Learner 1 scored low in "Learning Tasks" (3.8), and thus the design of the tasks may not meet their expectations. Learner 2 has a relatively low score for "Learning Tasks" (3.5) and "Recommendation Accuracy" (3.8), and is thus less satisfied with the task design and recommendation accuracy. Learner 3 has a relatively high score, and among them, "User Interface" (4.3) and "Feedback Quality" (4.3) are notably high; thus, the overall rating is moderate. Learner 4 has given similar scores in all categories, and since each is higher than 4.0, he is generally satisfied with the functions of the platform. Learner 5's ratings are also relatively balanced, and "recommendation accuracy" and "feedback quality" are particular examples, both at 4.3 points; thus, he is relatively satisfied with the recommendation system and feedback. His score in the "learning task" dimension is slightly lower at 3.9, and this may be due to the difficulty or changeability of the task.

4 Conclusion

This paper presents an adaptive intelligent Chinese language teaching platform for lifelong learning. Through the combination of deep learning, natural language processing and reinforcement learning, personalised learning paths and real-time feedback are provided for learners. Through learner profiling based on convolutional neural networks, a personalised recommendation system combining collaborative filtering and content recommendation is realised, oral interaction is implemented using speech recognition and generation technology, reinforcement learning-optimised learning strategies are employed, and the learners' language expression ability and task completion efficiency are effectively improved. Based on the experiment, the oral ability and learning-task efficiency of the test group were both relatively high. The fluency score of the test group is more than 3.9. However, there are still some deficiencies in this study, such as a limited scope of application for the model and a relatively small amount of training data.

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