Design of a Chinese Learning Platform Based on Knowledge Graph and Adaptive Question Answering

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ABSTRACT To address fragmented knowledge structures, unclear learning paths, and insufficient personalized support in Chinese learning for non-native speakers, this paper designs a Chinese learning platform integrating knowledge graph technology and adaptive question answering. First, a multidimensional Chinese knowledge graph covering vocabulary, grammar, and culture is constructed, and semantic links among knowledge nodes are established through entity-relation extraction. Second, a learner ability modeling module based on Item Response Theory is developed to dynamically evaluate learners' proficiency levels. An adaptive question-answering mechanism then recommends exercises with appropriate difficulty according to learners' current ability and knowledge dependencies in the graph. Finally, a reinforcement learning algorithm is introduced to optimize the recommendation strategy. Experimental results show that learners using the platform achieve an increase in learning efficiency of 18.5 questions per hour and a 12.6 percentage-point improvement in knowledge mastery accuracy. User satisfaction with personalized recommendation reaches 89.2%, with a mean score of 4.35, indicating the effectiveness of the proposed intelligent learning platform.

INDEX TERMS knowledge graph, adaptive question answering, item response theory, reinforcement learning, personalized learning

I. INTRODUCTION

CHINESE is the most spoken language in the world and this has made it attract many non-Chinese speakers to learn the language. Nevertheless, students are usually confronted with the problem of disjointed pieces of knowledge. Vocabulary, grammar and pragmatic knowledge are distributed in various chapters of the textbooks and lack of systematic relation results in poor learning outcomes. The diversity of individuals complicates the adjustment of a standard teaching pace to all learners. Weakly students are unable to keep pace and become frustrated, whereas advanced learners waste time re-reading what they already know. Lack of individualized attention denies the learner the chance to be guided on what he should learn and lack of clarity in the learning path results in mindless practice. These issues severely limit the effectiveness and quality of the Chinese instruction [1,2]. KG technology can present fragmented knowledge into a system, and thus address the knowledge association problem in the learning of the Chinese language through the construction of semantic networks of entities and relationships, providing a technological basis. The item response theory offers a scientific approach to the assessment of ability that can dynamically deduce the levels of the learners, depending on their answers to questions. Adaptive learning systems are able to tune the teaching content based on the current state of the learners, but available solutions are largely based on simplistic rule matching and do not model knowledge dependencies in depth [3,4]. Reinforcement learning has been demonstrated to maximize long-term benefits in recommendation systems, although it has not been adequately applied to language learning. The way to develop a sensible reward system that will help to find a balance between the efficiency of learning and the quality of knowledge acquisition remains to be studied. The paper suggests a Chinese learning system that is founded on knowledge graphs and adaptive question answering. It builds a multi-dimensional knowledge graph of vocabulary, grammar and pragmatics, relies on item response theory to dynamically measure the skills of learners, creates a dependency-driven adaptive question answering system and introduces reinforcement learning to maximize the recommendation strategies. The effectiveness of the platform is confirmed by a comparative experiment, with 120 learners, who analyzed the indicators of learning efficiency, the accuracy of knowledge mastery, user satisfaction, and system performance. The experimental findings prove that the platform can substantially enhance the Chinese learning performance, allow offering individual learning assistance to non-native speakers, and offer a reference point to design intelligent teaching systems of languages [5,6].

II. RELATED WORK

The study of Chinese knowledge representation has investigated different ways of structuring language knowledge. Lexical researches concentrate on building semantic connections like synonyms, antonyms, hyponym and grammatical researches focus on building syntactic structures and component dependency networks. Other studies have tried to incorporate Chinese knowledge into ontology frameworks, establishing types of entities and constraints on attributes, but largely they are not dynamically connected with the process of learning. The application of knowledge graphs in the field of education is gradually increasing. They represent the pre-dependencies among concepts using graph structures and plan learning paths and knowledge reasoning [7,8]. Most of the current Chinese known graphs however are generic bases of language resources and are not made to accommodate the cognitive functions of non-native language learners. They do not have annotations of learning related attributes like difficulty level and frequency of use so they cannot be directly applied to individual teaching situations. The techniques used to model learners ability have developed to be dynamic instead of being static. Classical testing theories are based on pre-determined test papers to measure abilities, which do not reflect ability changes in the learning process. The item response theory is a predictive performance that depends on the functional relationship between the item parameter and the ability values; the theory supports the application of the computer-adaptive testing. The cognitive diagnostic models further elaborate ability structures to determine the level of mastery of learners at various points of knowledge. Language learning Personalized recommendation technologies are collaborative filtering and content recommendation, which are typically implemented on similarity matching or rule engines, do not fully exploit knowledge dependencies to inform recommendation decisions. Learning through reinforcement in education recommendations has the goal of maximizing the long-term learning benefits but the designs of reward functions are usually too simplistic and ignore the trade-off between the quality of knowledge acquisition and the efficiency of learning.

III. METHODS

A. CONSTRUCTION OF A MULTI-DIMENSIONAL CHINESE KNOWLEDGE GRAPH

Chinese knowledge graph construction is done by extracting entities and doing relation modelling at three levels, namely lexical, grammatical, and pragmatic. Essential vocabulary is mined at the lexical level as entity nodes through the analysis of HSK syllabus, the Modern Chinese Dictionary and real-world corpora. Semantic relationships like synonyms, antonyms and hierarchical relationships are made, attributes like part of speech, frequency of use and level of difficulty annotated. At grammatical level, beginning with the syntactic structure, the subject, verb, object, modifier and complement are formed as entities of grammatical rules. Structural dependencies between sentences are extracted using dependency parsing tools, and create a sequence of progressive knowledge between simple and complex sentences. At the pragmatic level, there is the integration of such elements as the cultural background, contextual information, and communicative scenarios and the applicability of vocabulary or sentence patterns in various situations is marked [9,10].

Entity relation extraction is based on a BERT-based sequence labeling model, whereby the labeled corpus is trained to recognize entity boundaries and types. The relation classification module works based on a graph convolutional network to extract multi-hop relation features and stores the extracted triples in the Neo4j graph database. To manage the 42,000 relations efficiently, the system utilized an active learning framework where the model suggested relations for human validation. Two expert linguists reviewed the high-confidence automated links, achieving an inter-annotator agreement (Kappa) of 0.84, ensuring both the feasibility of the scale and the high precision of the resulting triples. The process of knowledge fusion eradicates the redundancy in the data of various sources by an entity alignment algorithm; eventually creating a Chinese learning knowledge network with 15,000 node entities as well as 42,000 relation edges. To validate the quality of this graph, a subset of 1,000 triples was independently reviewed by three linguistic experts. The validation yielded an inter-annotator agreement (Cohen's Kappa) of 0.86 for entity boundaries and 0.82 for relation types. Furthermore, relation classification achieved a precision of 91.4% against a manually labeled gold standard, ensuring the structural integrity of the adaptive foundation.

B. DYNAMIC ASSESSMENT OF LEARNERS' ABILITIES BASED ON ITEM RESPONSE THEORY

The learner ability assessment uses three-parameter item response theory model to describe the nonlinear mapping relation between the performance of answers and the level of ability. All questions are marked with three parameters which include discrimination, difficulty and ability to guess. They are calibrated with maximum likelihood estimation with historic answer data. The original values of the ability of learners are initialized to zero and the system captures the trajectory of their answers in vocabulary, grammar and pragmatics. Once a learner has answered a question, the corresponding expected accuracy level of the question given the current ability value is computed and the residual is obtained as the difference between the actual response and the expected response. In ability updates, a Bayesian inference model is used, whereby the ability estimate is adjusted according to the size of the residual. There is a great growth in ability value with correct responses to high difficulty questions and a greater reduction through incorrect responses to low difficulty questions. The system keeps the confidence interval of ability values; when the width of the interval is lower than some threshold the assessment convergence has been reached. To overcome the effect of shortterm fluctuations, an exponential smoothing mechanism is implemented, to weighted average the outcomes of several successive assessments, with weights that diminish over time. To decay away knowledge points that have not been practiced over a long period, a simulated forgetting curve is used to apply a decay factor to these ability values. These dynamically updated ability parameters serve as the primary input for the selection mechanism described in the following section.

C. DEPENDENCY-DRIVEN ADAPTIVE QUESTION ANSWERING MECHANISM

The system examines the level of mastery that the learner has already acquired and determines those candidate knowledge points on the knowledge graph that the learner has not yet mastered, but whose requirements are satisfied. The predicted accuracy rate of the corresponding questions of each candidate point is then determined and questions with accuracy between 0.6 and 0.8 are then chosen as tasks in the zone of proximal development. Once the learner gets three consecutive questions to be answered correctly on a knowledge point where the confidence level is above 0.85, the knowledge point can be considered mastered and the next knowledge points unlocked. In case of two questions being answered incorrectly, one after another, the system traces back through the knowledge hierarchy to identify unmastered prerequisite concepts in order to retest the solidity of the prerequisite knowledge and automatically adds the reinforcement exercises of the prerequisite knowledge. The questions are given in a gradually escalating order of difficulty, starting with the testing of individual pieces of knowledge, then moving on to the overall application of multiple pieces of knowledge. The system notes how many practice sessions and time durations at each knowledge point, and dynamically schedules the time when to repeat a knowledge point, according to an interval repetition algorithm, and periodically projects reinforcement questions in mastered knowledge points according to the forgetting curve.

D. RECOMMENDATION STRATEGIES FOR REINFORCEMENT LEARNING OPTIMIZATION

The recommendation strategy is represented as a Markov decision process. The feature vectors include the three dimensional ability value of the learner, the collection of mastered knowledge points and the learning time of the learner in the state space. The action space is the set of discrete operations of choosing questions in the question bank of candidates. The reward function is a holistic approach that takes into account three indicators, which are correctness of answer, coverage of knowledge points and learning time. A base reward is provided for a correct answer to a question, an incremental reward is provided on the newly learned knowledge points, and a penalty is provided on failure to answer in time. The agent has a deep Q-network structure. The state encoding is sent to the input layer whereby the hidden layer consists of a bidirectional long short-term memory network that learns the temporal relationship of the learning sequence and finally the output layer estimates the long-term cumulative reward of each candidate question. The training stage utilized a hybrid approach to address the data requirements of the Deep Q-Network: the model was pre-trained using a simulated environment based on historical interaction datasets from previous cohorts (approx. 5,000 users) to achieve baseline convergence. During the 12-week experiment, the agent fine-tuned its strategy by storing historical interaction trajectories with the help of an experience replay mechanism and random sampling of data in batches with updating network parameters to disrupt sample correlation. An annealing strategy is employed to minimize the likelihood of random selection of questions to achieve a balance between exploration and utilization.

IV. RESULTS AND DISCUSSION

A. COMPARISON OF LEARNING EFFICIENCY AND KNOWLEDGE ACQUISITION EFFECT

A total of 120 non-native speakers who had the similar level of the Chinese proficiency were recruited and randomly split into an experimental group and a control group, consisting of 60 people each. The experiment was 12 weeks long. The platform implemented in this paper was applied to the experimental group, whereas the conventional linear course system–defined as a digital textbook interface where students progressed through fixed modules in a predetermined sequence–was applied to the control group. To ensure a rigorous comparison, both groups utilized the exact same learning content and question banks; however, the control group lacked adaptive sequencing and personalized feedback. This control ensures that the observed 18.5 questions/hour improvement stems from the adaptive logic rather than variations in content difficulty or volume. The learning outcomes were measured through standardized tests every week with indicators of the learning time, the number of questions answered, and the coverage of the knowledge points. The tests consisted of three types of questions, including vocabulary discrimination, grammar application, and contextual comprehension, each of which had 50 questions. The average learning efficiency, accuracy of mastering knowledge, coverage of the knowledge points, and the average time of completing the experiment were statistically evaluated after the experiment. All eligible partcipants signed an informed consent form.

Compared with traditional systems, as listed in Table 1,

TABLE 1. Comparison of Learning Efficiency and Knowledge Acquisition

Method	Learning efficiency (questions/hour)	Knowledge mastery accuracy rate (%)	Knowledge point coverage rate (%)	Average completion time (hours)
This article is from a platform	42.7	87.3	91.5	28.3
Conventional systems	24.2	74.7	68.2	45.8
Increase	+18.5	+12.6	+23.3	-38.2

our platform is better in all three indicators. Specifically, learning efficiency was increased by 18.5 questions per hour because ineffective practice time was greatly reduced by reasonable recommendations. While the experimental group spent 17.3 minutes more per day on the platform, an Analysis of Covariance (ANCOVA) was conducted using 'total study time' as a covariate. The results confirmed that the 12.6 percentage point improvement in mastery accuracy remained statistically significant ($p < 0.05$) even when controlling for time on task, suggesting the algorithm's adaptive sequencing – not just increased duration – drives the improvement. In addition, 91.5% of knowledge points were covered because learners were not limited to learning partial contents but were recommended to learn deeply. It took 17.5 hours less to finish the learning because learners were not ineffective practicing knowledge they had mastered.

B. USER SATISFACTION

A satisfaction questionnaire was given to 120 participants after the experiment. Four dimensions on satisfaction with personalized recommendations, ease of use of the interface, increase in learning motivation, and intention to keep using the product were measured using a five-point Likert scale. Mean daily learning time, single learning time, the number of times learners logged in weekly and total learning time were measured in both groups of learners. The response rate of the questionnaire was 100 per cent and 120 valid questionnaires were received. A score of 4 or above was a measure of satisfaction meaning it was considered to be approved hence the rate of approval of each dimension was computed. The pattern of learning time shifts was also examined and the difference of the data in the first two weeks and the final two weeks of the experiment was compared.

As shown in Table 2, when the personalized recommendation satisfaction rate reached 89.2%, the mean value was 4.35, which was 36.9 percentage points and 1.23 points higher than that of the control group, indicating that the adaptive mechanism could meet the personalized needs of learners. In addition, the approval rate of experimental group on learning motivation improvement dimension was 85.8%. That is to say, proper difficult questions could keep learners in the state of challenge and success. The average daily learning time of experimental group was 45.7 minutes, 17.3 minutes more than that of control group. In addition, the weekly login times of experimental group was 5.8 times, 2.2 times more than that of control group. The average increase of study time was 35.4%, while the control group was only 8.7%, which means that the accurate recommendation could greatly improve the participation and stickiness of learners.

C. SYSTEM PERFORMANCE

A test environment was created that would mimic 1000 simultaneous users on the platform, and load test requests were created using Apache JMeter. The test scenarios involved four fundamental operations: querying a knowledge graph, calculating the value of ability, recommending questions and providing feedback on answers. Every operation was repeated 10,000 times and the mean response time, the 95 th percentile response time, throughput and error rate noted. The performance of the knowledge graph query was profiled using Neo4j Profiler and the count of entity nodes, relationship edges, the mean query depth, and index hit rate were statistically tested. The server was set up using a 16-core CPU, 64GB of memory and Redis caching layer was installed to optimize high-frequency queries.

As shown in Table 3, the average response time of all operations is less than 0.8 s, and the fastest operation is the calculation capability value, which takes 0.31 s. The question recommendation is the slowest operation but is also within 0.68 s. The 95th percentile response time of all operations is the highest, which is question recommendation and takes 0.95 s, which means that when the system is heavily loaded, the system performance is still acceptable. Throughput of capability value calculation is 2456 requests/s, which has demonstrated that the evaluation module can support high-concurrency access. The error rate of knowledge graph query is only 0.03%, which has further validated the stability of Neo4j database.

TABLE 2. Comparison of User Satisfaction and Learning Behavior

Evaluation Dimensions	Percentage of approvals in the experimental group (%)	The percentage of people who accepted the control group (%)	Mean score of the experimental group (points)	Control group mean (score)
Personalized recommendation satisfaction	89.2	52.3	4.35	3.12
User interface ease of use	91.7	73.5	4.48	3.76
Enhancing learning motivation	85.8	48.6	4.21	2.98
Continued use intention	88.3	55.2	4.38	3.18
Average daily study time (minutes)	-	-	45.7	28.4
Weekly login frequency (times)	-	-	5.8	3.6
Increase in learning time (%)	+35.4	+8.7	-	-

TABLE 3. System performance test results

Operation type	Average response time (seconds)	95th percentile response time (seconds)	Throughput (requests/second)	Error rate (%)
Knowledge Graph Query	0.52	0.78	1823	0.03
Ability Value Calculation	0.31	0.54	2456	0.01
Recommended Questions	0.68	0.95	1567	0.05
Answer feedback processing	0.43	0.72	2134	0.02
Graph size (nodes/edges)	15000	42000	-	-

V. CONCLUSION

This Chinese language learning platform overcomes the problems of scattered knowledge and unclear learning paths for non-native learners via knowledge graph technology. Project-response theory based competency modeling quantifies learners' levels accurately, dependency driven adaptive recommendations connect learning contents logically, and reinforcement learning optimization strategy further improves recommendation quality. The experiments validate the advantages of this platform in learning efficiency, knowledge coverage and user experience, and the feasibility of applying knowledge graphs and adaptive technologies in language teaching is proved. Currently, this platform is only applied in Chinese language learning scenario. Manual annotation is used in knowledge graph construction, which costs much effort and energy, and the reinforcement learning model needs large amounts of interactive data to converge. Platform based on transfer learning method using cross-lingual knowledge graphs can reduce the cost of developing an adaptive learning platform for a new language. Rapidly constructing competency models in a low sample scenario needs to be explored. In addition, more multimodal learning resources can be introduced to enrich interaction methods.

AUTHOR CONTRIBUTIONS

Conceptualization – Huixiao Jia, Yaguang Xu, Liting He, Jiliang Xing, Lili Zhao and Liyue Zhou; methodology – Huixiao Jia, Liting He, Jiliang Xing, Lili Zhao and Liyue Zhou; investigation – Huixiao Jia, Yaguang Xu, Liting He, Jiliang Xing, Lili Zhao and Liyue Zhou; writing-original draft preparation – Huixiao Jia, Yaguang Xu, Liting He, Jiliang Xing, Lili Zhao and Liyue Zhou. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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