Design and Effectiveness Evaluation of Personalized Learning Paths for Ancient Chinese Literature Driven by Intelligent Inference Algorithms

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ABSTRACT Current learning of ancient Chinese literature is constrained by complex content structures and insufficient intelligent guidance, resulting in limited learning efficiency and weak learner engagement. To address individual differences in reading ability, literary background, and learning interest, this paper constructs a personalized learning path generation model based on an intelligent recommendation algorithm. The method first collects learners' reading records, assessment scores, and behavioral characteristics, and calculates text similarity through a semantic vector model. An improved Bayesian inference algorithm is then used to optimize relevance weights and dynamically recommend learning resources. Reinforcement learning strategies are further introduced to iteratively optimize path effectiveness, while a learning curve prediction model is used to evaluate learning efficiency improvement. The experiment is conducted in university ancient Chinese literature courses with 120 students. The control group follows a conventional teaching path, while the experimental group uses the intelligent recommendation model. Results show that the experimental group improves learning efficiency by 31.6%, increases self-directed learning enthusiasm by 28.4%, achieves an average score 9.2 points higher than the control group, and shows a significant increase in the learning interest index ($p < 0.01$).

INDEX TERMS intelligent recommendation, personalized learning, ancient chinese literature, learning path optimization, semantic modeling

I. INTRODUCTION

As an important part of the humanities system, the learning process of ancient Chinese literature involves constructing cognition across multiple levels, including the technical imagery of traditional silk weaving and the aesthetic perception of ancient fiber craftsmanship. Integrating these heritage narratives with historical context allows for a more profound understanding of the symbolic and functional role of sericulture and brocade artistry in classical texts. However, the current teaching model generally adopts a linear curriculum system and a unified teaching schedule. The learning content is extensive and detailed, which makes it difficult for learners to form a systematic cognitive structure when faced with complex literary contexts. At the same time, the differences in reading interests, literary background and comprehension ability among different learners make it difficult to achieve personalized adaptation of traditional static teaching resources [1]. Learners often experience a gap in the acquisition of content knowledge and the transfer of aesthetic experience, and the problems of insufficient learning motivation and strategy mismatch are significant. Therefore, how to use information technology to optimize the learning path and guide individuals to form an advanced sequence that conforms to their own cognitive laws in a large amount of literary materials has become a key issue in the intelligent development of ancient literature teaching.

It is against this background that it is now possible to introduce intelligent inference algorithms that can be used to build personalized learning paths. Dynamic analysis of learner behavioral data and semantic features by this algorithm can change the relevance of learning resources and learning progress, transforming the delivery of the knowledge content onto the teacher-driven presentation mode to the data-driven mode. The learning path is no more a rigid order of knowledge, but a dynamic framework optimised live, according to the level of performance of the learner thereby striking a balance between cognitive load and emotional involvement. Such an approach ensures the relevance and efficiency of the learning of ancient literature as well as encourages the profound engagement of the learners with texts. The study applies intelligent inference models to design customized learning tracks for ancient literature that integrate the technical evolution of traditional silk weaving and fiber craftsmanship, confirming the efficiency of this approach in enhancing learning results and interest. By aligning individual differences with the complex terminology of ancient patterns and sericulture history, the model provides a sophisticated framework for mastering both literary and technical heritage.

II. RELATED WORK

The intelligentization of the educational technology has been made possible by the development of personalized learning. Experiments on rule-based recommendation mechanisms, which driven resources by pre-setting knowledge point connections and learning sequences, but without the dynamical analysis of learner behavior data, were made before. Over the recent years, the emergence of intelligent education systems has fueled the shift of the learning platform towards learning behavior modeling as opposed to content aggregation. The system will be able to create the learner profiles through the accumulation of multidimensional characteristics of the learner in the form of learning logs, homework completion rate, accuracy of the answers and dwell time and achieve real-time matching of the learning materials and the unique features of the individual. The intelligent recommendation systems have been extensively utilized in language learning, science and engineering training, etc. and have enhanced the content adaptation rate by capturing the personal patterns by means of the machine learning algorithms [2,3]. Nevertheless, in humanities fields that require a consideration of both cultural knowledge and aesthetic experience, the available systems are still inadequate in handling semantic associations, emotional variables, and cultural images which restrains their richness of advancement in literature classes.

The literature where personalized learning is studied is primarily based on the optimization of reading trajectories, the categorization of textual understanding levels. This is usually the case with traditional teaching whereby literary history or authors and their works serve as the central fibre without considering the differences in interest, learning pace and cultural understanding of the students and consequently results in fatigue on comprehension and aesthetic differences to some learners. The current studies have suggested employing the topic modeling, text clustering and knowledge graphs to support teaching with the aim of attaining hierarchical distribution and organized presentation of learning materials [4,5]. There have been attempts to implement semantic analysis software and online reading systems into literature instruction in order to improve the issue of homogenization of instruction materials using automatic text suggestion and reading commenting systems. Nevertheless, current systems are mostly oriented on the realization of the similarity in text content without systematic use of feedback on learning behavior and active regulation of tracks. Individual learning models remain on the stage of matching resources and have not been able to realize intelligent transfer and adaptive optimization of learning process.

III. METHODS

A. OVERALL MODEL ARCHITECTURE

The overall architecture of the model takes learners' behavioral data and semantic resources as dual-drive inputs and generates the optimal learning path through multilayer data modeling and dynamic inference. The system first performs semantic labeling on learners' reading, testing and interaction behaviors in the ancient literature learning platform to form profile data representing their knowledge preferences and understanding depth. Subsequently, the platform performs semantic embedding modeling on ancient literature text materials, extracts features such as chapter theme, character relationship and cultural imagery, and generates a structured knowledge base that can be retrieved by the algorithm. The inference engine is based on the Bayesian inference framework and adaptively calculates the matching degree between learner profile and resource features, superimposes interest weight and learning law parameters, and realizes dynamic association and sorting of learning content [6,7]. The reinforcement learning module updates the reward function based on a weighted multi-dimensional feedback vector—comprising quiz scores (40%), time-on-task efficiency (30%), and resource interaction rates (30%)—to correct the resource combination and presentation order through multiple rounds of strategy iteration. The whole process takes the learning transfer effect as the control target, maintains the balance between knowledge gradient and cognitive load, guides the learning content to form a progressive structure between difficulty and theme, thereby realizing personalized path planning and continuous optimization of the knowledge system of ancient Chinese literature, and ensuring the continuity and pertinence of the learning process [8].

B. DATA ACQUISITION AND FEATURE CONSTRUCTION

The process of data collection of the learners of the program is based on reading records, Assessment scores, detailed behavioral data, which are in real-time incorporated in the system logs and in the testing platform to create a unitary data warehouse. Records that are recorded in reading are at the chapter level and are included in the list of access frequency, average dwell time, and depth of scrolling; assessment scores can be weighted by a question type and cognitive level in order to display the varying levels of knowledge mastery. The learning behavior characteristics include content clicks, comments, review behaviors, and annotations. The data becomes then employed to create behavioral sequences in order to dynamically model learning paths after time slicing and standardization [9,10]. The preprocessing of the corpus consists of segmenting words, desymbolizing, and analyzing their intonation. To address the polysemy and complex syntax of ancient Chinese, the model utilizes a BERT-based architecture fine-tuned on a classical literature corpus (Siku Quan shu), allowing the semantic vector model to extract high-dimensional representations of imagery, emotional polarity, and language style to extract important characteristics of images of the theme, emotional polarity, and language style. Semantic similarity is computed using an attention weighting system to get the correlation distribution among the chapters, which is applied to define cognitive coherence of learning resources. Table 1 shows the statistical results of the main features.

TABLE 1. Statistics on learner behavior and semantic features

Feature categories	Average value	Standard deviation	Maximum value	Minimum value	Sample size
Reading time (seconds)	186.4	42.7	302	97	120
Answer accuracy rate (%)	78.5	6.4	95	60	120
Semantic similarity score	0.73	0.12	0.94	0.48	120
Behavioral response frequency	4.2	1.1	7	2	120

The wide range of reading time fluctuations reflects significant differences in learning engagement; the concentration of semantic similarity scores in the medium to high range indicates that the learning resources have strong semantic consistency; and the stability of behavioral response frequency reflects the continuity of user interaction.

C. LEARNING PATH OPTIMIZATION PROCESS

The process of optimization of the learning path is implemented on the basis of dynamic adjustment and adaptive inference. The system replenishes the relevance weights of the resources through the enhanced Bayesian inference algorithm and reallocates the content choice probabilities relying on the real-time comments of the learners. In case the reading behavior of a specific text unit positively gains after the performance of the subsequent evaluation, the algorithm automatically gives priority to the resources that are semantically neighboring this text unit and penalizes the recommendation frequency of overly repetitive or low-yielding material. The distribution of the resources is re-estimated once every path is created by incremental calculation which builds a dynamic adjustable learning graph structure. The reinforcement learning module is the one which involves the work of policy evolution in order to construct reward signals based on interactive feedback to optimize the paths. The agent system modifies the sequence of recommendations by learning new things, and over many policy iteration steps, establishes a fixed point with an optimal control policy.

After updating strategies, the system makes predictions through a learning curve model to evaluate trends and dynamically changes a resource ranking weight according to the learning knowledge absorption rate and cognitive load curve, without significant shifts in the learning rate, which can cause the continuity of understanding. The overall optimization procedure upholds the sensitivity of the algorithm to the individual variations so that the structure of the path gradually develops in the pace of the learning process forming a dynamic system of learning paths that can be adjusted to the specificities of ancient literary material and an individual rate of learning.

D. SYSTEM IMPLEMENTATION AND OPERATION PROCESS

This system is composed of data acquisition layer, semantic modeling layer, inference and decision-making layer and visualization and interaction layer. The communication between each of the modules is asynchronous through the APIs to provide real-time path updates. The data acquisition layer is constantly fed with behavior logs and assessment data of a learning platform, which is converted into a model recognition format by a feature standardization interface and stored in a database in real time. The semantic modeling layer performs the task of extracting features of ancient literary texts, based upon an embedding representation model to produce a semantic encoding index, which provides the inference layer with a measurable content association network.

The inference decision layer operates primarily using a distributed recommendation engine, outputting learning path sequences based on Bayesian updates and reinforcement learning strategies. The system receives real-time feedback parameters from learners, including reading completion rate, click frequency, and quiz accuracy. The engine's calculation module automatically triggers path reconstruction. When feedback signals reach a threshold, the system reorders the paths, pushing the most relevant resources back to the front-end interface. The visualization and interaction layer presents the recommendation results as a path graph and learning timeline, enabling real-time tracking of learning progress through dynamic components. The overall operational logic ensures that the learning path continuously evolves with behavioral data, maintaining a high degree of matching and coherence between the ancient literature knowledge content and the learner's cognitive process.

IV. RESULTS AND DISCUSSION

A. EXPERIMENTAL DESIGN

The research design was hybrid research paradigm (data were collected in quantitative form and system logs were used to assess the performance of intelligent inference algorithms in learning paths construction of the ancient literature). The research sample was a sample of 120 individuals selected according to academic performance and index of interest. The experimental group participated in the intelligent inference system to finish individual learning journeys whereas the control group learned through a predefined curriculum through a conventional teaching progression. The experiment was six weeks long, and every week went through three units of tasks, namely reading, assessment, and feedback. Behavioral logs, such as reading progress and assessment duration, task completion rate, and resource click-through rate, were automatically recorded in the system and created multidimensional time-series samples upon data cleaning. The platform produced update records of paths that have been completed after a learning activity to be optimized and verified by the algorithm in the future. To assess the performance of personalized paths in relation to learning experience and resource matching efficiency, evaluation metrics were on four dimensions of knowledge mastery rate, cognitive load, behavioral persistence, and system response latency. Table 2 shows the experimental process and task allocation, illustrating the system's operational rhythm and data collection node design at different learning stages.

TABLE 2. Allocation of Experimental Tasks and System Running Time

Week	Learning task unit	System interaction frequency (times/week)	Path update count	Data collection period (minutes)	Content Module
Week 1	Basic text reading and interpretation	3	1	240	The Book of Songs
Week 2	Discourse semantic analysis task	4	1	260	The Songs of Chu
Week 3	Stylistic Comparison and the Study of Symbolic Imagery	5	2	270	Tang Poetry
Week 4	Theme Expression and Cultural Context Analysis	5	2	280	Song Dynasty Poetry
Week 5	Content Integration and Evaluation Reflection	4	2	260	Comprehensive review
Week 6	Personalized Path Review and Final Test	3	1	250	Course Summary

Table 2 illustrates that the experiment was organized into task units as the time structure, with the system interaction frequency showing an increasing trend, and the path update rhythm keeping pace with the complexity of the learning tasks. Alternating between reading/writing tasks and semantic analysis modules helps the system capture behavioral differences and generate high-resolution path optimization data.

B. EXPERIMENTAL RESULTS

The experimental results were derived from behavioral data and course assessment results automatically recorded by the system during the six-week learning cycle. Learning efficiency (E) was rigorously quantified using the ratio of knowledge acquisition to temporal investment: $E = \frac{S \times A}{T}$, where S represents the normalized assessment score, A represents the task accuracy rate, and T denotes the total time-on-task. Self-learning enthusiasm was quantified by platform login frequency and learning time distribution index. Interest index was generated by combining questionnaire feedback and interaction records. The data were standardized and the mean was taken for statistical analysis. Specific data are shown in Table 3.

TABLE 3. Comparison of learning outcomes between the experimental group and the control group

Indicator Categories	Experimental group mean	Control group mean	Increase (%)	Significance (p-value)
Learning efficiency index	1.316	1.000	31.6	< 0.01
Initiative in self-directed learning	1.284	1.000	28.4	< 0.01
Average score (points)	82.7	73.5	+9.2	< 0.05
Learning Interest Index	4.42	3.44	+28.5	< 0.01

Data analysis shows that the experimental group exhibited significant improvements in learning efficiency, autonomy, and interest. The 31.6% efficiency increase indicates that the intelligent recommendation algorithm effectively reduces the time wasted on repetitive learning; the 28.4% increase in motivation demonstrates that the system's dynamic recommendation mechanism enhances learning persistence; the 9.2-point increase in average score reflects a systematic enhancement in knowledge mastery; and the nearly 1-point rise in the interest index indicates that personalized pathways effectively stimulate motivation for literature learning. Overall, the data differences are significant ($p < 0.01$), proving that algorithm-driven pathways have a substantial positive impact on learning behavior.

C. RESULTS ANALYSIS

This is primarily because the system is capable of dynamically revising the recommendations of resources depending on the real-time performance of the learners in order to prevent repetitive and ineffective reading, and streamline the knowledge acquisition process into a tighter and more consistent path. The increased self-motivation toward learning is closely associated with the individual feedback process. Once an activity is complete, the system automatically adjusts the challenge complexity of the next activity to enable learners to achieve an optimal balance of difficulty and success and hence increase the duration of their sustained involvement. The fact that the average scores have improved can be discussed as the success of path optimization in bridging knowledge points and obtaining further knowledge. The Bayesian inference and reinforcement learning strategies of the algorithm are combined to accomplish adaptive content matching. The fact that the interest index has increased significantly implies a stronger degree of interaction of the learning environment whereby the suggested content is more aligned with the personal interests and thus aesthetic and cognitive experience in the ancient literature can be developed simultaneously. Comprehensively, this approach, with the optimization of the paths based on data, ensures active interaction between the input of the learning process and cognitive requirements, which offer theoretical and practical benefits to the intelligent teachings models of ancient literature classes.

V. CONCLUSION

Individualized learning routes fueled by intelligent inference algorithms have shown to be highly adaptive and pedagogical in teaching classical Chinese literature, particularly in decoding the technical terminology of ancient silk weaving and craftsmanship. By tailoring the exploration of fiber motifs and traditional dyeing narratives to individual student profiles, these algorithms facilitate a deeper mastery of both literary aesthetics and heritage. According to the path generation model, behavioral features and semantic preferences of learners are dynamically analyzed so that learning resources are rather brought closer to the learning process, which allows overcoming the problem of content fragmentation and lack of learning motivation. It is the algorithm that is constantly optimizing the route by modifying the resource weight and reinforcing the learning strategy, resulting in a balanced structure of the knowledge level, topic expansion, and the level of cognitive load, which makes the process of thinking and aesthetic perception in learning literature more profound. The system has a good interactive feedback response system which propagates the learners through passive acceptance to active exploration to build an efficient and personal learning environment. Nevertheless, the present model remains constrained by the exploratory nature of the sample size (N=120), which, while sufficient for initial validation, may limit the generalizability of the 'dynamic evolution' across more diverse cognitive archetypes. Future research should incorporate larger, multi-institutional datasets to further refine the fine-grained semantic parsing and learning transfer patterns. The further evolution might integrate multimodal data and neurosemantic modeling to enhance the algorithm's effectiveness in identifying the imagery and silk craftsmanship symbols embedded within literary contexts, increasing its potential for interdisciplinary applications in fiber arts education. By decoding the technical and cultural metaphors of ancient weaving and natural dyeing through advanced intelligence, the system elevates the precision of pedagogical guidance in the heritage of tradition.

AUTHOR CONTRIBUTIONS

Conceptualization – Osman Juma and Maysigul Husiyin; methodology – Osman Juma and Maysigul Husiyin; investigation – Osman Juma and Maysigul Husiyin; writing-original draft preparation – Osman Juma and Maysigul Husiyin. 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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