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PAPER

Adaptive Chinese Language Teaching and Evaluation via Big Data and Mobile Interaction

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ABSTRACT

With mobile devices becoming the mainstream platform for learning Chinese, how to utilize the big data generated by these platforms to achieve precise and personalized teaching has become a central issue. This study aims to construct a framework for Chinese language learning behavior analysis and management based on big data and interactive mobile devices. Existing research often focuses on static, unidimensional behavior analysis, with insufficient intelligence in adaptive evaluation. To address these limitations, this paper first develops a multidimensional learning behavior trajectory model that deconstructs the learning process from the cognitive, behavioral, and emotional/metacognitive dimensions. It employs lag sequence analysis (LSA) to deeply explore the temporal patterns and learning strategies embedded in the behavioral data, enabling a dynamic and detailed representation of learners' states. Building on this, the paper proposes an adaptive teaching evaluation model, which uses the behavior trajectory features as input and innovatively applies a particle swarm optimization – backpropagation neural network (PSO-BP) hybrid neural network algorithm to solve the problem of mapping complex nonlinear behavior features to optimal teaching decisions. The model ultimately provides a personalized teaching solution that includes knowledge state diagnosis, learning path recommendations, weak point warnings, and content difficulty adjustments. This study offers a comprehensive approach-from theoretical models to technical implementation-to address the "one-size-fits-all" dilemma in mobile Chinese learning and lays a solid foundation for developing the next generation of intelligent adaptive Chinese teaching systems.

KEYWORDS

Chinese language learning, behavior trajectory modeling, adaptive teaching evaluation, big data, lag sequence analysis (LSA), particle swarm optimization-backpropagation neural network (PSO-BP) neural network

1 INTRODUCTION

With the continuous rise of the global "Chinese fever" [1–3] and the deep integration of mobile internet technology [4–6], interactive mobile terminals [7, 8] have

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become the primary platform for learners worldwide to access and learn Chinese. This trend has led to an unprecedented scale and variety of learning behavior data, covering the entire process of interaction, including clicks [9], answering questions [10, 11], writing, etc. This marks a significant step forward as the field of Chinese language teaching enters the "big data era." These data are not simple operation logs but a valuable treasure hidden with cognitive patterns, learning strategies, and emotional states of learners. How to fully mine the value of this big data, originating from real learning scenarios, and transform it into a driving force to deepen the understanding of the learning process and enhance teaching effectiveness has become a critical and challenging frontier issue in the context of the technological empowerment of educational reform.

Although the importance of learning behavior analysis has been widely recognized, existing research still has significant limitations in methodology. First, in terms of learning behavior modeling, most studies, such as those in references [12–14], tend to focus on descriptive statistics or simple clustering of isolated, static behavior indicators, failing to effectively capture the intrinsic temporal dynamics and multidimensional relationships in the behavior data, making it difficult to interpret the complete "learning story" from the "behavior sequence." Second, in adaptive evaluation, many mainstream learning apps' recommendation logic, as pointed out in references [15–18], generally relies on pre-set "if-then" rules or relatively basic algorithms such as collaborative filtering. These methods struggle to handle the complex nonlinear relationships between Chinese language knowledge points and cannot provide dynamic and accurate knowledge state diagnosis and intervention based on real-time behavior trajectories. As a result, their "adaptive" effect often remains superficial, lacking deep insight into and foresight of the evolution of learners' cognitive states.

To address the aforementioned research gaps, the core content of this paper consists of two interrelated parts. The first part is the construction of a multidimensional learning behavior trajectory model. This study will go beyond the shallow analysis of "click streams," defining a data complex that integrates the cognitive, behavioral, and emotional/metacognitive dimensions, and introducing advanced methods such as lag sequence analysis (LSA), aiming to depict a complete, dynamic behavior map of learners from micro-skill acquisition to macro-strategy selection. The second part is the construction of an adaptive teaching evaluation model. This study will design a dynamic evaluation cycle with real-time behavior trajectories as input and personalized teaching decisions as output and innovatively apply the particle swarm optimization-backpropagation neural network (PSO-BP) hybrid neural network algorithm to solve the problem of accurately mapping complex, nonlinear behavior features to optimal teaching strategies. The goal is to realize the automation and intelligence of knowledge state diagnosis, learning path recommendations, weak point warnings, and content difficulty adjustments. The main value of this research lies in proposing a complete methodological framework from "data perception" to "intelligent decision-making," which not only provides a new analytical paradigm for Chinese language learning behavior research but also lays a solid theoretical and technical foundation for developing the next generation of truly intelligent adaptive Chinese language teaching systems.

2 PROBLEM DESCRIPTION

The core issue of the "Chinese language learning behavior trajectory modeling" problem studied in this paper is to break through the limitations of traditional learning analysis, where behavioral data is simply viewed as a collection of isolated events. The aim is to construct a digital portrait that can comprehensively and dynamically reflect learners' cognitive, behavioral, and metacognitive states. In the immersive learning environment created by interactive mobile terminals, each action taken by the learner forms a continuous, context-rich micro-behavior sequence. However, most existing mobile learning apps only perform shallow, descriptive statistics on this data, failing to deeply explore the hidden learning patterns, cognitive rules, and emotional states behind it. Specifically, the problem lies in how to transform vast, heterogeneous, time-sequenced raw data into a structured, pedagogically interpretable multidimensional behavior trajectory model. This model must simultaneously capture the dynamic evolution of learners' knowledge structures in the cognitive dimension, the differences in strategy selection and engagement levels in the behavioral dimension, and the potential impact of non-intellectual factors on the learning process in the emotional/metacognitive dimension. To address this problem, this paper proposes an analytical framework based on multidimensional fusion and sequence pattern mining. First, we perform feature engineering on the raw big data to construct a fusion feature vector that covers cognition, behavior, and emotion. The key step is to introduce the LSA method to deeply process this multidimensional feature sequence. The advantage of LSA is its ability to accurately identify sequence patterns where one learning behavior significantly leads to another after a specific time interval. Through LSA, we can connect discrete behavior points into meaningful "behavior chains," thus achieving the leap from "data statistics" to "behavior trajectory modeling."

After constructing a high-fidelity learning behavior trajectory model, the next step is to perform "adaptive teaching evaluation," which refers to how to dynamically and accurately diagnose learners' knowledge states and learning needs based on this trajectory and automatically generate optimal teaching intervention strategies. Traditional evaluation systems have latency, while the "adaptive" features of existing mobile apps mostly rely on simple rule engines, which cannot handle the complex nonlinear relationships between the vast number of knowledge points in Chinese learning and the individual cognitive psychological differences among learners. Therefore, the essence of the problem is how to design an intelligent evaluation and intervention system that can continuously perceive learner states, simulate the decision-making thinking of excellent teachers, and implement personalized content delivery. The input to this system consists of high-dimensional, continuous, and nonlinear behavior trajectory data, and the output should be accurate knowledge state diagnosis, proactive weak point warnings, and personalized learning path planning. To meet the modeling requirements of this complex nonlinear system, this paper chooses the PSO-BP neural network algorithm as the core processing engine. First, the BP neural network itself has strong nonlinear mapping and pattern recognition capabilities, making it very suitable for learning the complex functional relationships between "multidimensional behavior trajectory features" and "latent knowledge states" or "optimal teaching actions." However, traditional BP neural networks are prone to local optima, and the convergence speed depends on the initial weight settings. To solve this bottleneck, we introduce the PSO algorithm. As an efficient global optimization algorithm, PSO simulates swarm intelligence to parallelly search for optimal initial connection weights and thresholds in the solution space. This process significantly improves the convergence speed and prediction accuracy of the BP network, ensuring that the adaptive evaluation model can start learning from a better starting point, thus generating more stable and reliable teaching decisions.

3 METHOD INTRODUCTION

3.1 Construction of multidimensional learning behavior trajectory model

The basic premise of this study on Chinese language learning behavior trajectory modeling is to acknowledge that learning is a complex process occurring in a multidimensional space, rather than a simple linear progression. Interactive mobile terminals, as the forefront of data collection, provide us with unprecedented, continuous, and fine-grained behavioral observation data. The core principle of constructing the data complex lies in the "educational semantic fusion of multimodal data." It is not simply about stacking different types of data together but about categorizing, abstracting, and labeling the raw low-level data from mobile terminals based on cognitive science, educational psychology, and second language acquisition theory, thus endowing them with clear educational meanings. Specifically:

- Cognitive dimension data construction requires using data association and mapping techniques to link each interaction to a specific Chinese language knowledge point or skill. Reaction time should be differentiated using clustering algorithms into "proficient fast reactions," "hesitant slow reactions," and "hasty guesses," thus transforming the original "correct/incorrect answers + time spent" into semantic indicators of "knowledge point mastery + cognitive processing stability."
- Behavioral dimension data construction focuses on quantifying learning strategies and engagement. For example, "repetition frequency" can indicate the learner's review strategy; "interaction completion" is calculated by comparing sensor data from the terminal with a predefined model, directly reflecting the precision of skill training.
- Emotional/Metacognitive dimension data construction is the most complex. Its principle involves using behavioral proxy indicators and natural language processing for indirect inference. For example, in the "comment section" or "note-taking function," text content can be analyzed for emotional polarity using sentiment analysis models; behaviors such as "quickly skipping videos," "staying on the same screen with no operation for long periods," and "repeatedly answering the same type of question incorrectly" can serve as strong proxy indicators of learning frustration, attention distraction, or learning difficulties.

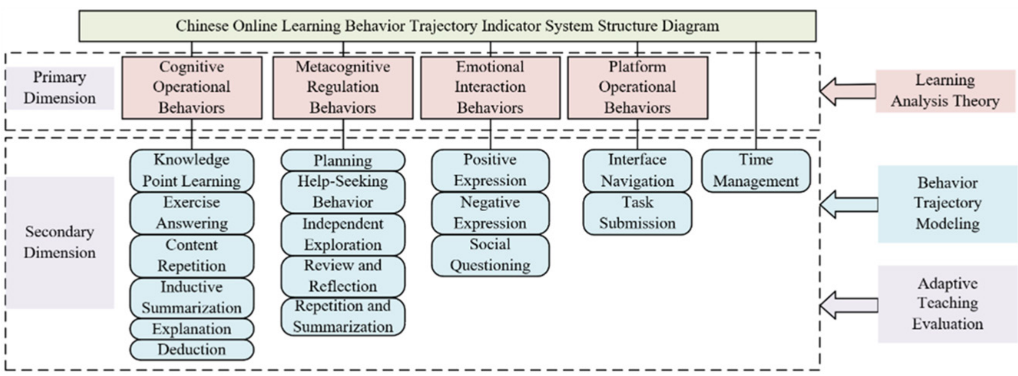

Fig. 1. Chinese online learning behavior trajectory indicator system architecture diagram

Figure 1 shows the architecture diagram of the Chinese online learning behavior trajectory indicator system. After constructing multidimensional data points with educational semantics, the key to trajectory modeling is revealing the dynamic associations and evolutionary patterns between these data points. The core principle is to treat learning as a time-series event, where each learning session generates a sequence composed of behaviors. LSA is a statistical method designed to decode the stable patterns hidden in these sequences. The basic principle of LSA is to identify the conversion patterns between behaviors by calculating the statistically significant frequency of one behavior occurring after another, exceeding random probability. The workflow is as follows:

1. Sequence Encoding and Lag Definition: First, all behaviors of each learner are encoded into a sequence according to the chronological order. Then, the researcher defines a "lag," where Lag=1 typically represents the direct successor behavior.
2. Conversion Frequency Matrix Construction: The frequency of all transitions from behavior A to behavior B in the entire dataset is counted as $O_{A\to B}$, forming a behavior-to-behavior conversion frequency matrix.
3. Significance Test: This is the core of LSA. It checks whether the observed conversion frequency is significant by adjusting for residuals. The calculation is based on the expected frequency of a transition, $E_{A\to B}$, which is typically derived under the null hypothesis of independent sequential behaviors. A common and robust calculation formula is:

$$E_{A\to B} = \frac{O_{A\to *} \times O_{*\to A}}{N} \tag{1}$$

where $O_{A\to *}$ is the total number of occurrences of behavior A, $O_{*\to B}$ is the total number of times behavior B occurs as the successor behavior, and N is the total number of behavior transitions. Then, the Z-score is calculated:

$$z - score = \frac{O_{A\to B} - E_{A\to B}}{\sqrt{E_{A\to B}}} \tag{2}$$

If $Z\_A\to B$ is significantly greater than 1.96 (corresponding to $p < 0.05$), we consider "behavior $A \to$ behavior B" as a statistically significant behavior sequence.

Through LSA, we can elevate low-level behavioral clickstreams into high-level learning strategy maps with clear pedagogical interpretations. This not only describes "what the student did," but also reveals the causal relationships and teaching significance between behaviors through quantified associations. In identifying effective learning paths, LSA can uncover "golden paths" that strongly correlate with high learning outcomes. For example, a significant sequence might be discovered: "watch micro-course (A) $\to$ complete basic exercise (B) $\to$ engage in situational dialogue (C)." Not only do we know that this sequence exists, but we can also evaluate the stability and universality of this path through its conditional probability $P(C|A, B)$ and the overall significance Z-score. This path, representing a complete closed-loop from "input" to "internalization" and then "output," can be recommended as a positive template. In diagnosing ineffective or negative learning patterns, LSA can sharply capture "problem paths" that signal learning difficulties. For example, finding "answering grammar questions incorrectly repeatedly (X) $\to$ quickly skipping the instructional video (Y)" as a significant sequence ($Z\_X \to Y > 1.96$). To more accurately assess its risk, we can further calculate the intensity or importance indicator of the behavior conversion, such as using Lift:

$$Lift(X \to Y) = \frac{P\left(Y \middle| X\right)}{P(Y)} \tag{3}$$

Lift measures how the occurrence of behavior X influences the probability of behavior Y occurring. If $Lift(X \rightarrow Y) >> 1$, it indicates that behavior X greatly increases the likelihood of behavior Y. This is no longer just two isolated events but a clear "cognitive blockage → avoidance of learning" strongly associated behavior trajectory. The system can immediately trigger intervention as soon as this sequence shows signs, thereby breaking this negative chain.

Ultimately, the goal of Chinese language learning behavior trajectory modeling is to provide a dynamic and accurate input source for adaptive teaching evaluation. The output of the trajectory model constructed through LSA and other sequence analysis methods consists of a series of quantified, causally suggestive behavior rules and state transition probabilities. These rules and probabilities form the core feature input for the subsequent adaptive decision-making engine.

3.2 Construction of adaptive teaching evaluation model

The core of the adaptive teaching evaluation model constructed in this paper is to establish an intelligent mapping function from "learning behaviors" to "teaching interventions." Figure 2 shows the theoretical framework of the Chinese adaptive teaching model based on behavior trajectories. The input to the constructed model is a real-time feature vector enriched with educational semantics, which has been processed by the previously mentioned "multidimensional learning behavior trajectory model." This vector is far more than just raw data; it is a highly abstract and structured data complex. Its typical features include: 1) Cognitive state features, such as the mastery probability of several key knowledge points currently being studied, based on the output of a deep knowledge tracking model; 2) Real-time behavior sequence features, such as the encoding of significant behavior patterns currently occurring (e.g., "avoidance of practice" or "deep exploration"), identified through LSA; 3) Emotional and metacognitive features, such as real-time engagement index or frustration index, calculated through behavioral proxy indicators. All of these features are derived from the learner's continuous, multimodal interactive behavior on the mobile terminal, ensuring the real-time and contextual nature of the evaluation.

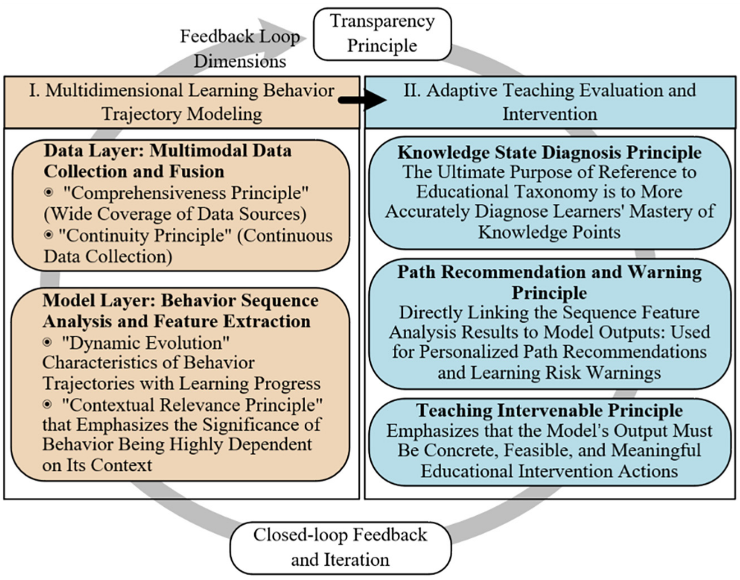

Fig. 2. Theoretical framework of Chinese adaptive teaching model based on behavior trajectories

The output of the model is the corresponding executable personalized teaching decision. This is also a multidimensional vector, mainly including: 1) Personalized knowledge state diagnosis, visualized in a knowledge map form, precisely marking the learner's strengths, weaknesses, and the mastery relationships between various knowledge points; 2) Learning path recommendation, outputting the unique identifier of the next most suitable content or activity to study, realizing "one size does not fit all" content flow; 3) Weak point early warning, when the model predicts that the learner may soon encounter a learning bottleneck or face the risk of giving up, an early warning signal and its reason encoding are output; 4) Content difficulty adjustment, outputting a specific difficulty coefficient to dynamically adjust the complexity of subsequent learning materials. This precise input-output definition transforms the vague teaching evaluation issue into a clear, data-driven nonlinear function approximation problem.

The choice of the PSO-BP neural network as the core processing engine is based on the inherent high-dimensional, nonlinear, and dynamically changing nature of the Chinese adaptive teaching evaluation problem. A pure BP neural network has strong nonlinear mapping capabilities, able to simulate the extremely complex functional relationship between "behavioral features" and "teaching decisions" by learning historical data. Its multilayer perceptron structure is well-suited to handle the associations between the multidimensional input features and the multidimensional output decisions that we have defined. However, traditional BP neural networks use gradient descent for learning, and their performance is highly dependent on the initial weight and threshold settings. Improper initialization can lead to the network getting trapped in local optima rather than global optima, which, in practical applications, means that teaching decisions may not be "optimal strategies" but merely "not the worst strategies," severely affecting the effectiveness of adaptive teaching. In addition, the slow convergence speed of BP networks cannot meet the real-time response requirements of mobile terminals.

Therefore, we introduce the PSO algorithm as a pre-optimizer for the BP neural network. PSO is a swarm intelligence optimization algorithm that simulates the foraging behavior of birds. Its advantage lies in its strong global search capability and resistance to being trapped in local optima. By encoding the weights and thresholds of the BP network as particles in the solution space, the PSO algorithm enables a group of "particles" to search for the optimal initialization points in parallel across the entire space. This "powerful partnership" forms the PSO-BP hybrid algorithm: PSO is responsible for the macro, global "strategic search" to find the optimal initialization region; then, the BP network performs micro, local "tactical adjustments" on this basis to quickly converge to a high-precision solution near the global optimum. This ensures that our adaptive evaluation model starts with a highly optimized foundation, which leads to more stable and accurate teaching decisions.

The workflow of the PSO-BP algorithm is a clear two-stage optimization process, as follows:

First Stage: PSO Global Optimization Initialization

First, particle encoding and population initialization are carried out. All connection weights and neuron thresholds of the BP neural network are encoded as a long vector, and this vector constitutes a "particle" in the solution space. A particle swarm of size N is randomly initialized. Next, the fitness function is evaluated. This is the key coupling between PSO and the specific application. The "quality" of each particle is determined by the performance of the network it represents on the validation dataset. The fitness function F we define is usually a comprehensive measure of teaching effectiveness:

$$F = \alpha \cdot accuracy + \beta \cdot precision + \gamma \cdot complexity \tag{4}$$

where accuracy measures the correctness of knowledge state diagnosis, precision measures the effectiveness of path recommendation, and complexity controls the model scale to ensure real-time performance on mobile terminals. Each particle calculates its fitness value.

Next, particle position and velocity are updated. Each particle updates its status according to its own historical best position and the global historical best position of the swarm, based on PSO's velocity-position update formula, continuously exploring the solution space.

$$v_{id}^{k+1} = \omega v_{id}^{k} + c_1 r_1 \left(p_{id}^{k} - x_{id}^{k} + c_2 r_2 \left(p_{gd}^{k} - x_{id}^{k} \right) \right) \tag{5}$$

$$x_{id}^{k+1} = x_{id}^{k} + v_{id}^{k+1} \tag{6}$$

where v_{id}^{k} and v_{id}^{k+1} represent the current and updated velocity of particle i in the d-dimensional space at iterations k and $k + 1$, respectively. x_{id}^{k} and x_{id}^{k+1} represent the current and updated positions of particle i in the d-dimensional space at iteration k and $k + 1$, respectively. ω is the inertia weight. c_1 and c_2 are acceleration constants. r_1 and r_2 are random numbers. p_{id}^{k} represents the individual best position found by particle i from iteration start to iteration k, and p_{gd}^{k} represents the global best position found by the entire particle swarm from iteration start to iteration k. Through iterations, the particle swarm will gradually converge to the region with the highest fitness, which is the global optimum or approximate optimum initial weight and threshold combination for the BP network.

Second Stage: BP Neural Network Fine-Tuning and Deployment

The network initialization and training begin by assigning the optimal initial weights and thresholds found by PSO to the BP neural network. Then, the network is trained using the full training dataset with standard error backpropagation. Due to the excellent starting point, the BP network can quickly and stably converge to a high-performance state. The trained PSO-BP model is deployed on the server side or directly integrated into the mobile app. When new behavior trajectory data flows in, the model can complete the calculations and output the corresponding personalized teaching evaluation and decision results within milliseconds.

Finally, all the components are integrated into a continuous dynamic evaluation loop to achieve system self-optimization and evolution. The specific process of this loop is as follows:

- **Perception:** The mobile terminal continuously collects the learner's raw interaction data.
- **Modeling:** The data preprocessing and behavior trajectory modeling module processes the data to generate real-time feature vectors, which serve as inputs to the PSO-BP model.
- **Decision:** The PSO-BP model receives the input, performs forward computation, and outputs the four core teaching decisions.
- **Intervention:** The system converts the decision results into specific UI interactions, such as pushing new learning content, adjusting interface difficulty, displaying encouragement messages, or generating learning reports.
- **Feedback and Learning:** The learner's response to the intervention generates new data, which is recorded by the system. This new "behavior-result" pair data is periodically added to the model's training set for triggering incremental learning or periodic retraining of the PSO-BP model.

This closed loop ensures that the system is not a static expert system but an intelligent teaching entity that evolves continuously as user data accumulates. By maximizing the value of behavior trajectories and big data, it truly provides every Chinese language learner with a "personalized growth partner" that adapts to time and material.

4 EXPERIMENT RESULTS AND ANALYSIS

In the learning behavior trajectory analysis based on big data, factual knowledge and conceptual knowledge exhibit distinctly different learning behavior patterns. For factual knowledge, efficient learning trajectories present a close sequence of "multisensory encoding – immediate practice – active management": learners immediate conduct recognition tests after watching animated diagrams that show meaning associations, completing repetition and transcription, and finally adding new words to the review plan. The entire process has short response times and stable transition sequences; whereas inefficient trajectories show a "mechanical testing – repeated mistakes" closed loop, or a "skipping instruction – direct answering – abandoning the task" broken path. In the latter, the sequence "wrong answer → exit" has a Z-value as high as 4.5, which becomes a key indicator of learning frustration. For conceptual knowledge, deep understanding trajectories follow a progressive path of "contextual input – rule induction – comparison and analysis – contextual output." Learners repeatedly view between contextual videos and structural decomposition diagrams and eventually achieve knowledge transfer in dialog tasks. In contrast, rule memorization trajectories, though they complete exercises through "reading formulas – mechanical transformation," exhibit significantly longer response times and higher error rates in situational multiple-choice questions, revealing their failure to establish conceptual understanding at the pragmatic level.

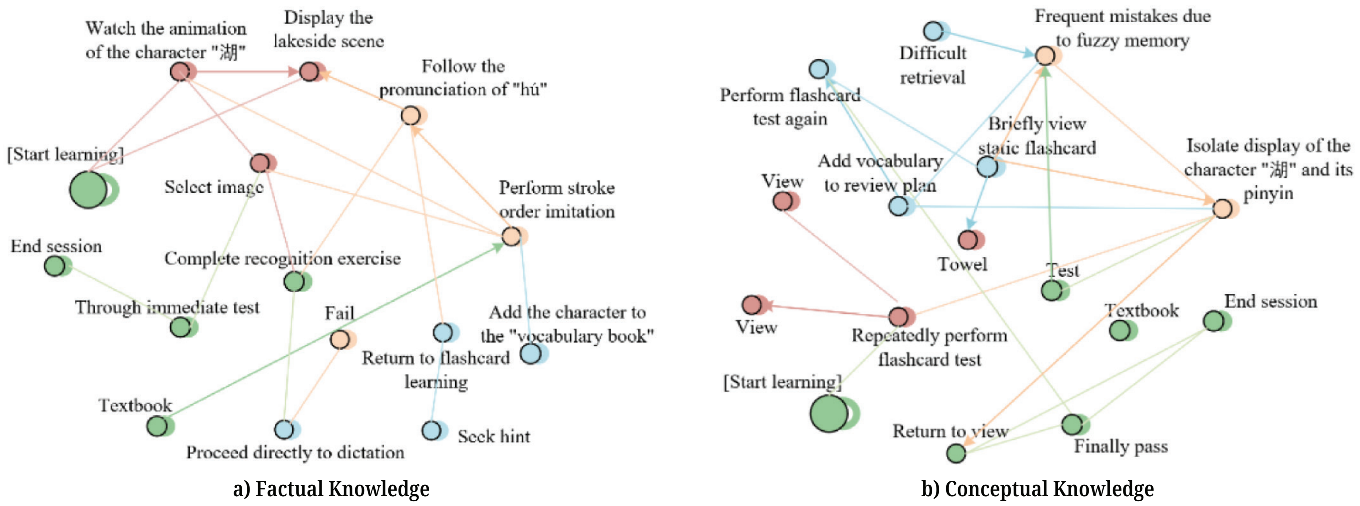

Fig. 3. Comparison of typical learning behavior sequences under different knowledge types

Figure 3 presents the comparison results of typical learning behavior sequence patterns under different knowledge types. Experimental result analysis shows that the behavior trajectory modeling method can effectively reveal differentiated learning patterns across various knowledge types. For factual knowledge, the efficient path with "multisensory encoding – immediate extraction – active management" as its core shows Z-values for key behavior transitions all above 3.0, and learners' unit test pass rates are significantly improved under this path. In contrast, the optimal path for conceptual knowledge appears as a progressive sequence of "contextual immersion – rule induction – comparison and analysis – creative application," where learners' duration in the comparison and analysis step shows a significant positive correlation with the score in the final contextual application task. Most importantly, the model successfully diagnoses typical behavior patterns that lead to learning difficulties: in factual knowledge, the sequence "skip instruction and go directly to testing → continuous mistakes" serves as a key precursor to learning abandonment; in conceptual knowledge, the path "mechanical rule memorization → repeated sentence transformation," while showing high accuracy in mechanical exercises, performs poorly with high error rates and long response times in situational judgment questions, profoundly revealing the cognitive flaw of "knowing what but not why." These clear pattern comparisons not only validate the analytical effectiveness of the behavior trajectory model but also provide direct and reliable decision-making support for subsequent adaptive teaching in accurate path recommendation and weak point early warning.

Table 1. LSA results for key behavior sequences

Behavior Sequence (A → B)	Knowledge Type	Sequence Type	Observation Frequency	Z-Score	Significance ($p < 0.05$)
Watch micro-lecture → Complete specialized exercise	Factual	Efficient Path	1,542	5.82	Yes
Complete specialized exercise → Add new words to review list	Factual	Metacognitive Behavior	893	4.21	Yes
Directly answer → Incorrect answer → Abandon learning	Factual	Difficulty/Abandonment Path	587	6.15	Yes
Watch contextual dialogue → Analyze structure diagram	Conceptual	Inductive Reasoning	1,208	5.11	Yes
Analyze structure diagram → Complete contextual application	Conceptual	Knowledge Transfer	976	4.87	Yes
Memorize grammar rules → Mechanical transformation practice	Conceptual	Mechanical Learning	1,654	7.02	Yes
Mechanical transformation practice → Situational judgment error	Conceptual	Transfer Failure	1,019	5.94	Yes
Incorrect answer → Click for hint	General	Help-Seeking Behavior	1,325	5.33	Yes

To verify the existence of stable and significant sequence patterns in learning behaviors, this study performed LSA on the high-frequency behavior transitions collected. As shown in Table 1, LSA successfully identified several key behavior paths. Among them, sequences 1, 2, 4, and 5 form the "successful paths" related to deep learning, with high Z-values indicating that these behavior transitions are not random but rather represent effective strategies habitually used by learners. Importantly, sequences 3 and 6–7 reveal the typical "problem paths" that lead to failures in factual and conceptual knowledge learning. Specifically, the high Z-value chain of "mechanical learning → transfer failure" clearly outlines the behavior trajectory of learners falling into the "knowing what but not why" dilemma. These significant sequence patterns prove that learning behaviors are not isolated events but follow an internal logical trajectory, and the behavior trajectory model constructed in this study can accurately capture these patterns, providing clear targets for subsequent adaptive interventions.

Table 2. Correlation analysis between learning behavior indicators and final scores (N = 356)

Behavior Indicator	Knowledge Type	Pearson Correlation Coefficient (r)	P-Value
Efficient Path Participation	General	0.72	<0.001
Metacognitive Behavior Frequency	General	0.65	<0.001
Average Response Time	General	–0.58	<0.001
Help-Seeking Behavior Proportion	General	0.31	<0.01
Mechanical Learning Path Participation	Conceptual	–0.69	<0.001
Learning Dropout Rate	General	–0.76	<0.001
Knowledge Transfer Success Rate	Conceptual	0.81	<0.001
Immediate Exercise Accuracy Rate	Factual	0.74	<0.001

Table 3. Comparison analysis of content difficulty adaptive adjustment effect

Evaluation Dimension	Specific Indicator	Experimental Group (Dynamic Adjustment)	Control Group (Fixed Difficulty)	P-Value
Learning Efficiency	Average Mastery Time per Knowledge Point (minutes)	12.3 ± 2.1	16.8 ± 3.5	<0.01
	Average Learning Session Duration (minutes)	25.6 ± 4.2	21.4 ± 5.7	<0.05
Learning Performance	Average Exercise Accuracy (%)	78.5 ± 6.3	65.2 ± 10.1	<0.001
	High-Difficulty Challenge Question Attempt Rate (%)	45.7	28.3	<0.01
	Learning Path and Preset Optimal Path Matching (%)	85.6	60.2	<0.001
Emotional Involvement	Learning Dropout Rate (%)	5.2	15.7	<0.001
	Positive Emotional Behavior Frequency (times/hour)	3.5	1.8	<0.01

To test the predictive power of the identified behavior features on learning outcomes, this study calculated the correlation coefficients between each behavior indicator and final scores. The results in Table 2 strongly demonstrate that learning behaviors are significant predictors of academic performance. The data shows that "Efficient Path Participation" (r = 0.72) and "Metacognitive Behavior Frequency" (r = 0.65) are strongly positively correlated with final scores, indicating that students who use deep strategies and manage their learning effectively tend to perform better. Conversely, "Mechanical Learning Path Participation" (r = –0.69) and "Learning Dropout Rate" (r = –0.76) show a strong negative correlation, particularly revealing the severe harm of rote memorization in conceptual knowledge. Notably, the correlation between "Knowledge Transfer Success Rate" and final scores is the highest (r = 0.81), emphasizing that the ability to apply knowledge to new contexts is the gold standard for measuring conceptual understanding. The robust and interpretable statistical associations between behavior data and scores fully prove that using learning behavior trajectories as the core basis for adaptive teaching evaluation is scientifically and effectively viable. The model can precisely diagnose learning states and predict academic risks by monitoring real-time behaviors.

To verify the rationale and effectiveness of the PSO-BP adaptive teaching evaluation model in dynamically adjusting the difficulty of learning content, this study compared the learning performance of the experimental group and the control group. The purpose of this experiment was to test whether the adaptive model could, such as an excellent teacher, keep the difficulty of learning tasks accurately within the student's "zone of proximal development." As shown in Table 3, the experimental group significantly outperformed the control group in both learning efficiency and performance. The experimental group's "Average Mastery Time per Knowledge Point" was significantly shorter, and the "Average Exercise Accuracy" was significantly higher, indicating that adaptive difficulty adjustment effectively avoids frustration caused by overly difficult content and boredom caused by content being too easy, ensuring that learning stays within an efficient range. Moreover, the experimental group had a higher "High-Difficulty Challenge Question Attempt Rate" and a lower "Learning Dropout Rate," demonstrating that the system significantly enhanced students' confidence and perseverance while maintaining an appropriate level of challenge. Therefore, the content difficulty adaptive adjustment strategy based on the PSO-BP model is reasonable and efficient. It achieves personalized difficulty adaptation through a data-driven approach, significantly improving learning efficiency, effectiveness, and engagement.

To evaluate the timeliness and effectiveness of the system in early identifying learning weaknesses and providing automated interventions, this study tracked the cases that triggered warnings. The results in Table 4 show that the system can rapidly implement warnings and interventions for all types of weaknesses, with an average "intervention response time" at the second level, providing near real-time support. In terms of intervention effectiveness, the success rate for "Knowledge Weakness" interventions is the highest at 88.5%, indicating that behavior sequence-based diagnostics are very accurate, and the remedial content pushed is highly effective. For "Behavioral Weakness," although the success rate is relatively low, the system successfully rescued more than 70% of the learning sessions at risk of abandonment by sending encouragement and adjusting content within seconds, which is crucial for maintaining learning motivation. The adaptive teaching evaluation model developed in this study demonstrates excellent real-time monitoring and intervention capabilities. It can proactively identify learning risks based on behavior trajectory data and mitigate those risks through immediate and precise teaching interventions, significantly reducing the probability of learning failure, fully proving its huge application potential as an intelligent teaching assistant system.

Table 4. Statistical analysis of weakness point early warning and intervention effects

Warning Type	Key Warning Indicators	Intervention Measures After Triggering	Intervention Response Time	Intervention Success Rate (%)	Recurrence Rate of the Same Weakness (%)
Knowledge Weakness	Continuous Errors on the Same Knowledge Point ≥ 3	Push targeted micro-courses and simplified exercises	<30 seconds	88.5	12.3
	Concept Confusion	Push contrast analysis modules and specialized training	<45 seconds	82.1	18.6
Behavioral Weakness	Occurrence of "Give Up Learning" Sequence	Send encouragement messages and recommend interesting review content	<15 seconds	75.4	25.8
	Abnormal Increase in Response Time During Testing	Pop-up prompt asking if help is needed	<10 seconds	70.2	31.5
Process Weakness	Unit Test Score < 60%	Automatically generate and execute personalized review paths	<2 minutes	85.9	15.1

5 CONCLUSION

The core contribution of this study lies in the successful construction of a complete methodological framework from “data perception” to “intelligent decision-making” to address the personalization bottleneck in interactive mobile Chinese language teaching. By introducing a multi-dimensional learning behavior trajectory model, this study breaks away from traditional analyses that rely on static and isolated behavior indicators. For the first time, it dynamically and sequentially depicts the learning process of Chinese language learners from cognitive, behavioral, emotional, and metacognitive perspectives. The research not only uses methods like LSA to reveal the distinctly different efficient and inefficient learning paths for factual and conceptual knowledge but also innovatively applies the PSO-BP neural network hybrid algorithm to build an adaptive teaching evaluation model capable of precise diagnosis and intervention based on real-time behavior trajectories. Experimental results show that the model demonstrates significant advantages in areas such as dynamic content difficulty adjustment, early warning and immediate intervention for learning weaknesses, effectively improving learning efficiency, consolidating learning achievements, and enhancing learner engagement. This fully proves that combining big data-driven learning behavior trajectory modeling with intelligent algorithms can provide a solid technical path and theoretical support for achieving truly personalized teaching.

However, there are certain limitations in this study. First, the breadth and depth of behavior data still have room for expansion. For example, the measurement of emotional dimensions primarily relies on behavioral proxy indicators, and in the future, multi-modal data such as facial expressions and speech tone can be integrated to enhance inference accuracy. Secondly, while the PSO-BP model performs excellently, its real-time computational efficiency and energy consumption on mobile devices still need further optimization to support large-scale concurrent user requests. Additionally, the current model mainly focuses on individual cognitive dimensions for adaptive learning and lacks sufficient support for collaborative learning and social interactive behaviors. Looking ahead, research directions can focus on three aspects: first, exploring multi-modal fusion technologies to construct a more comprehensive and robust learner state perception system; second, developing lighter, more interpretable adaptive algorithms to balance model performance and deployment costs; and third, expanding the research framework to broader subject areas and learning scenarios to verify its universality and build a cross-domain smart education ecosystem.

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