

PAPER

An Intelligent Feedback Mechanism for Mobile English Learning Based on Learning Behavior Analytics

Jingyi Cai()Xuchang Vocational Technical
College, Xuchang, Chinacaijingyi1984@163.com**ABSTRACT**

The rapid proliferation of mobile learning technologies has reshaped English learning contexts, giving rise to fragmented learning patterns and increasing demands for personalization. However, feedback mechanisms in current mobile English learning systems remain overly focused on knowledge error correction, with limited consideration of learners' cognitive processes, thereby constraining learning effectiveness. The deep integration of learning behavior analytics with intelligent feedback is regarded as a promising pathway to address this limitation. This study aims to address a central research question: how can fine-grained learning behavior analytics be leveraged to integrate observable behavioral data with latent metacognitive states in order to construct a pedagogically adaptive and personalized intelligent feedback mechanism for mobile English learning? To this end, a multi-task deep knowledge tracing (DKT) approach incorporating metacognitive assessment was proposed. On this basis, a closed-loop framework integrating data perception, joint modeling, and multidimensional feedback was constructed, with optimization strategies tailored to mobile learning scenarios. Experimental results based on real-world mobile learning data demonstrated that the proposed approach significantly outperformed conventional DKT models in both knowledge tracing accuracy and metacognitive state recognition accuracy. Moreover, the resulting intelligent feedback mechanism effectively enhanced learners' English learning performance and metacognitive abilities. This study extends existing language learning theory through the integration of metacognitive modeling with knowledge tracing, introduces a discipline-adaptive multi-task intelligent feedback modeling paradigm, and provides a practical pathway for the intelligent enhancement of mobile English learning systems.

KEYWORDS

mobile English learning, learning behavior analytics, metacognitive assessment, deep knowledge tracing (DKT), intelligent feedback mechanism, multi-task learning

1 INTRODUCTION

The widespread adoption of mobile terminals and the continuous evolution of mobile Internet technologies have profoundly redefined the temporal and

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spatial boundaries of English learning. As a result, fragmentation and ubiquity have emerged as defining characteristics of contemporary mobile English learning environments [1–3]. In parallel, the deep integration of intelligent technologies—such as artificial intelligence and big data—with the educational domain [4, 5] has reached a global consensus as a critical driver of digital education transformation, thereby offering technological opportunities to address the long-standing limitations of personalization in traditional language education. Despite these advances, substantial deficiencies remain in the feedback mechanisms employed by current mobile English learning platforms. First, feedback content has tended to be highly homogenized, rendering it insufficiently responsive to individual learners' cognitive differences [6, 7]. Second, feedback logic has been predominantly restricted to correctness judgments at the knowledge level, while the underlying cognitive processes and psychological states reflected in learning behaviors have largely been neglected. Third, feedback delivery has shown limited adaptability to fragmented mobile learning contexts, with inadequate lightweight design and insufficient immediacy, thereby constraining its practical effectiveness [8, 9].

Against this backdrop, the introduction of learning behavior analytics and metacognitive theory has been widely recognized as providing essential support for optimizing intelligent feedback mechanisms [10–12]. Learning behavior data encompass not only observable indicators—such as response accuracy and interaction operations—but also latent dimensions, including confidence perception and strategy selection, enabling a more precise characterization of learners' authentic learning states [13, 14]. Moreover, metacognitive interventions have been demonstrated to effectively guide learners' self-monitoring and self-regulation processes, playing a critical role in enhancing learner autonomy and learning effectiveness in language acquisition contexts [15, 16]. The systematic integration of learning behavior analytics and metacognitive modeling therefore establishes a solid foundation for the development of intelligent feedback mechanisms with enhanced pedagogical value in mobile English learning environments.

Building on the foregoing context, four core research questions are addressed in this study: (a) how a multidimensional learning behavior and metacognitive data acquisition system can be constructed to accommodate mobile English learning scenarios; (b) how metacognitive assessment can be integrated with DKT to enable accurate joint modeling of learners' knowledge states and cognitive characteristics in English learning; (c) how a three-dimensional intelligent feedback mechanism—encompassing knowledge error correction, metacognitive guidance, and learning behavior strategy optimization—can be designed based on precise modeling outcomes; and (d) how the effectiveness of the proposed intelligent feedback mechanism in improving English learning performance and metacognitive ability can be empirically validated. In response to these questions, the primary objective of this study is defined as the construction of a behavior-cognition-metacognition integrated intelligent feedback mechanism for mobile English learning. Through this framework, feedback content is intended to be fully personalized, feedback logic is pedagogically grounded, and feedback presentation is contextually adapted, thereby providing learners with comprehensive and multidimensional learning support.

The remainder of this study is organized below. Section 2 elaborates on the core theoretical foundations underpinning the research and establishes the overall research framework. Section 3 designs and implements a multidimensional learning behavior and metacognitive data acquisition system tailored to mobile learning contexts. Section 4 proposes a multi-task DKT model incorporating metacognitive assessment, with detailed descriptions of the model architecture and training optimization procedures. Section 5

constructs a three-dimensional intelligent feedback mechanism based on model outputs and optimizes feedback presentation and delivery strategies for mobile scenarios. Section 6 validates the performance of the proposed model and the effectiveness of the intelligent feedback mechanism through controlled experiments. The final section summarizes the principal findings and conclusions.

2 RESEARCH FRAMEWORK

A closed-loop research framework consisting of data acquisition-joint modeling-feedback generation-effect validation was established in this study. The constituent modules are tightly interconnected and iteratively refined through bidirectional interactions, thereby ensuring the precision, adaptability, and effectiveness of the intelligent feedback mechanism. The data acquisition module is designed to collect multidimensional data aligned with mobile English learning scenarios. Inputs include learners' diverse learning behaviors on mobile platforms as well as metacognition-related information. Through data cleaning and feature engineering procedures, standardized datasets are produced as outputs, providing high-quality data support for subsequent modeling processes. The joint modeling module is driven by a multi-task DKT model incorporating metacognitive assessment. Standardized data generated by the data acquisition module are taken as inputs. Through a multi-task learning architecture, knowledge state tracing and metacognitive trait identification are simultaneously performed. Outputs consist of precise diagnostic results, including learners' knowledge weaknesses, metacognitive state categories, and behavioral strategy tendencies.

The feedback generation module constructs three-dimensional intelligent feedback content based on the diagnostic outcomes of the joint modeling module while optimizing feedback presentation and delivery strategies for mobile learning contexts. Inputs comprise the diagnostic results produced by joint modeling, whereas outputs include personalized feedback targeting knowledge error correction, metacognitive guidance, and learning behavior strategy optimization. Through this process, feedback content is ensured to align closely with learners' needs, and feedback forms are adapted to fragmented mobile learning scenarios. The effect validation module evaluates the effectiveness of the intelligent feedback mechanism through controlled experiments. Data on learning performance, metacognitive ability, and user experience are collected after the deployment of the feedback mechanism. These evaluation data serve as inputs, and empirical conclusions regarding feedback effectiveness are generated as outputs. Issues identified during validation are subsequently fed back into the data acquisition and joint modeling modules, enabling iterative optimization of the overall framework. Within the entire framework, the MetaKD-DKT model serves as the core driving component. Its capability for joint diagnosis of knowledge and metacognition functions as a critical bridge between data acquisition and feedback generation, ensuring that the intelligent feedback mechanism achieves its central objectives of personalization, pedagogical grounding, and contextual adaptation through fine-grained learning behavior analytics.

3 CONSTRUCTION OF THE MOBILE ENGLISH LEARNING BEHAVIOR AND METACOGNITIVE DATA SYSTEM

Data acquisition is designed with the primary objective of supporting the joint assessment of knowledge states and metacognition. The construction of the data

system adheres to three core principles—multidimensionality, quantifiability, and contextual adaptability—to ensure that learners’ learning states and cognitive traits can be comprehensively and accurately characterized. The data system encompasses three categories of core data. Basic profile data, including learners’ age, English proficiency level, and learning goals, are collected to provide a foundational basis for subsequent personalization. Observable learning behavior data comprise response sequences, mobile interaction behaviors, fragmented learning characteristics, and device-assisted behaviors. Specifically, response sequences include item identifiers, correctness, and response time; mobile interaction behaviors involve touch duration, swipe frequency, and mis-touch rollback actions; fragmented learning characteristics cover learning time slots, session duration, and interruption frequency; and device-assisted behaviors include voice reading and dictionary usage. Metacognitive data consist of response confidence, problem-solving traces, and post-task reflective behaviors. Response confidence is categorized into four levels—guessing, uncertain, relatively certain, and highly certain. Problem-solving traces include hint viewing and option switching, whereas post-task reflective behaviors encompass incorrect-item marking, note taking, and willingness to reattempt practice.

Data acquisition is implemented through a combination of automated logging and supplementary survey-based collection. The primary acquisition tool is an event-logging plug-in developed using the Flutter framework and embedded within the mobile English learning application. This plug-in enables real-time and automated collection of observable learning behavior data, thereby ensuring objectivity and temporal accuracy. For metacognitive information that is difficult to capture automatically, supplementary online questionnaires are employed to enhance the completeness of metacognitive data. Data storage adopts a hybrid strategy integrating local caching and cloud synchronization. SQLite is used to support temporary local data caching, while cloud synchronization is implemented through Alibaba Cloud Object Storage Service (OSS). This design effectively mitigates data loss risks caused by unstable mobile network conditions and ensures the integrity and security of the collected data.

4 DESIGN OF THE META-KD-DKT MODEL INCORPORATING METACOGNITIVE ASSESSMENT

The MetaKD-DKT model is designed around the dual core objectives of knowledge tracing and metacognitive assessment, thereby overcoming the limitation of conventional knowledge tracing models that focus exclusively on knowledge states. This design is grounded in the intrinsic association between learning behaviors and metacognition. By simultaneously capturing learners’ levels of knowledge mastery and metacognitive characteristics, a comprehensive and precise diagnosis of learner states is achieved. A multitask learning architecture is adopted, in which collaborative training of the primary and auxiliary tasks enables the model to acquire discriminative metacognitive features while learning the core capability of knowledge tracing. As a result, model generalization performance and diagnostic accuracy are effectively enhanced, providing high-precision data support for the subsequent construction of a three-dimensional intelligent feedback mechanism. The overall architecture of the MetaKD-DKT model incorporating metacognitive assessment is illustrated in Figure 1.

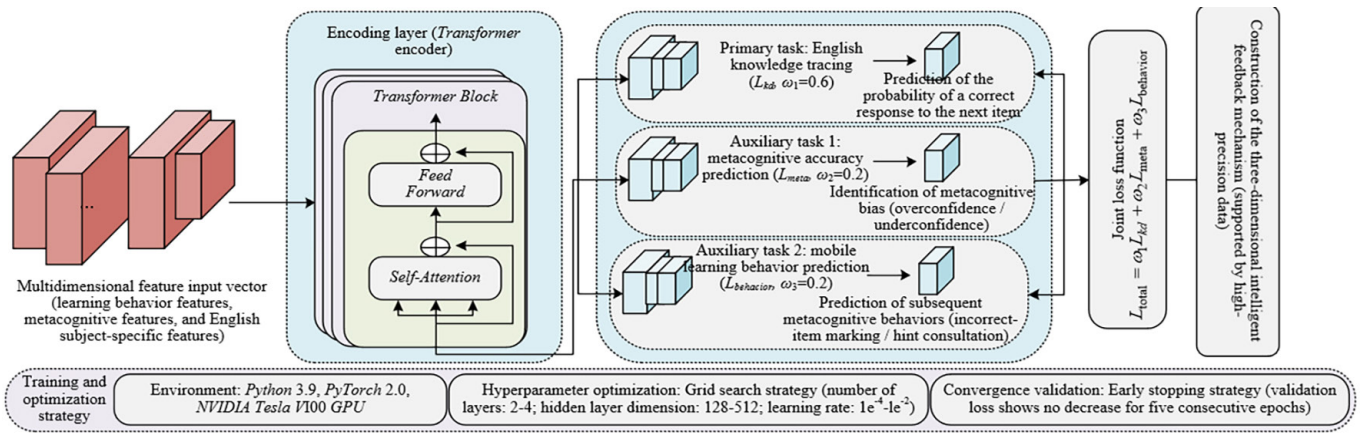


Fig. 1. Architecture of the MetaKD-DKT model incorporating metacognitive assessment

The model architecture consists of an encoding layer and a multi-task learning layer, enabling multidimensional feature fusion and multi-objective joint optimization. The encoding layer employs a Transformer encoder, whose self-attention mechanism is more effective than traditional structures based on long short-term memory (LSTM) in capturing long-range dependencies in sequential learning behaviors. Inputs are provided in the form of multidimensional vectors integrating learning behavior features, metacognitive features, and English subject-specific features. After encoding, historical state representations embedding comprehensive information are generated. The multi-task learning layer comprises one primary task and two auxiliary tasks. The primary task is English knowledge tracing, with the objective of predicting the probability of a learner’s correct response to the next item, thereby enabling precise identification of knowledge weaknesses. Auxiliary Task 1 focuses on metacognitive accuracy prediction, in which metacognitive biases—such as overconfidence or underconfidence—are identified by evaluating the alignment between learners’ confidence levels and their actual knowledge mastery. Auxiliary Task 2 targets mobile learning behavior prediction, with emphasis placed on anticipating learners’ subsequent metacognitive behaviors, including incorrect-item marking and hint consultation. To balance training priorities across tasks, a weighted loss function is adopted, which is defined as:

$$L_{total} = \omega_1 L_{kd} + \omega_2 L_{meta} + \omega_3 L_{behavior} \tag{1}$$

where, L_{kd} denotes the loss associated with the knowledge tracing task, with $\omega_1 = 0.6$. The term L_{meta} represents the loss for metacognitive accuracy prediction, whereas $L_{behavior}$ corresponds to the loss for mobile learning behavior prediction, with $\omega_2 = \omega_3 = 0.2$.

Model training was implemented using Python 3.9 and the PyTorch 2.0 framework. Parallel acceleration was achieved with an NVIDIA Tesla V100 GPU, thereby ensuring computational efficiency during training. Hyperparameter optimization was conducted via a grid search strategy, with primary attention devoted to key parameters of the Transformer encoder. The search space included 2–4 encoder layers, hidden layer dimensions ranging from 128 to 512, and learning rates spanning from $1e^{-4}$ to $1e^{-2}$. Optimal hyperparameter configurations were selected through exhaustive traversal of parameter combinations in conjunction with validation set performance. Model convergence was assessed by continuous monitoring of the validation loss curve. When no decrease in validation loss was observed for five

consecutive epochs, an early stopping strategy was triggered to terminate training. This procedure can effectively mitigate the risk of overfitting and ensure robust generalization performance on unseen data.

5 CONSTRUCTION OF A THREE-DIMENSIONAL INTELLIGENT FEEDBACK MECHANISM FOR MOBILE ENGLISH LEARNING BASED ON METAKD-DKT

The design of the three-dimensional intelligent feedback mechanism is guided by three core principles: pedagogical adaptability, personalization, and contextual adaptability. These principles are intended to ensure the educational value, precision, and practical usability of the feedback. Under the principle of pedagogical adaptability, feedback content is required to closely align with the instructional logic of English language education and to focus on the core objectives of language knowledge construction and learning ability development. Consequently, feedback is designed not only to perform error correction but also to provide instructional guidance. The principle of personalization is grounded in the diagnostic outputs of the MetaKD-DKT model. Differentiated feedback content is generated based on learners' identified knowledge weaknesses and metacognitive characteristics, thereby avoiding homogenized feedback delivery. The principle of contextual adaptability emphasizes the fragmented nature of mobile learning scenarios. Accordingly, lightweight and multimodal feedback forms are adopted to balance informational completeness with contextual convenience, ultimately enhancing feedback reception efficiency and learners' willingness to apply the feedback.

The generation of three-dimensional feedback content is driven by the high-precision diagnostic results produced by the MetaKD-DKT model. Through a quantitative matching mechanism, diagnostic features are accurately mapped to feedback content, forming three mutually coordinated feedback dimensions: knowledge-level feedback, metacognitive feedback, and learning behavior strategy feedback. To quantify the degree of correspondence between model diagnostic results and feedback templates, a feedback matching score model is introduced and defined as follows:

$$S_f = \sum_{i=1}^n \omega_i \cdot \text{sim}(F_i, T_i) \quad (2)$$

where, S_f denotes the feedback matching score. The term F_i represents the i -th category of diagnostic features output by the MetaKD-DKT model, such as identified knowledge weaknesses, types of metacognitive bias, and behavioral tendencies. The term T_i corresponds to the feature representation of the feedback template in the same dimension. The function $\text{sim}(\)$ denotes the cosine similarity, which is used to compute the degree of correspondence between features. The weight ω_i reflects the relative importance of the i -th diagnostic feature, satisfying $\sum_{i=1}^n \omega_i = 1$. Weight allocation is determined using the analytic hierarchy process (AHP) based on the contribution of each feature to learning improvement.

At the knowledge level, feedback is centered on the knowledge weaknesses predicted by the model. Optimal knowledge correction templates are selected according to the feedback matching score, and targeted feedback content is delivered to directly remediate language knowledge gaps. At the metacognitive level, which constitutes

the core innovation of the proposed mechanism, feedback is generated based on the model's metacognitive accuracy assessment. For distinct bias patterns, such as overconfidence and underconfidence, targeted guidance templates are selected through matching score computation. Specifically, overconfidence patterns are addressed by templates emphasizing checking habits and self-verification strategies, whereas underconfidence patterns are matched with positive reinforcement-oriented templates. At the behavioral strategy level, feedback is driven by the model's mobile learning behavior predictions. Strategy templates suited to English learning contexts are selected via matching score evaluation, and content such as efficient answering strategies for long reading passages and fragmented vocabulary memorization techniques is delivered.

To accommodate fragmented mobile learning scenarios, targeted optimizations are implemented with respect to both feedback presentation format and delivery timing. For presentation, a hybrid approach combining pop-up notifications and message center archiving is adopted to support immediate alerts as well as subsequent review. Knowledge-level feedback is presented in the form of text accompanied by micro-lesson thumbnails, balancing informational brevity with opportunities for deeper exploration. Metacognitive feedback is delivered through a dual-modality design integrating audio and text, thereby accommodating contexts such as commuting in which reading is inconvenient. Behavioral strategy feedback is displayed using step-by-step graphical and textual representations to reduce cognitive load and lower the threshold for strategy adoption. Feedback delivery timing is dynamically adjusted based on learners' fragmented learning patterns. To this end, a learning time-slot effectiveness evaluation index is introduced and defined as follows:

$$E_t = \frac{T_{focus}}{T_{total}} \cdot \alpha + \frac{1}{1 + \exp(-\beta T_{total})} \quad (3)$$

where, E_t denotes the learning time-slot effectiveness score, T_{focus} represents focused learning duration, and T_{total} denotes the total duration of a single learning session. The parameter α corresponds to the focus weight, whereas β represents the duration decay coefficient. When $E_t < \theta$, the learning session is classified as short-duration fragmented learning, and concise, highly distilled core prompts are delivered, where θ denotes a predefined threshold. When $E_t \geq \theta$, the session is identified as a complete learning time slot, and in-depth feedback incorporating principle explanations and practice recommendations is delivered, thereby ensuring alignment between feedback depth and learning context.

The intelligent feedback mechanism is implemented through an end-cloud collaborative architecture, enabling full-process closed-loop operation while balancing the lightweight constraints of mobile terminals with the computational demands of model inference. To quantitatively evaluate the system's real-time performance, the total feedback latency is defined as:

$$D_{total} = D_{upload} + D_{infer} + D_{push} \quad (4)$$

where, D_{total} denotes the overall feedback latency, D_{upload} represents the latency associated with data transmission from the mobile device to the cloud, D_{infer} denotes the latency incurred by cloud-based MetaKD-DKT model inference and feedback generation, and D_{push} corresponds to the latency involved in delivering feedback from the cloud to the mobile terminal. This formulation enables quantitative assessment of system responsiveness and provides guidance for optimizing end-cloud interaction parameters.

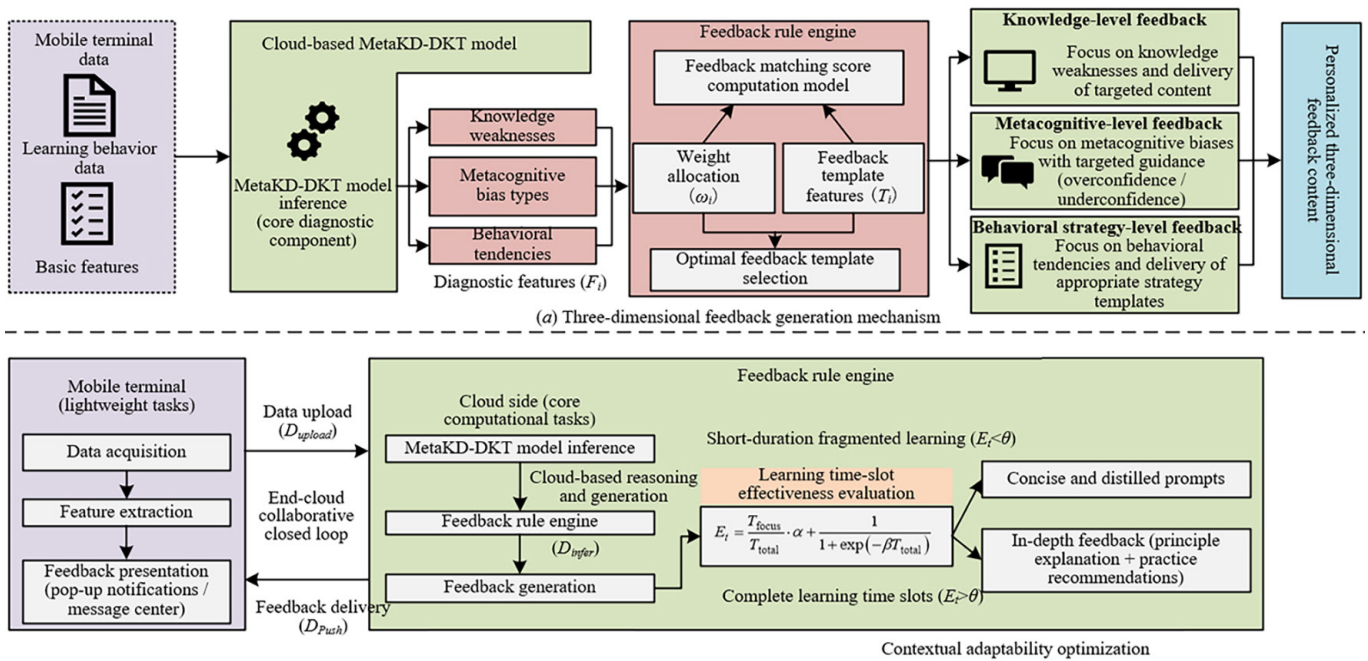


Fig. 2. Principle of the three-dimensional intelligent feedback mechanism for mobile English learning

The mobile terminal is responsible for lightweight tasks, including the real-time acquisition of learning behavior data, preliminary extraction of basic features, and terminal-level presentation of feedback content. Through localized lightweight processing, network transmission load and energy consumption are effectively reduced. The cloud side is tasked with core computational tasks. The MetaKD-DKT model is deployed to perform inference-based diagnostics, and the feedback rule engine is executed to generate personalized feedback content. Cloud computing resources are leveraged to ensure the efficiency of both model inference and feedback generation. The overall interaction process forms a closed loop consisting of data upload, cloud-based inference, feedback generation, and real-time delivery, thereby ensuring both the timeliness and precision of feedback. The operational principle of the three-dimensional intelligent feedback mechanism for mobile English learning is illustrated in Figure 2.

6 EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

6.1 Experimental objectives and hypotheses

The core objectives of the experiments are twofold. First, the superiority of the MetaKD-DKT model incorporating metacognitive assessment is evaluated with respect to knowledge tracing accuracy and metacognitive state identification. Second, the effectiveness of the three-dimensional intelligent feedback mechanism constructed on the basis of the MetaKD-DKT model is examined in terms of its ability to enhance mobile English learning outcomes and learners’ metacognitive ability. In accordance with these objectives, the following experimental hypotheses were formulated:

H1: The MetaKD-DKT model achieves significantly higher knowledge tracing accuracy than the conventional DKT model and single-task DKT models.

- H2: Learners' metacognitive states can be accurately identified by the MetaKD-DKT model, with metacognitive accuracy prediction performance superior to that of the comparison models.
- H3: The three-dimensional intelligent feedback mechanism based on MetaKD-DKT leads to significantly greater improvements in English learning performance and metacognitive ability than the traditional "answer-feedback" mechanism focused solely on response correctness.

6.2 Experimental variables and design

A controlled experimental design was adopted, in which the variable structure and implementation procedure were explicitly specified. The independent variable was the type of intelligent feedback mechanism, defined at two levels: the experimental group was provided with the three-dimensional intelligent feedback mechanism based on MetaKD-DKT, whereas the control group was provided with a traditional correctness-based "answer-feedback" mechanism. The dependent variables comprised four categories of core indicators: knowledge mastery, metacognitive ability, learning behavior characteristics, and user experience. The experimental participants consisted of 200 active users of a mobile English learning application, covering three proficiency levels (beginner, intermediate, and advanced). Participants were randomly assigned to an experimental group ($n = 100$) and a control group ($n = 100$). No statistically significant differences were observed between the two groups with respect to age distribution, baseline English proficiency, or average learning duration, thereby ensuring intergroup comparability. The experimental period spanned two months and was divided into three phases. During the pretest phase (Week 1), baseline data for both groups were collected through standardized tests and questionnaires. During the intervention phase (Weeks 2–7), identical learning content was used by both groups, while different feedback mechanisms were applied during routine learning activities. During the posttest phase (Week 8), outcome evaluation was conducted using tests and questionnaires that are parallel to those administered during the pretest phase.

6.3 Experimental results and analysis

Model performance comparison results. Table 1 reports the performance differences between the MetaKD-DKT model and the comparison models. The results indicate that the knowledge tracing accuracy of MetaKD-DKT reaches 86.3%, which is substantially higher than that of the conventional DKT model (78.5%) and the single-task DKT model (81.2%). In terms of prediction error, the MetaKD-DKT model achieves an RMSE of 0.182, which is lower than the corresponding values observed for the comparison models (0.235 and 0.207, respectively). These findings demonstrate that knowledge state prediction is performed with greater precision and reduced error by the proposed model. With respect to metacognitive accuracy prediction, the MetaKD-DKT model attains an F1-score of 83.7%, markedly exceeding that of the conventional DKT model (62.1%) and the single-task DKT model (69.5%). This result confirms that metacognitive states and their alignment with knowledge mastery are effectively captured by the MetaKD-DKT model. The observed performance differences were further validated through one-way analysis of variance (ANOVA), yielding a statistically significant effect ($F = 28.63$, $p < 0.001$). Post hoc multiple comparisons indicate that the performance differences between MetaKD-DKT

and each comparison model are statistically significant, thereby providing empirical support for Hypotheses H1 and H2.

Table 1. Performance comparison of different models

Model	Knowledge Tracing Accuracy (%)	RMSE	Metacognitive Accuracy Prediction F1 (%)
Conventional DKT	78.5 ± 3.2	0.235 ± 0.021	62.1 ± 4.5
Single-task DKT	81.2 ± 2.8	0.207 ± 0.018	69.5 ± 3.8
MetaKD-DKT	86.3 ± 2.1	0.182 ± 0.015	83.7 ± 3.1

Learning outcome comparison results. Table 2 presents a comparison of English learning outcomes between the experimental group and the control group. During the pretest phase, no statistically significant differences are observed between the two groups across the vocabulary, grammar, reading, and listening modules ($p > 0.05$), indicating comparable baseline performance. During the posttest phase, accuracies in the experimental group increase to 82.4%, 79.6%, 77.3%, and 75.8% for vocabulary, grammar, reading, and listening, respectively, corresponding to improvement gains ranging from 15.2% to 18.7%. By contrast, posttest accuracies in the control group increase to 72.3%, 68.9%, 65.7%, and 64.2%, with improvement gains limited to 6.8%–9.3%. In addition, the correctness rate for reattempted incorrect items reaches 89.2% in the experimental group, which is substantially higher than that observed in the control group (73.5%). Independent-samples t-tests indicate that the between-group differences in posttest accuracies and improvement gains across all modules are statistically significant ($t = 4.28$ – 6.35 , $p < 0.001$). These results demonstrate that the three-dimensional intelligent feedback mechanism yields a significant enhancement in English learning outcomes, thereby providing empirical support for Hypothesis H3.

Table 2. Comparison of learning outcomes between the experimental and control groups

Indicator	Experimental Group (pretest)	Experimental Group (posttest)	Improvement (%)	Control Group (pretest)	Control Group (posttest)	Improvement (%)
Vocabulary module accuracy (%)	64.2 ± 5.3	82.4 ± 4.1	18.2	63.8 ± 5.5	72.3 ± 4.8	8.5
Grammar module accuracy (%)	62.1 ± 5.7	79.6 ± 4.5	17.5	61.9 ± 5.9	68.9 ± 5.2	7.0
Reading module accuracy (%)	60.5 ± 6.1	77.3 ± 4.9	16.8	60.2 ± 6.3	65.7 ± 5.6	5.5
Listening module accuracy (%)	59.3 ± 6.4	75.8 ± 5.2	16.5	58.9 ± 6.6	64.2 ± 5.9	5.3
Reattempted incorrect-item accuracy (%)	65.7 ± 5.8	89.2 ± 4.3	23.5	64.9 ± 6.0	73.5 ± 5.1	8.6

Metacognitive and behavioral improvement results. Table 3 summarizes changes in metacognitive ability and learning behaviors for both groups. Following the intervention, the alignment between confidence level and response accuracy in the experimental group increases to 84.6%, representing a gain of 21.3% relative to

the pretest. The occurrence rate of proactive reflective behaviors rises from 32.5% to 68.3%, while the adoption rate of recommended learning strategies reaches 72.5%. Concurrently, the average number of learning interruptions decreases from 2.8 times per week to 1.1 times per week. In the control group, modest improvements are observed across several indicators; however, all gains remain below 10%, and no statistically significant change is detected in the frequency of learning interruptions. Paired-samples t-tests indicate that pre- and post-test differences for all indicators in the experimental group are statistically significant ($t = 5.12\text{--}7.43$, $p < 0.001$). In contrast, only marginal improvements in confidence-accuracy alignment and reflective behavior occurrence are observed in the control group ($p < 0.05$). These findings demonstrate that the three-dimensional intelligent feedback mechanism effectively enhances learners' metacognitive regulation and promotes the formation of more scientifically grounded learning behavior patterns, thereby providing further empirical support for Hypothesis H3.

Table 3. Comparison of metacognitive and behavioral indicators between the experimental and control groups

Indicator	Experimental Group (pre-Test)	Experimental Group (post-Test)	Control Group (pre-Test)	Control Group (post-Test)
Confidence-accuracy alignment (%)	63.3 ± 6.2	84.6 ± 4.5	62.8 ± 6.4	69.5 ± 5.8
Proactive reflective behavior occurrence (%)	32.5 ± 7.1	68.3 ± 6.3	31.9 ± 7.3	38.6 ± 6.9
Recommended strategy adoption rate (%)	–	72.5 ± 5.7	–	23.8 ± 6.2
Average learning interruptions (times/week)	2.8 ± 0.9	1.1 ± 0.6	2.7 ± 1.0	2.5 ± 0.8

To examine whether the three-dimensional intelligent feedback mechanism promotes the coordinated development of cognition and metacognition—a core criterion for evaluating the pedagogical adaptability of the mechanism—the individual-level association between metacognitive accuracy and knowledge mastery was analyzed at the posttest stage. As illustrated in Figure 3, data points from the experimental group are densely clustered around the fitted regression line, exhibiting a strong positive correlation ($r = 0.78$, $p < 0.001$). This pattern indicates that higher levels of knowledge mastery are accompanied by greater accuracy in learners' judgments of their own cognitive states. By contrast, data points from the control group display substantially greater dispersion and demonstrate only a weak positive correlation ($r = 0.42$, $p < 0.01$), suggesting that improvements in knowledge mastery are not accompanied by commensurate gains in metacognitive regulation. These findings confirm that the three-dimensional intelligent feedback mechanism based on MetaKD-DKT not only enhances knowledge mastery among mobile English learners but also facilitates the synergistic development of cognitive performance and self-regulatory capability through the metacognitive guidance module. In comparison, the traditional correctness-based “answer-feedback” mechanism is shown to yield limited gains at the knowledge level and fails to achieve synchronized optimization of cognition and metacognition, thereby underscoring the educational value of the proposed feedback mechanism in mobile English learning contexts.

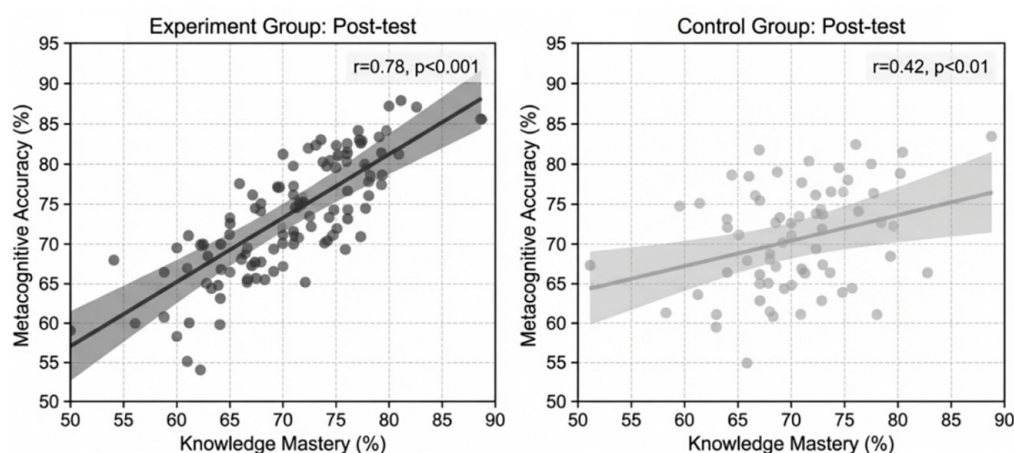


Fig. 3. Scatter plot of the correlation between metacognitive accuracy and knowledge mastery

User experience analysis results. Table 4 presents the user experience scores for both groups, together with the results of the reliability and validity analyses of the measurement scales. The experimental group achieves a mean score of 4.23 for application usage satisfaction and 4.31 for perceived feedback usefulness, both of which are significantly higher than the corresponding scores observed in the control group (3.15 and 2.98, respectively). Independent-samples t-tests confirm that these differences are statistically significant ($t = 8.62, 9.35; p < 0.001$). According to the reliability and validity analyses, the Cronbach’s α coefficients for the satisfaction scale and the feedback usefulness scale are 0.86 and 0.88, respectively, exceeding the commonly accepted threshold of 0.80 and indicating good internal consistency. Construct validity is verified through confirmatory factor analysis, yielding a goodness-of-fit index (GFI) of 0.92 and a root mean square error of approximation (RMSEA) of 0.06, which satisfy established psychometric criteria. These results confirm that the presentation format and delivery timing of the three-dimensional intelligent feedback mechanism are well adapted to fragmented mobile learning contexts and are effective in enhancing users’ learning experience.

Table 4. Comparison of user experience between the experimental and control groups and reliability analysis

Indicator	Experimental Group (mean ± SD)	Control Group (mean ± SD)	Cronbach’s α
Application usage satisfaction	4.23 ± 0.52	3.15 ± 0.68	0.86
Perceived feedback usefulness	4.31 ± 0.48	2.98 ± 0.72	0.88

Figure 4 provides an intuitive illustration of performance differences and trend variations among the three models across learners with different English proficiency levels, thereby validating the generality and stratified adaptability of the MetaKD-DKT model. Overall, performance improvements are observed for all three models as learners’ English proficiency increases. However, the MetaKD-DKT model consistently outperforms both the conventional DKT and the single-task DKT across all proficiency groups, with the most pronounced advantage observed in the beginner group, highlighting its strong adaptive value for learners with weaker foundational knowledge. With respect to knowledge tracing accuracy, the MetaKD-DKT model

maintains the highest performance across beginner, intermediate, and advanced groups, with the largest performance gap relative to the comparison models occurring in the beginner group. An inverse trend is observed for RMSE, where the MetaKD-DKT model achieves the lowest values across all proficiency levels, with errors decreasing steadily as proficiency increases. This pattern indicates superior predictive precision of learners' knowledge states across varying baseline levels. In terms of metacognitive accuracy, the MetaKD-DKT model again demonstrates leading performance across all proficiency groups. Notably, the performance gains over the conventional DKT and single-task DKT are most substantial in the beginner group, confirming the model's effectiveness in capturing metacognitive state differences among learners with diverse proficiency levels. Statistical testing further indicates that performance differences among the three models are statistically significant across all proficiency groups ($p < 0.001$).

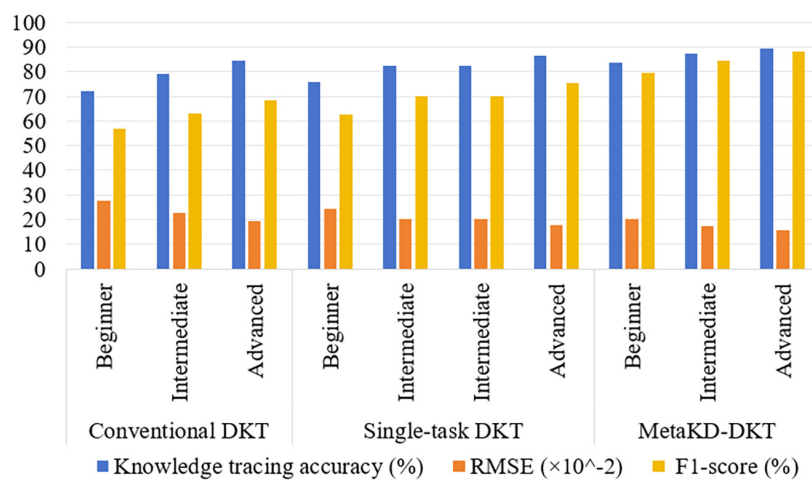


Fig. 4. Stratified comparison of model performance across English proficiency levels

7 CONCLUSION

In this study, the optimization of the intelligent feedback mechanism for mobile English learning was systematically investigated through the integration of learning behavior analytics and metacognitive assessment. The principal findings and core contributions are summarized as follows:

The key findings demonstrate that the MetaKD-DKT model incorporating metacognitive assessment substantially enhances the precision of English learning state diagnosis. Knowledge tracing accuracy reaches 86.3%, while the F1-score for metacognitive accuracy prediction attains 83.7%, both of which significantly exceeded the performance of conventional DKT models and single-task variants, enabling coordinated and accurate modeling of knowledge states and metacognitive characteristics. The three-dimensional intelligent feedback mechanism constructed on the basis of this model exhibits strong practical effectiveness. Experimental results confirm that accuracy across English learning modules is improved by 15.2%–18.7%, metacognitive accuracy alignment is increased by 21.3%, proactive reflective behavior occurrence and strategy adoption rates are significantly enhanced, learning interruption frequency is reduced, and user experience ratings are markedly superior to those associated with traditional feedback mechanisms.

The core innovations of this study are reflected in three dimensions. First, a multidimensional learning behavior and metacognitive data system tailored to mobile learning contexts is established, integrating observable behaviors, mobile interaction features, and latent metacognitive data, thereby providing high-quality data support for precise diagnosis. Second, a multi-task DKT model incorporating metacognitive assessment is proposed. Through the use of transformer-based encoding and a weighted loss function, coordinated optimization of knowledge tracing and metacognitive assessment is achieved, overcoming the limitations of traditional models constrained to a single cognitive dimension. Third, a three-dimensional intelligent feedback mechanism integrating knowledge, metacognition, and behavioral strategy is designed. By combining an end-cloud collaborative architecture with context-adaptive optimization strategies, feedback personalization, pedagogical grounding, and contextual adaptability are simultaneously realized, addressing a critical research gap in cognitive regulation and behavioral guidance within mobile English learning feedback systems.

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9 AUTHOR

Jingyi Cai graduated from Henan Normal University with a Master’s degree and is currently employed at the School of International Education, Xuchang Vocational and Technical College, focusing on research in the field of English (E-mail: caijingyi1984@163.com).