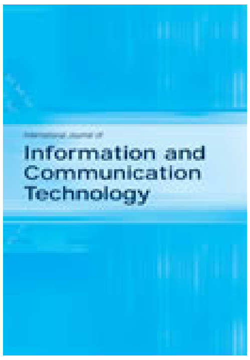

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Construction of an adaptive model for English learning tasks based on cognitive diagnosis in a smart classroom

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Abstract: Accurate instruction has become the main need with the development of smart classrooms. Although cognitive diagnostic tests can show students' cognitive status, it is primarily applied for static assessment, which is challenging to satisfy the dynamic adaptation requirements of English learning activities. This work, therefore, concentrates on the smart classroom scenario and builds a cognitive diagnosis-based adaptive model for English learning activities (CD-ELAM). The model realises the exact identification of students' cognitive state and the dynamic optimisation of task pushing by combining four modules: cognitive state modelling, task feature expression, task regulating mechanism and personalised learning strategies, so forming a closed-loop task adaptation mechanism. In terms of cognitive diagnosis accuracy and learning effect improvement, the experimental results reveal that CD-ELAM beats the current approaches; moreover, it has good adaptability and practicality.

Keywords: smart classroom; cognitive diagnosis; adaptive learning; English learning tasks.

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1 Introduction

1.1 Background and significance of the study

From the conventional classroom to the smart classroom, the area of education has changed dramatically in recent years with the fast advancement of innovative technologies including artificial intelligence, the Internet of Things, and learning analytics. The smart classroom has changed teachers' approaches and students' learning paths by including data perception, real-time feedback and tailored services into a teaching environment (Meylani, 2024). In English teaching, how to construct and dynamically modify assignments depending on learners' real ability and states has become a crucial focus of smart education research.

The present English classroom usually suffers from lack of pertinence in task design, difficulty in effectively covering students' ability differences, and unbalanced distribution of learning resources, which results in a disconnect between the teaching content and the actual cognitive level of the students, so influencing the optimisation of the teaching effect. The conventional integrated teaching approach limits the development of teaching accuracy to a certain degree by making it difficult to precisely identify students' mastery of various knowledge points and to dynamically change the type and difficulty of tasks in real time depending on students' individual differences (Ateş, 2025).

Cognitive diagnostic offers theoretical and practical help for addressing the foregoing issues by means of a technique of mining students' knowledge status and ability structure depending on their behavioural data. By means of fine-grained studies of the competency characteristics displayed by students in certain learning activities, it can determine their mastery status on several knowledge domains (Qi et al., 2024). Including cognitive diagnostics into the smart classroom not only helps to dynamically monitor students' learning process but also offers a foundation for intelligent matching and pushing of teaching responsibilities.

Aiming to build a cognitive diagnosis-driven task adaptive model, CD-ELAM, which dynamically adjusts the content, difficulty, and sequence of English tasks based on students' cognitive characteristics and learning feedback, this paper focuses on the design of English learning tasks in a smart classroom environment, so improving learning efficiency and motivation. Simultaneously, CD-ELAM may also give teachers real-time data assistance on the changes in students' cognitive structure, so helping them to create scientific teaching plans and promote the intelligent transformation of classroom management. This work has good practical relevance for enhancing the quality of English instruction and advancing the building of intelligent education system in addition to certain theoretical exploration value.

1.2 Objectives and methodology of the study

Examining how to reach dynamic matching of learning activities depending on students' cognitive traits has become a focus of education informatisation research in the framework of the ongoing development of the intelligent education environment. Particularly in English instruction, the conventional set task path and uniform teaching rhythm cannot presently satisfy the learning needs of many students due to the great variations in learners' language skills, knowledge mastery and thinking processes. To increase the accuracy and flexibility of teaching, an intelligent model that can recognise students' cognitive state and modify the learning activities in real time is thus desperately needed.

In this work, we seek to build an adaptive model of English learning tasks, CD-ELAM, which integrates cognitive diagnostic mechanisms, and uses the smart classroom as an application scenario to achieve personalised recommendation and dynamic adjustment of English learning tasks by considering the matching relationship between students' cognitive ability state and task characteristic. In order to support the fine-grained allocation, difficulty adaptation and path optimisation of learning tasks, so enhancing learning effectiveness and motivation, the model not only pays attention to students' present knowledge mastery but also emphasises the detailed analysis of their potential cognitive structure. This helps to promote the general development of students' language proficiency.

This study will focus on the two following elements to reach these objectives:

1 Theoretical level: The model framework of CD-ELAM is built to clarify the fundamental components and functional modules of the model based on the research results of cognitive diagnostic theory and adaptive learning system. Key subsystems including cognitive state modelling, task feature expression, task regulating mechanism, etc., will constitute a full closed-loop mechanism for task adaptation in the model (Azgomi et al., 2021).

2 Experimental verification level: Experimental research is carried out to assess the efficacy of CD-ELAM in improving students' learning outcomes, adaptive ability and cognitive matching using real English learning problem samples and student behaviour datasets. Apart from useful references for the promotion and implementation of the adaptive teaching system in the smart classroom, the trial findings will offer data support for the iteration of the model aimed at optimisation.

This work integrates cognitive diagnosis and adaptive task mechanism to build an English learning model fit for smart classroom, so committed to promote the deepening development of education informatisation and provide new theoretical support and technological paths for realising accurate teaching and personalised learning.

2 Theoretical foundations

2.1 Cognitive diagnosis

Based on the theoretical foundation of cognitive psychology and educational assessment, cognitive diagnostic is a class of modelling techniques that examine learners' outer behavioural data to deduce their internal knowledge structure, ability level, and thinking patterns. Cognitive diagnosis stresses fine-grained, multi-dimensional modelling and reasoning about students' mastery of many cognitive dimensions or knowledge qualities, unlike conventional assessment approaches that concentrate on providing an overall score (Shi et al., 2024). Its objectives are not only to ascertain whether pupils have acquired a particular ability but also more crucially to pinpoint what has been mastered, what has not, and to what degree, therefore offering a scientific basis for tailored instruction and exact intervention.

Cognitive diagnostics first emerged in the 1970s, with the foundations originally provided by knowledge of space theory and rule space models (Tilak et al., 2022). These models underlined the inversion of students' knowledge status by means of the answer patterns of test items and suggested the idea of presenting the structure of knowledge mastery in the form of space or sets. Cognitive diagnosis has progressively changed in the 21st century as latent variable modelling approaches have developed into a class of methodologically consistent latent variable modelling approaches. These models combine statistical modelling techniques with psychometric, probabilistic reasoning to statistically show pupils' mastery of several hidden cognitive traits, hence realising reverse modelling from data to cognition.

Two main groups define cognitive diagnostic models: probability-based modelling and logic-gate-based modelling. More classical versions consist of deterministic inputs, noisy 'and' gate (DINA) model and deterministic inputs, noisy 'or' (DINO) model (Bu et al., 2022). Whereas the DINO model is more flexible and considers that partial mastery of some of the qualities is sufficient for a right answer, the DINA model holds that learners can only respond a question correctly if they have mastered all the knowledge attributes required by the question. These two models with their straightforward and unambiguous logical framework are suited for several learning environments. The researcher suggested the more generalised generalised DINA model, which may dynamically describe the relationship between characteristics and response outcomes without the need of a specified logical structure, to overcome the expressive constraints of the logic-gate model. Furthermore, extensively applied in certain jobs are the additive CDM model, reduced reparameterised unified model (RRUM), etc (Ravand et al., 2024). By means of flexible selection based on educational goals and evaluation requirements, these models can be formed as a more complete cognitive diagnostic model system.

Cognitive diagnostic models' efficient operation depends on the support of the Q-matrix, which defines the dependencies between topics and knowledge attributes, and acts as a link between the observable variables (students' responses) and the possible variables (knowledge mastery status). The building of Q-matrix usually depends on the experience of lecturers or domain experts, which is somewhat arbitrary and challenging to measure (Pelánek, 2022). This has led to the emergence of a range of automated or semi-automated Q matrix generating and optimisation techniques including iterative adjustment based on expectation maximisation (EM), statistical inference based on students' response patterns, and structural reconfiguration based on knowledge mapping, which have effectively improved the adaptability of the model and diagnostic accuracy.

The application scenarios of cognitive diagnostics are growing even as research techniques change. From the stationary diagnostic model used for high-stakes tests and standardised assessments in the early days to the dynamic diagnostic model generally used in online education platforms and intelligent teaching systems nowadays, the scope of its application is fast widening to a wider range of intelligent education scenarios. Particularly in individualised learning paths recommendations, early academic warning, and learning behaviour prediction, cognitive diagnostic is indispensable.

When confronted with vast-scale, multi-dimensional, continuous learning data, conventional cognitive diagnostic models still have some restrictions, nevertheless. For instance, most models are constructed on the presumption of topic-independence and response-independence, which makes it challenging to depict the dynamic change of students' cognitive states during the learning process. Furthermore, lacking the capacity to automatically extract underlying cognitive processes, the inference process of these models usually depends on manually created feature representations. Researchers have lately sought to combine deep learning with cognitive diagnosis and proposed several knowledge tracing models under neural network structures, such as deep knowledge tracing (DKT), dynamic key-value memory network (DKVMN) and attentive knowledge tracing (AKT) (He et al., 2023). In order to solve problems, these models improve the real-time and accuracy of diagnosis by modelling and predicting learners' cognitive states at several time points, depending on structures with strong temporal modelling capacity such LSTM or attention mechanisms.

Deep models have shown great ability in managing complex learning behaviour data, but they also suffer from issues including poor model interpretability, strong dependence on training samples, and difficult integration of priori knowledge. There is still research space for integration and balance with conventional cognitive diagnostic models. To improve the interpretability and diagnostic utility of the deep model, some researchers currently attempt to include attribute label structure, Q-matrix information, causal modelling, etc. into the model.

From static to dynamic, from shallow to deep, and from explanatory to predictive in its theoretical growth and practical application, cognitive diagnostic, as a learner-centred modelling tool, has experienced a multidimensional developmental process overall. Cognitive diagnosis will be increasingly combined with developing technologies including artificial intelligence, big data, graph neural networks (GNN), cross-modal analysis, etc., to support its deeper application in settings including smart education, personalised learning, and virtual tutor systems. Simultaneously, depending on preserving the predictive capacity of the model, how to enhance its interpretability, migratability, and low-cost deployment capability will also become a major focus of research.

2.2 Adaptive learning

Aiming to accomplish personalised teaching in the genuine sense, adaptive learning is an educational paradigm based on the individual variations of learners and the use of modern information technology to dynamically alter learning content, learning paths and teaching tactics. Adaptive learning has been increasingly significant in intelligent education as information technology, especially big data, along with artificial intelligence and Internet technologies expand rapidly. Its fundamental idea is in completely exploring and using learners' multi-dimensional characteristics, including knowledge level, cognitive ability, learning habits, emotional state and interest preferences, and dynamically adjusting the presentation of learning resources and teaching strategies using real-time monitoring and analysis of behavioural data in the learning process, in order to maximally meet the personalised needs of the learners, and so improve the learning effect and learning satisfaction.

Adaptive learning's theoretical beginnings can be found in the concept of individualised instruction and the in-depth research of cognitive psychology since the middle of the century. Multiple intelligences theory points out that individuals have differences in their performance of various intelligences, such as linguistic, logical, spatial, and musical intelligence, etc., which provides a solid theoretical support for the design of the adaptive learning system; cognitive load theory stresses that the design of learning materials should be in line with the cognitive processing ability of learners to avoid excessive cognitive load; constructivism theory advocates that learning These ideas give the construction of adaptive learning systems strong theoretical justification. Early adaptive learning systems derived from artificially created teaching rules and routes and depended on rule engines and expert systems. Although first personalisation was attained, the system lacked the capacity to dynamically sense and flexibly modify the condition of the learner, which made it challenging to satisfy the complicated and evolving teaching needs.

Entering the 21st century with the extensive use of artificial intelligence technologies, data mining, and machine learning, adaptive learning is progressively headed towards data-driven and intelligent direction. Modern adaptive learning systems construct a multi-dimensional learner model to reflect the cognitive state and learning needs of learners in real time by means of the collection and analysis of learning behaviour data, including question answering, study time, study frequency, browsing trajectory, interactive behaviour, etc., so reflecting the cognitive state and learning needs of learners (Li et al., 2021). The system uses statistical methods, probability models and deep learning technologies to dig out possible cognitive laws from the data, dynamically predict learners' knowledge mastery and learning tendency, and change the difficulty, order and presentation of learning content accordingly to achieve personalised recommendation and precise teaching.

Constructing a multi-dimensional representation of the learner's comprehensive cognition, behaviour, and emotion by combining cognitive diagnosis, knowledge tracking, affective computing and other technical techniques, the learner model is the fundamental component of the adaptive learning system. Apart from reflecting the present degree of information mastery, an accurate learner model forecasts learning bottlenecks and possible issues, therefore offering a scientific basis for tailored intervention (Huang et al., 2023). The knowledge tracking model, for instance, dynamically estimates the learner's probability of mastering each knowledge point using sequence data and time-series analysis technologies; the cognitive diagnosis technology is refined to the level of knowledge attributes to accurately locate the learner's strengths and weaknesses; and the affective computing technology senses the learner's emotional state in real time by recognising facial expressions, voice tones, and physiological indicators to support for adjusting teaching strategies.

Furthermore, stressed by adaptive learning is the immediacy and responsiveness of input. By means of the intelligent feedback system, students can acquire tailored recommendations, error correction assistance, and strategy suggestions during instruction in a timely way, therefore enabling rapid adjustment of learning behaviours and cognitive strategies and support of deep learning. Feedback covers not only the assessment of correctness or incorrectness but also the direction of metacognitive level, which enables students to consider the learning process and build independent learning ability (Kolloff et al., 2025). At the same time, incentive mechanism is equally crucial in adaptive learning through customised rewards, performance display and other ways to inspire learning motivation and continuous involvement.

With the fast expansion of smart classrooms and intelligent education systems in recent years, adaptive learning technologies and applications have kept developing. Combining cognitive diagnosis, knowledge mapping, and artificial intelligence algorithms to reach accurate pushing of learning resources and adaptive assignment of tasks, adaptive learning technology has been extensively adopted in online education, massive open online courses (MOOCs), intelligent tutoring systems, and other fields (Troussas et al., 2020). Particularly in language courses like English acquisition, adaptive learning greatly enhances students' language skill mastery efficiency and learning experience by means of fine-grained cognitive diagnosis supported by individualised task design.

Still, adaptive learning has several difficulties. First, the secret to raising the intelligence of adaptive systems is how effectively heterogeneous data from many sources can be combined to create dynamic, thorough and accurate learners' profiles. Second, the system design must provide fair and open teaching, eliminate data bias and over-labelling, and consider justice and personalism. Third, difficulties of cross-platform and cross-system data interoperability restrict the advancement and spread of adaptive systems. Particularly in the gathering of sensitive behavioural and physiological data, privacy protection is also a major issue that has to be given top attention on how to guarantee data security and user privacy.

Future adaptive learning will concentrate more on including cognitive diagnostic technology to precisely capture and fine-grained adjust learners' cognitive states and change instructional design from memorising a single knowledge point to developing sophisticated abilities. Context-awareness, virtual reality (VR), augmented reality (AR) technologies will enhance the learning environment and raise immersion and realism as intelligent hardware advances. GNN-based, multimodal fusion and reinforcement learning among other modern technologies would enhance the intelligent decision-making and real-time reaction of the adaptive learning system.

All things considered, adaptive learning, which is a pillar of intelligent education promotes tailored instruction and exact intervention using multi-dimensional data-driven, intelligent algorithmic support, so improving the learning effect and experience. Adaptive learning will become more important in the domains of smart classroom, online education and lifelong learning as technology develops constantly, and the depth of theoretical study increases helps to encourage the ongoing improvement of educational fairness and quality.

3 English learning tasks and adaptive model design in smart classroom

3.1 Analysis of smart classroom and English learning tasks

Aiming to create an intelligent, personalised and interactive learning environment by the application of modern information technology, smart classroom is a product of the deep integration of information technology and education teaching, so achieving the dynamic optimisation of the teaching process and the continuous enhancement of the learning effect. Using big data, cloud computing, artificial intelligence and other advanced technological means, teachers in the smart classroom not only can monitor the learning status and cognitive level of students in real time, but also instantly modify their teaching strategies depending on the diagnostic results and encourage students' active participation and independent learning. Smart classroom stresses the digitisation and intelligence of teaching materials, the diversity and personalising of teaching activities, and the visibility and precision of the learning process, and is a significant means to promote the modernism of education and educational justice.

Regarding English acquisition, the design of a smart classroom is particularly crucial. English learning activities, as a language topic, involve a broad spectrum of skills including listening, speaking, reading, writing, translating, and demand a high degree of learners' cognitive structure, language application ability and cultural knowledge. Traditional classroom instruction sometimes uses uniform progress and content, so neglecting the unique diversity of learners and making it impossible to suit the learning demands of diverse pupils, so producing unequal learning outcomes (Padilla-Carmona et al., 2020). Building a learner-centred teaching environment helps the smart classroom to create diversified learning activities based on the various linguistic competencies and cognitive traits of the pupils, thereby attaining custom-made teaching and personalised learning.

English learning activities in smart classrooms are often separated into three levels: knowledge acquisition, skills development and application practice. Knowledge acquisition concentrates on the mastery of basic language knowledge such as vocabulary, grammar, scenarios, etc., requiring systematic and coherent; skills training covers the development of listening comprehension, oral expression, reading comprehension and writing ability, stressing on practicability and communicative function; application practice stresses the real-life use of the language scenarios, and enhances the students' comprehensive use of language and cross-cultural The practical exercise stresses the actual application of the language in natural contexts. These three components interact to form the whole framework of English education.

Furthermore, English learning activities in the smart classroom have to consider variations in learning strategies and cognitive development degree of the pupils. Task design should consider the cognitive load theory, reasonably control the difficulty of the task and the amount of information to avoid cognitive overload and stimulate the motivation of learning and the demand for independent investigation. Cognitive resources, information processing and knowledge transfer ability of learners at different levels should be significantly different considered (Hajian, 2019). Diverse tasks of different kinds also enable learners with various learning styles, visual, auditory, hands-on, etc., to suit their demands, therefore improving the learning efficiency and effectiveness.

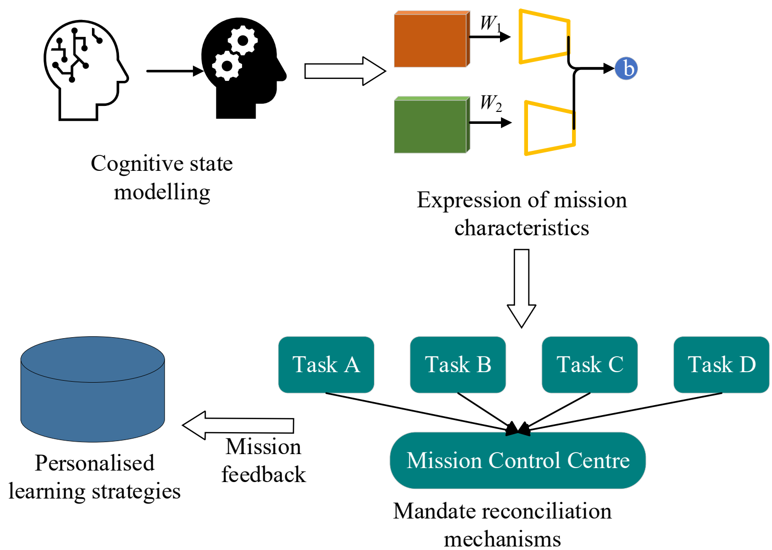
English learning activities in the smart classroom should also include adaptive adjusting tools and instantaneous feedback systems. The system can dynamically ascertain learners' knowledge mastery status and cognitive needs by means of real-time analysis of learners' response data, behavioural data, and emotional data; subsequently, it can modify the task content, difficulty level, and teaching strategies to attain exact tutoring and personalised support. This adaptive design of activities depending on cognitive diagnostic not only increases the relevance and efficacy of instruction but also supports the development of students' metacognitive ability and helps them better plan and control their own learning process.

All things considered, the smart classroom advances the change of the teaching mode from the conventional teacher-centered to learner-centred and offers technical and theoretical assistance for the design and execution of English learning activities.

3.2 Adaptive modelling for English learning tasks

Construction of a model that effectively and dynamically responds to students' cognitive states is essential to achieve cognitive diagnosis-based English learning task adaption in a smart classroom setting, see Figure 1. The CD-ELAM suggested in this paper dynamically adjusts the difficulty and content of learning tasks and further generates personalised learning strategies by precisely grasping students' cognitive level, combined with a thorough representation of task features, so effectively enhancing students' learning effectiveness and teaching quality.

Figure 1 Design of the CD-ELAM model (see online version for colours)



3.2.1 *Cognitive state modelling module*

The main element of the CD-ELAM model and the cognitive basis of the whole adaptive mechanism is the module of cognitive state modelling. This module's fundamental goal is to build a fine-grained and dynamic cognitive portrait by inferring students' mastery of several English knowledge qualities from their episodic behavioural data. This module stresses diagnosis and modelling on several cognitive aspects to provide a precise and practical basis for the next task adaptation, unlike the conventional approach of evaluating learning levels based just on total scores.

Knowledge qualities in English learning activities normally include several aspects, including vocabulary, grammar, reading comprehension and pragmatics. The collection of knowledge attributes for systematic modelling follows:

$$A = \{A_1, A_2, \ldots, A_K\} \tag{1}$$

where A_k is the k^{th} cognitive dimension and K is the overall count of English knowledge characteristics involved. Every student's knowledge state at any one time can be expressed as an attribute mastery variable a_i:

$$a_i = (a_{i1}, a_{i2}, \ldots, a_{iK}) \in \{0, 1\}^K \tag{2}$$

where $a_{iK} = 1$ is the learner has perfected the k^{th} attribute; $a_{iK} = 0$ is he or she has not yet done so. Models of the student's state in the cognitive space are built on this fluctuation.

The system must take more account of the knowledge structure underlying an English learning activity to ascertain if a student is qualified to complete the task. Every learning task j can be expressed as an attribute demand variable q_{jk}, which indicates the knowledge dimensions needed for the task. A writing assignment can, for instance, be quite dependent on grammar, logical structure, and lexical arrangement. The following matching function gauges students' competency fit for job *j*:

$$\eta_{ij} = \prod_{k=1}^{K} \alpha_{ik}^{q_{jk}} \tag{3}$$

where η_{ij} is the student has mastered all the qualities needed for the job and has the potential to do the task; if there is a trait A_k the student does not yet possess, then $\eta_{ij} = 0$, suggesting the student lacks the capacity to finish the mission. Task matching and diagnosis are built on this logic gate structure, which also faithfully replics the mechanism of minimum competence requirements for learning activities (Allchin and Zemplén, 2020).

In actual learning environments, though, random events often compromise students' performance. For instance, carelessness may cause somebody to get the answer wrong even if they have perfected all the required skills; conversely, guessing may lead to the correct response even if they may not have perfect knowledge. This module presents the classical DINA model in cognitive diagnosis to model student performance probabilistically using the following formula:

$$P\left(R_{ij} = 1 \middle| a_i, q_j\right) = \left(1 - s_j\right)^{\eta_{ij}} \cdot g_j^{1-\eta_{ij}} \tag{4}$$

where R_{ij} marks the completion result of task *j* by student *i* (1 is success, 0 is failure); s_j is the slip rate, i.e., the likelihood of failing despite knowing knowledge; and g_j is the guess rate, i.e., the probability of completing the work without mastering knowledge. By considering the logical structure of the competence requirements and allowing the contingencies in the learning activities, the model efficiently combines cognitive matching with behavioural probabilistic modelling, so improving the realism and robustness of the cognitive state modelling.

The system uses EM algorithms to fit students' attribute variables and bases on their history learning records, so building the cognitive state distribution of every learner in the process of model implementation. This method may dynamically monitor and diagnose by real-time updating the cognitive status unlike the stationary evaluation strategy. If a student performs well on several consecutive grammar assignments, the system can automatically upwardly modify his or her weight in the grammar mastery dimension; if he or her fails often under a certain attribute, it is noted as a learning bottleneck and recorded for use in the next task regulating mechanism.

It is important to underline that students' learning behaviour data in a smart classroom environment comprise multimodal information including classroom interactions, resource use, and task response time in addition to answer records (Zhan et al., 2021). To increase the operability and explanatory capacity of the model, the system therefore discretises some of the continuous aspects in cognitive state modelling and integrates them with attribute modelling mechanisms.

By building cognitive attribute variables, matching functions and behavioural probability models, so providing basic support for the scientific operation of the task adaptation mechanism, the cognitive state modelling module faithfully reflects the structure of students' English learning ability.

3.2.2 Task characterisation module

Personalised matching in adaptive assignment of English learning tasks depends on precise and thorough description of problem properties. Usually showing great cognitive complexity, close knowledge relationships, and flexible semantic expressions, English learning activities span a broad spectrum of language abilities including listening, speaking, reading, and writing. Adaptive models limit the diagnostic accuracy and recommendation effect by means of traditional feature representations that depend just on labelling, classification, or single dimensions; however, it is often impossible to completely capture the fundamental structure and practical needs of the tasks. This work thus suggests a multidimensional task feature representation method combining cognitive diagnostic theory with contemporary natural language processing methods to more precisely depict the fundamental characteristics of English learning tasks.

Drawing on the Q-matrix idea in cognitive diagnostic theory, first a K-dimensional Boolean variable is utilised to structurally encode the cognitive traits involved in every learning task (Lim, 2024). Assume the j^{th} learning task to be T_j, its corresponding attribute variable is designated as:

$$q_j = \left(q_{j1}, q_{j2}, \ldots, q_{jK}\right) \in \{0, 1\}^K \tag{5}$$

where the element q_{jk} denotes 1 if task T_j incorporates the k^{th} cognitive trait, 0 otherwise. This allows the task's knowledge to be exactly mapped to the chosen cognitive attribute space. This organised presentation not only provides a strong basis for later tailored task recommendation but also helps with direct matching and similarity computation with the cognitive state variable of the student.

Still, depending just on the discrete coding of cognitive qualities makes it challenging to capture the semantic information and language aspects of tasks. The model thus adds a deep learning-based text semantic embedding method to solve this shortfall. Specifically, the task description text D_j is encoded using the pre-trained BERT model and then its high-dimensional semantic variables are extracted:

$$v_j = \text{BERT}\left(D_j\right) \in \mathbb{R}^d \tag{6}$$

This variable greatly increases the depth and accuracy of task representation since it not only reflects the surface information of the work but also catches its suggested deeper characteristics including linguistic skill needs, contextual context and difficulty degree.

At last, the model combines the cognitive attribute variable q_j with the semantic embedding variable v_j to generate a unified task representation variable, therefore allowing full play of the complimentary advantages of cognitive structure and semantic features:

$$t_j = W_1 \cdot q_j + W_2 \cdot v_j + b \tag{7}$$

where t_j is the multidimensional feature representation of the fused task and the parameter matrices W_1, W_2 and the bias term b are the learnt weights during model training. Realising the natural synthesis of structured and unstructured information, the fused representation not only preserves the cognitive attribute information of the task but also introduces the linguistic semantic aspects of the task.

All things considered, the task feature representation module can faithfully and comprehensively depict the multilevel characteristics of English learning activities.

3.2.3 Task reconciliation mechanism module

The core link to achieve adaptive assignment of English learning tasks is the task regulation mechanism, which mostly serves to dynamically adjust and recommend the tasks most suitable for the learners' current ability and needs depending on their cognitive state and task characteristics, so promoting the optimisation of personalised learning paths. This mechanism guarantees accurate and effective control of the learning process by considering the knowledge coverage of the task, the balance of skill training, and the stimulation of learning motivation, so ensuring that the difficulty of the task matches the cognitive level of the student.

Specifically, the task regulating mechanism generates a task matching scoring function depending on two main information inputs: the cognitive state variable of the learner a_i, and the task characteristic variable t_j. Task's suitability for learner i is gauged using the scoring function $S(i, j)$, which defines:

$$S(i,\ j) = \alpha \cdot \operatorname{sim}\left(a_i, q_j\right) + (1-\alpha) \cdot \cos\left(v_i, v_j\right) \tag{8}$$

Usually computed using metrics like the weighted inner product or the Hamming distance to reflect the cognitive attribute fit, the first term sim(a_i, q_j) denotes the match between the student's cognitive state variables and the task's cognitive attribute variables; and the second term cos(v_i, v_j) cosine similarity between the student's current learning semantic state and the task's semantic features, so capturing the semantic level correlation. The contribution ratio between cognitive and semantic matching is balanced with the weighting coefficient α.

The algorithm chooses a suitable set of tasks T^* depending on the matching score to maximise the total of the matching degrees of all chosen tasks:

$$T^* = \arg \max_{T \subseteq \{T_j\}} \sum_{T_j \in T} S(i,\ j) \tag{9}$$

where N represents the maximum quantity of single recommendation assignments. By means of this goal, the task adjustment system not only guarantees the relevancy of the suggested activities but also manages the learning load to improve the learning effect and student motivation.

Furthermore, the task adjustment mechanism presents a dynamic feedback adjustment strategy that constantly optimises the matching parameters and task recommendations depending on the real-time performance and cognitive state changes of the learners, so attaining dynamic adaptation and optimisation of the learning path. This closed-loop system guarantees that the model is quite versatile and adaptable to fit individual variances and evolving learning surroundings.

Ultimately, the task adjustment mechanism module dynamically changes the task allocation strategy by means of cognitive and semantic dual perspectives, builds the key support of the intelligent adaptive system based on the cognitive needs of the learners so offering a strong guarantee for the personalised teaching effect of the CD-ELAM model.

3.2.4 Personalised learning strategies module

To maximise learning outcomes and active student involvement, the personalised learning techniques module seeks to dynamically modify learning paths and techniques depending on cognitive level and task completion. The module integrates cognitive diagnosis findings and examines student learning performance data to create tailored instructional interventions for varying degrees of instruction and refined management.

First, using students' cognitive state variable a_i and task completion feedback f_i, the system assesses learning efficacy. The function of the learning effect evaluation is stated as:

$$E_i = \frac{1}{M}\sum_{j=1}^{M} w_j f_{ij} \tag{10}$$

where M is the total number of tasks and w_j is the weight of task T_j, therefore representing their significance in the general learning goals.

The customised learning approach maximises the students' learning path by changing the task difficulty and content order, according to the learning effect evaluation (Vanitha and Krishnan, 2019). Let θ_i be the present learning strategy parameter; the model uses the function of strategy update:

$$\theta_i^{(t+1)} = \theta_i^{(t)} + \eta \nabla_{\theta_i} E_i \tag{11}$$

where η represents the learning rate; $\nabla_{\theta i} E_i$ indicates the gradient of the learning effect on the strategy parameters, therefore guiding the direction of dynamic adjustment of the strategy.

Furthermore, by means of multi-dimensional data fusion, the personalised strategy module incorporates non-cognitive elements such students' hobbies and learning preferences to improve the adaptability and flexibility of the strategy. Working in combination with cognitive state modelling and task control systems, the module creates a closed-loop feedback system that achieves exact reaction and support for student needs.

Overall, by means of scientific learning effect assessment and dynamic strategy modification, the personalised learning strategy module offers intelligent support at the strategy level for the self-adaptive model of English learning tasks in the smart classroom and motivates learners to achieve independent exploration and continuous optimisation of the best learning path.

4 Experimental results and analyses

4.1 Data collection

This work used the ASSISTments dataset as the experimental data source. Widely utilised in both elementary and secondary schools, the ASSISTments platform is an online tutoring system offering real-time feedback and individualised learning support. Suitable for cognitive diagnosis-based learning status analysis and adaptive modelling, the dataset includes students' answer records, time stamps, student ID, topic ID, and relevant knowledge qualities (Q-matrix) in English and other topics.

The selection of this dataset has multiple aptitudes: first, the ASSISTments platform contains a large amount of student behavioural data in real teaching environments, with high data quality and coverage of diversified learning tasks; second, the dataset provides a rich set of elements required for cognitive diagnosis, such as the correspondence between questions and knowledge points, which is conducive to the construction and validation of the cognitive state modelling module; third, the source of the data is the

Smart education platform, which is highly compatible with the technological background of the smart classroom and facilitates the promotion and validation of the model in practical applications; finally, the data is of moderate size, which can support the training and evaluation of the complex model and at the same time guarantee the repeatability and scientificity of the experiment.

Table 1 enumerates the fundamental details of the ASSISTments dataset applied in this research.

Table 1 Information on the ASSISTments dataset

Data item	*Description*	*Value / details*
Data version / year	Public release circa 2017	Most commonly used public version
Subject coverage	Primarily Mathematics, includes some English items	English-related items filtered and selected
Number of response records	Over 200,000 entries	Includes correctness, response times, etc.
Data format	CSV files	Fields include student ID, item ID, responses, timestamp

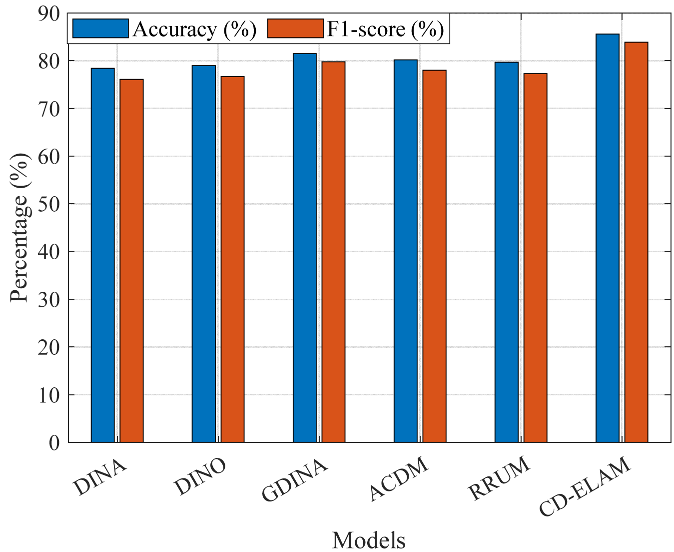
This research extracts the answer records and related knowledge attributes covering the English learning tasks by means of the screening and pre-processing of this dataset, therefore ensuring the validity and representateness of the data. To guarantee the correctness and stability of the model input, the data preparation process comprises of missing value processing, aberrant data removal, and the building and calibration of the Q matrix.

4.2 Diagnostic accuracy experiments with cognitive state modelling

The objective of this experiment is to assess how well the proposed cognitive diagnosis-driven English learning task adaptive model (CD-ELAM) detects cognitive states of students. Personalised teaching and task adaptation are based on accurate diagnosis of cognitive states, which directly influences the matching and adjusting effects of next learning activities. Thus, the main goal of this investigation becomes to confirm the performance variations of CD-ELAM among several models by means of a comparison with several conventional and advanced cognitive diagnostic models. Widely used and validated in the field of cognitive diagnosis, the chosen benchmark models are the DINA model, the DINO model, the GDINA model, the additive cognitive diagnostic model (ACDM), and the reduced reparameterised unified model (RRUM) (De La Torre, 2019).

The trials used two criteria, accuracy and F1-score, to fully assess the diagnostic performance of the models. The most natural success indicator is accuracy, which shows the whole percentage of students' cognitive states the model correctly detected. Particularly crucial in preventing too high misclassification and deletion, F1-score aggregates the precision and recall of the model, therefore measuring its competence in handling imbalanced categories. The two metrics used together enable a thorough evaluation of the model's diagnostic performance from several angles. Figure 2 shows the experimental findings.

Figure 2 Accuracy results of cognitive diagnosis (see online version for colours)



With an accuracy of 81.5%, GDINA is the top-performing benchmark model; CD-ELAM has improved by 4.1%. This development suggests that CD-ELAM can more successfully capture students' cognitive qualities and knowledge mastery, hence lowering misjudgments and omissions.

Regarding the F1-score measure, CD-ELAM also does rather well (83.9%). By contrast, the F1-score of the ACDM is 78.0%; that of the GDINA model is 79.8%. The increase in F1-score suggests that CD-ELAM achieves a better balance between precision and recall, so effectively recognising both cognitive traits that have not been mastered and mastered knowledge as well as supporting more focused instructional interventions.

Though with 79.0% and 79.7%, 76.7% and 77.3%, respectively, the DINO and RRUM models are still lower than the CD-ELAM even if they consistently show in terms of accuracy and F1-score. This shows that improving cognitive diagnosis performance depends much on the multidimensional task feature representation and customised learning strategy modules presented by the CD-ELAM.

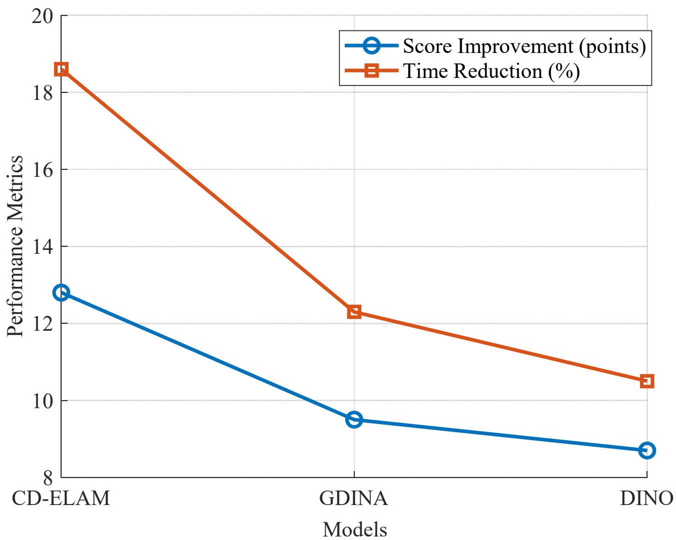
All things considered, the CD-ELAM model has achieved notable improvement in the cognitive state modelling diagnostic accuracy. This not only confirms the efficiency of the model design but also offers a strong technological support for cognitive diagnosis-based English learning task adaption in the smart classroom environment, so laying a strong basis for further study and application.

4.3 Experiments on adaptive task recommendation and learning effectiveness enhancement

With an emphasis on assessing the influence of the proposed cognitive state-based adaptive model for English learning tasks (CD-ELAM) on task suggestion, this experiment intends to confirm its effectiveness in task recommendation. Real teaching data was used for experiments; the performance of several approaches in task suggestion was thoroughly investigated by means of a comparison with the conventional cognitive diagnostic models GDINA, DINO, and random task recommendation approaches.

This paper uses two main indicators to evaluate the performance of the model. Time Reduction measures the model's capacity to optimise the learning path through the task moderation mechanism to enhance learning efficiency; Score Improvement refers to the average increase in students's test scores after completing the recommended tasks, so reflecting the progress of cognitive mastery. Time reduction tests the model's capacity to maximise the learning path via the task control mechanism, hence improving learning efficiency. Figure 3 displays on the indicators the experimental findings of several models:

Figure 3 Adaptive task recommendation learning effect (see online version for colours)



First, in terms of academic performance improvement, the CD-ELAM model attained a notable gain of 12.8 points on average, well above the other relative models. By contrast, the GDINA and DINO models attained effective but rather large performance increases of 9.5 and 8.7 points respectively. This implies that CD-ELAM can more successfully match tasks appropriate for learners' present level by means of accurate modelling of learners' cognitive state and thorough expression of task aspects, therefore fostering their knowledge mastery and skill enhancement.

Second, in terms of learning time optimisation, CD-ELAM reduces time by 18.6%, well above 12.3% of GDINA and 10.5% of DINO. This result greatly increases the learning efficiency by showing that the task control mechanism of CD-ELAM can suitably arrange the order and complexity of tasks, thereby avoiding the time-consuming repetition of tasks too difficult or too simple. Random recommendation, on the other hand, only slightly reduced 2.1% of the time, underscoring the need for tailored recommendations in terms of saving instructional time.

With both learning performance gains (5.3 points) and time savings (2.1%) far lower than the cognitive diagnostic model-based approach, random recommendations lagged the most as well. This shows that random task recommendations make it difficult to create efficient learning paths by ignoring learners' unique variations and cognitive needs, therefore producing either unsatisfactory learning outcomes or efficiency. In general, the CD-ELAM model reflects the potential and utility of combining cognitive diagnosis with adaptive techniques and offers great benefits in intelligent English learning task recommendation.

5 Conclusions

This research presents a cognitive diagnosis-based adaptive model for English learning tasks (CD-ELAM), designed to provide personalised task recommendations through four primary modules, hence improving learning efficiency and effectiveness. Experiments demonstrate that the model surpasses conventional models and fosters the advancement of personalised learning.

However, it possesses limitations, such as a restricted capacity to manage intricate cognitive structures, inadequate dynamic modeling, a singular data source, and the necessity for enhancement in user experience. To address the above limitations, future research can be carried out in the following aspects:

1 Multi-dimensional learning data integration: Forming a more comprehensive and dynamic learner portrait by incorporating non-cognitive factors like learners' emotions, behavioural trajectories, learning motivation, etc. helps achieve more personalised learning task recommendation and precise intervention in the smart classroom environment and enhance teaching interactivity and adaptability (McGrew, 2022).

2 Enhance the real-time performance and computational efficiency: To meet the real-time processing needs of large-scale and diverse learning data in the smart classroom, we optimise the model's computational performance and response speed, develop a lightweight algorithmic framework, ensure the system's efficient operation and instant feedback in actual teaching, and support teachers' and students' dynamic teaching activities.

3 Enhance the interpretability and the user experience: Strengthen research on model diagnosis and recommendation results interpretability, improve teachers' and students' understanding and trust in system feedback, optimise the learning interface with smart classroom interaction design, increase teaching transparency and user participation, and promote smart classroom teaching quality improvement (Saini and Goel, 2019).

4 Interdisciplinary and cross-cultural smart classroom promotion: We can investigate the application and validation of the adaptive model in smart classrooms of many disciplines and cultures, improve the generalisation capacity of the model, and support personalised learning theory and technology to land in the practice of smart education globally in the future.

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Declarations

All authors declare that they have no conflicts of interest.

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