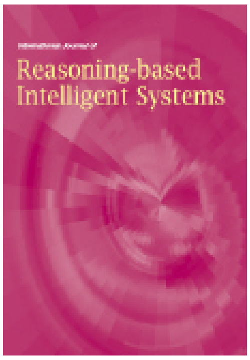

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A diagnostic model of students' civic education achievement based on multi-feature cognitive diagnosis in digital perspective

Xiaoqin Chen

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A diagnostic model of students' civic education achievement based on multi-feature cognitive diagnosis in digital perspective

Xiaoqin Chen

Institute of Marxism,
Shanghai Lida University,
Shanghai 201609, China
Email: shcelery@163.com

Abstract: With the framework of digital education, conventional approaches for civic and political education must be creative to satisfy evolving learning requirements. This work presents a new diagnostic model of students' performance in civic and political education (MCRD-IEEM), comprising four main layers and generates a thorough intelligent assessment system by means of multimodal features including behavioural data, knowledge mastery degree and emotional feedback. This work planned and carried out two tests to confirm the efficacy of the model: a multi-feature fusion effect analysis experiment and a model effect validation experiment both of which revealed that the MCRD-IEEM model was better than the comparison model in many facets. This paper offers theoretical support and practical advice for the creative application of educational technology and the digital transformation of the educational assessment system as well as a fresh perspective for the quality evaluation of ideological education.

Keywords: civic education; multi-trait cognitive diagnosis; digital; behavioural analysis.

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Biographical notes: Xiaoqin Chen received her Master's degree from Shanghai University in 2006. She is currently a Lecturer in the Institute of Marxism at Shanghai Lida University. Her research interest is Marxist theory education and big data analysis model.

1 Introduction

1.1 Background of the study

The field of education is changing profoundly as digital technology develops quickly. Particularly civic education, more and more new technologies are progressively driving the conventional form of education (Burbules et al., 2020). Using information technology not only improves the quality and efficiency of education but also offers fresh opportunities for tailored instruction and precise evaluation. Particularly in civic education, evaluating students' civic learning outcomes has become a hot issue for academic study. Although they can somewhat reflect students' learning status, traditional assessment techniques mostly rely on quantitative indicators, such as test and exam results, which tend to ignore the multi-dimensional variations in students' cognition and emotion, so producing one-sided and limited evaluation results (Belchior and Lyons, 2022).

The development of cognitive diagnostic techniques offers a fresh viewpoint for evaluation of education. By use of task performance analysis, cognitive diagnostic seeks to expose pupils' underlying cognitive structures and thought processes. Cognitive diagnosis can produce more exact and customised assessment findings than conventional assessment techniques, so allowing a better knowledge of students' cognitive biases and learning challenges (Griffith et al., 2021). Particularly in the disciplines of subject teaching and psychology, where major advancement has been made, educational evaluation techniques based on cognitive diagnosis have been extensively used in recent years with the ongoing development of artificial intelligence and big data technology.

1.2 Significance of the study

This paper is suggested to close the present void in the subject of performance evaluation in political and civic education. In civic and political education, conventional performance evaluation largely depends on a single standardised test, therefore neglecting multi-dimensional elements including students' cognitive traits, emotional reactions and learning strategies. By means of in-depth analysis, the multi-featured cognitive diagnostic model may consider the cognitive structure, emotional attitude and behavioural data of individuals and offer individualised performance assessment for every student. This not only shows more fully the students' learning level in civics education but also gives teachers more focused teaching improvement tools.

This study's creative use of educational technology adds still another great relevance. Within the framework of the digital transformation of education, how best to apply contemporary information technology to enhance the accuracy and intelligence of educational evaluation is a major concern now confronting the educational sector. This paper offers a fresh approach to civic education performance assessment by providing a multi-featured cognitive diagnostic model and aggregating students' learning process data and the contents of civic education. This approach cannot only raise the scientificity of performance assessment but also offer statistics backing for intelligent tutoring and tailored instruction.

This work also offers a great spectrum of social application value. Political and ideological education has lately acquired formerly unheard-of relevance in modern life (Lee et al., 2019). Among the strategic goals of national education development are improving the quality of ideological and political education and raising students' ideological and political literacy. Thus, this study offers a fresh approach of thinking for the quality assessment of ideological and political education, which can give educational administrators, instructional designers and teachers a scientific basis for decision making and help the deepening of the reform of ideological and political education.

1.3 Objectives and content of the study

Aiming to increase the accuracy and personalisation of civic and political education performance evaluation, this project mostly intends to create and apply a multi-feature cognitive diagnosis-based model for diagnosing students' performance in civic and political education. Combining students' behavioural data, cognitive traits, and emotional expressions in the process of civic and political education creates a comprehensive intelligent assessment system using the multi-dimensional cognitive diagnosis method, so attaining a more scientific and personalised performance assessment.

First, a multi-feature fusion assessment model will be built in the research process by means of a plausible model framework to combine several kinds of student feature data, including learning attitudes, classroom involvement, emotional feedback and other elements. Second, the work will apply cutting-edge feature extraction and selection methods to guarantee that the chosen features have great representativeness and predictive capacity to maximise the performance of the model. By means of this framework, the study will also be based on cognitive diagnostic approaches to extensively examine students' cognitive performance in civic education learning, so revealing their possible cognitive blind spots or understanding biases in the learning process, so enabling teachers with more focused teaching feedback and counselling strategies. At last, this work will perform experimental validation on actual datasets in order to assess the benefits of the suggested model in terms of accuracy, operability and personalised assessment in comparison with conventional performance evaluation systems.

This work aims to support the intelligent and digital transformation of the civic education assessment system and give educational policy makers and teachers a scientific instrument for evaluating student performance in civic education.

2 Relevant work

2.1 Current status of research on civic education

Civic and political education has progressively grown in significance in recent years as social development and the demands of the times change. Particularly in developing students' ideological and political traits and sense of social responsibility, which is absolutely vital. Civic and political education shapes values, enlightens ideas, develops personality, and not only provides knowledge but also the means of transmission for knowledge. Consequently, for academics and teachers both domestically and internationally, how best to implement civic and political education becomes a major topic of discussion.

In civic education, it is important to establish a structured mapping between knowledge points and cognitive abilities. Civic education involves not only the transmission of knowledge but also focuses on the development of students' affective attitudes, values, and critical thinking skills. Unlike traditional subjects, the goal of civic education is to help students develop comprehensive civic literacy, which requires us to assess students' learning outcomes from multiple dimensions. By creating a structured mapping, we can get a clear picture of students' mastery of different knowledge points and how these interact with their cognitive abilities. This mapping not only helps teachers to identify students' learning needs more precisely but also provides theoretical support for personalised teaching. In addition, it ensures consistency between the pedagogical objectives of civic education and the assessment criteria, thus better serving the holistic development of students.

Research on civic and political education mostly addresses the following elements: first of all, with regard to the goals and contents of civic and political education, scholars have proposed a range of frameworks and systems stressing that civic and political education not only emphasises on the teaching of knowledge but also should develop students' sense of social responsibility, spirit of innovation and practical ability (Amin et al., 2023). Second, a growing focus of research is now civic and political education's approaches and strategies. Diverse teaching strategies including interactive, case-based, discussion-based, etc. have progressively taken place of the conventional lecture-based model. These fresh approaches seek to increase students' sense of involvement and identification as well as enable them to grasp and accept political and ideological notions.

In the sphere of computers, particularly with regard to the fast expansion of artificial intelligence and data analysis tools, customised evaluation and intelligent coaching in civic and political education now present fresh chances (Li, 2025). For an analysis of students' learning behaviours, affective feedbacks, and cognitive traits in civic and political education, academics have recently used a range of machine learning and data mining techniques including decision trees, support vector machine (SVM), random forests (RF), and deep learning. These algorithms are able to expose students' learning status and any issues by modelling and evaluating their learning process data, so guiding teachers with tailored instruction plans. For instance, decision tree algorithms can forecast students' future learning performance by assessing their past learning data and offer tutoring recommendations to teachers, SVM-based models can help identify students' affective preferences to customise teaching approaches (Hananto et al., 2024). Particularly recurrent neural networks (RNN), deep learning algorithms have shown great capacity in the processing of vast amounts of learning data and the analysis of behavioural patterns of students. They can also efficiently extract deep-level characteristics from learning paths.

Furthermore, showing its special benefits in civic education is research based on deep learning models including convolutional neural network (CNN) and graph neural network (GNN). These technologies may extract information from multi-dimensional data including students' interaction records, behavioural patterns, and social networks to enable teachers precisely detect students' learning progress and psychological dynamics. GNN, for instance, can examine student collective learning habits and emotional changes via their social networks, therefore offering data support for group educational interventions. CNN may thus further examine students' emotional and psychological states by recognising their facial expressions and body language in picture and video data (Sharma and Mansotra, 2019). By means of these technologies, teachers can more precisely assist tailored instruction and psychological counselling as well as grasp the dynamic changes of pupils in civic education.

Though most of the approaches still concentrate on the assessment of knowledge-based performance, and there is a relative lack of attention of non-knowledge-based factors such as multi-dimensional cognitive processes and affective attitudes in students' civic education. Studies have attempted to use machine learning and artificial intelligence technologies for personalised teaching and performance assessment in civic education still show this (Tedre et al., 2021). Few research have looked closely at how to combine students' multidimensional traits using cognitive diagnostic theory for thorough performance evaluation. Thus, a major focus of present research is on how to combine modern algorithms in the computer area with cognitive diagnostic approaches to build a scientific and comprehensive evaluation model for civic education.

In this regard, as a new educational evaluation instrument, the assessment approach grounded on multi-featured cognitive diagnosis has progressively drawn the attention of the academic world. The approach offers a more scientific and complete viewpoint for the evaluation of the efficacy of ideological education since it can analyses students' cognitive performance, emotional feedback, and behavioural traits in many directions. Consequently, in the present study on civic education, how to mix the cognitive diagnostic approach with civic education to create an efficient system of student performance assessment and tailored counselling becomes a crucial question.

2.2 Cognitive diagnostic methods

In the field of education today, with the rapid development of digital technology, educational formats and assessment methods are undergoing profound changes. Cognitive diagnostic methods, as an emerging assessment tool, are gradually being applied in a few subject areas, including mathematics, language and science. However, despite the remarkable progress of these methods in other disciplines, their application in citizenship education remains relatively rare. Civic education, as an important area for developing students' social responsibility, political literacy and civic engagement, has unique pedagogical goals and assessment needs. Most of the existing research focuses on knowledge transfer and traditional testing methods, while comprehensive assessment of students' multidimensional performance (e.g., affective attitudes, behavioural performance, and cognitive abilities) in civic education has not yet received sufficient attention. Therefore, introducing cognitive diagnostic methods into the field of civic education cannot only fill the gaps in existing research, but also provide a more scientific and comprehensive perspective on the assessment of civic education.

Aiming to expose students' knowledge of several cognitive domains in the learning process, cognitive diagnostic approaches are a useful instrument in educational assessment. Its main objective is to use student response patterns to precisely discover knowledge blind spots and cognitive misconceptions, therefore supporting data for individualised teaching and counselling. Although cognitive diagnostic approaches are extensively used in the learning diagnosis of mathematics, language and other disciplines, their application in civic and political education has progressively attracted attention recently, especially for the accurate assessment of students' political and ideological cognition.

Cognitive diagnostic techniques nowadays mostly fall into two groups: models based on ability estimation and conventional diagnostic approaches depending on answer replies. Although this approach is sometimes oversimplified and ignores the multidimensional performance of students in the process of knowledge acquisition, traditional approaches mainly depend on students' replies to standardised test questions and employ the wrong-correct response paradigm for assessment (Vittorini and Galassi, 2023).

Cognitive diagnostic approaches that utilise ability estimates employ advanced statistical models for cognitive studies, providing more accurate and multidimensional assessments of learning compared to conventional methods. By employing probabilistic evaluations of students' capabilities, these approaches reveal the extent of students' competence across various knowledge domains. The two most used cognitive diagnostic models are item response theory (IRT) and the local independence model (LIM). These models enable the determination of a student's level of competence in a specific subject area through in-depth analyses of their response patterns, thereby estimating not just correct or incorrect answers.

Specifically, IRT is a commonly used method in educational assessment based on the fundamental presumption that the combination of the student's aptitude and the test item's difficulty determines each student's response, correct or incorrect (Lee, 2019). The IRT model has as its fundamental form:

$$P(\theta) = \frac{1}{1 + \exp(-(a(\theta - b)))} \tag{1}$$

where a is the differentiation of the question; θ is the student's ability parameter; b is the difficulty parameter of the question; $P(\theta)$ is the likelihood of a student selecting the right response given a question. Based on a student's answers to a set of test questions, this model helps one to estimate their degree of competence.

Model-based diagnosis (CDM) is another often used cognitive diagnosis tool. This approach supposes that knowledge points in the learning process have certain dependencies and that students' abilities are tied to their cognitive patterns and learning processes in addition to what they have learnt. By use of multidimensional data fusion analysis, CDM models can probe deeper into students' knowledge structures and pinpoint their shortcomings in several learning aspects (Du and Ma, 2021). Typical used CDM models include cognitive diagnostic model (DINA) and rule space model (RSM). Examining the DINA model, its fundamental form is as follows:

$$P(Y = 1|\theta) = \prod_{i=1}^{n} p_i^{d_i} \left(1 - p_i\right)^{(1-d_i)} \tag{2}$$

where $P(Y = 1|\theta)$ is the likelihood of a student responding properly in a given cognitive mode; p_i is the probability of a student acquiring the i^{th} talent; d_i is whether the skill is in the student's knowledge structure; θ is the student's ability vector. The DINA model can evaluate the students' competencies in several spheres and assist in the identification of cognitive flaws and learning requirements of each individual (Xu et al., 2023).

Furthermore, cognitive diagnosis techniques based on neural networks have progressively attracted attention in recent years as deep learning and artificial intelligence technologies have developed. Constructing multilayer nonlinear mapping relationships allows deep learning models to automatically extract features in large-scale data, therefore offering more accurate ability estimate. For instance, students' learning process data has been extensively analysed using CNNs and RNNs in sentiment analysis and behaviour recognition, therefore enabling a comprehensive knowledge of their cognitive processes and psychological dynamics (Velagaleti et al., 2024). By use of these cutting-edge approaches, cognitive diagnostic not only enhances the accuracy of evaluation but also offers more thorough and complete assistance for tailored instruction.

All things considered, cognitive diagnostic tools have provided an accurate evaluation of students' learning processes and a multi-dimensional analysis through ongoing development. Integrating cognitive diagnostic techniques into the teaching of ideology and politics allows for a more scientific assessment of students' ideological and political cognition, enabling teachers to offer data-driven feedback on their instruction.

3 Design of the diagnostic model of students' civic education achievement based on multi-feature cognitive diagnosis

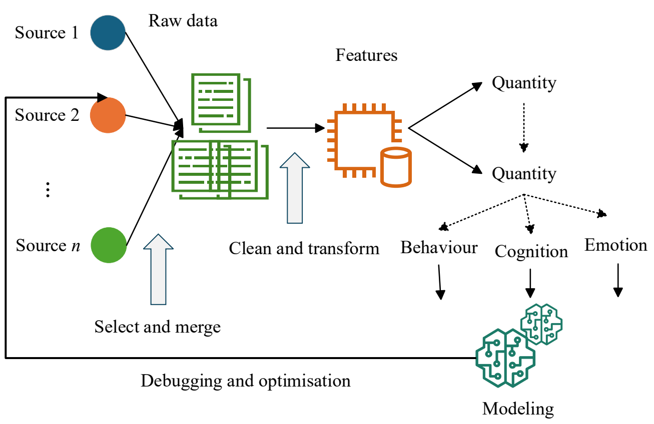
3.1 Model architectural design

This work develops an intelligent evaluation model for digital teaching environment, namely MCRD-IEEM model, to raise the scientific and personalised degree of the assessment of civic and political education. Reflecting the actual learning status of students from a multi-dimensional perspective, which has greater explanatory power and application value, MCRD-IEEM model not only emphasises on the correctness of students' answers but also systematically integrates their learning behaviours, emotional responses, and cognitive mastery, compared with the conventional performance assessment.

See Figure 1 for an entire MCRD-IEEM model consisting of four main components: data acquisition and feature modelling layer; knowledge point and ability association modelling layer; multi-feature cognitive diagnosis and reasoning layer; performance comprehensive evaluation and feedback layer.

Among them, the first layer collects students' multimodal learning data through the education platform and constructs feature representations that can be used for modelling; the second layer constructs a cognitive structure model based on the knowledge system of the civics and political science course to achieve the mapping between knowledge points and competency dimensions; the third layer adopts a combination of cognitive diagnostic models and in-depth reasoning networks to estimate students' mastery in each dimension; and the last layer combines the cognitive results, behavioural indicators, and affective feedback are weighted and fused to output students' comprehensive performance assessment results in civic education.

Figure 1 MCRD-IEEM model architecture (see online version for colours)



3.1.1 *Data acquisition and feature modelling layer*

Under the MCRD-IEEM model, the layer of data acquisition and feature modelling is mostly in charge of gathering multimodal behavioural data in the course of civic and political education from the digital teaching platform and organising them to support later cognitive diagnostic modelling. Dependent on the intelligent teaching system, learning management platform, interactive tools, this layer gathers click records, resource access behaviour, question-answering process data, online discussion material, text input, audio-video interaction data, and so on (Castelo et al., 2023). These raw data help to build three primary kinds of features: emotional, cognitive, and behavioural ones.

Measuring students' motivation and learning patterns, behavioural traits mostly consist in the number of video viewings, online length, frequency of engagement in classroom activities, and homework submission after class. Students' response times, mistake patterns, knowledge coverage, etc. allow cognitive traits, which capture their thinking style and level of comprehension, to be extracted. Conversely, affective features use methods including text sentiment analysis, speech tone recognition, facial expression capture, etc., to deduce from unstructured data students' emotional states, including uneasiness, bewilderment, engagement and so on.

First numerically encoded, the above multidimensional characteristics are combined by normalisation to generate a feature vector x_i for every student in every learning cycle:

$$x_i = [b_1, b_2, \ldots, b_j, c_1, c_2, \ldots, c_k, e_1, e_2, \ldots, e_l] \tag{3}$$

where the j^{th} behavioural feature is b_j; the k^{th} cognitive feature is c_k; the l^{th} affective trait is e_l; and i is the student number.

This work presents the method based on principal component analysis (PCA) for feature dimensionality reduction and redundancy elimination to guarantee that the model has good generalisation ability in high dimensional space, thereby improving the quality of features. One may represent the processed feature set as:

$$z_i = PCA(x_i) \tag{4}$$

While lowering the model complexity, z_i is the dimensionality reduced student feature vector that preserves the main information. By means of a methodical data modelling procedure, this layer creates a complete, multi-dimensional picture of the learning status of the pupils, therefore offering a premium input basis for the next diagnostic layer.

3.1.2 *Knowledge point and ability association modelling layer*

The second tier of the MCRD-IEEM model addresses building a theoretical framework for students' ability portraits and generating a structured mapping relationship between knowledge points and cognitive skills in civic and political education.

Based on the course curriculum and knowledge system, this layer first identifies several important knowledge points and specifies the relevant set of cognitive ability dimensions depending on expert annotation and task analysis approach (Mosqueira-Rey et al., 2023). The Q matrix modelling approach is then used to build the binary value matrix defined below, therefore establishing the link structure between knowledge points and abilities:

$$Q = [q_{jk}] \in \{0, 1\}^{J \times K} \tag{5}$$

$$q_{jk} = 1 \tag{6}$$

where J is the total number of question items; K is the total umber of competency dimensions; q_{jk} indicates that the j^{th} question item involves the k^{th} competency dimension and vice versa. The competency criteria behind each question may be exactly stated with the Q matrix, therefore offering a priori framework for cognitive modelling.

Furthermore, considering the multi-level and uncertainty of students' knowledge point performance in real answers, this work presents a probabilistic mastery variable α_{ik}, which represents the degree of competency k by student i. The cognitive diagnostic approach makes advantage of this variable. The later cognitive diagnostic model with the following basic expression estimates this variable:

$$P(r_{ij} = 1 | \alpha_i, Q) = f(\alpha_i, q_j) \tag{7}$$

where r_{ij} is the response of student i to question j (1 is correct, 0 is incorrect), and $f(\cdot)$ is the diagnostic function, which combines the degree of matching of cognitive traits and student characteristics.

By means of the building of this layer, the model not only achieves the logical mapping from questions to ability dimensions but also lays the theoretical and structural basis for the later diagnostic process, so rendering the personalised ability analysis of students interpretable and traceable.

3.1.3 Multi-feature cognitive diagnosis and reasoning layer

The fundamental module of the MCRD-IEEM model is the multi-feature cognitive diagnosis and inference layer; its main goal is to combine the knowledge-competence mapping relationship to estimate students' mastery of several cognitive dimensions by means of cognitive diagnostic models, so integrating their behavioural, cognitive, and affective features. Conventional cognitive diagnostic approaches ignore the impact of dynamic elements such learning practices and affective states on cognitive levels by depending on stationary reasoning based on response data and Q-matrix. This work presents deep neural networks to overcome this problem by means of cognitive diagnosis-based deep neural network fusion and nonlinear mapping of multimodal information (Zheng et al., 2021), so improving the accuracy and adaptability of students' cognitive state modelling.

This work uses the DINA model, extensively applied in the field of cognitive diagnostics, as the basis model to explain the effect of students' mastery state on question-answering performance in every ability dimension. Its form is probabilistic:

$$P\left(r_{ij}=1 \middle| \alpha_i\right)=\left(1-s_j\right)^{\eta_{ij}} \cdot g_j^{1-\eta_{ij}} \tag{8}$$

where g_j is the guessing parameter, indicating the probability of answering correctly despite not mastering the abilities; η_{ij} is the matching index, should student i master all the abilities needed for the question, then η_{ij} is 1, otherwise 0; sj is the sliding parameter of question j, indicating the probability of mastering all relevant abilities but still answering incorrectly.

This work builds a feature-enhanced cognitive diagnostic network based on this premise, which jointly inputs students' feature vectors and their possible cognitive states into the deep network and forecasts students' performance on the questions by nonlinear transformation. One can obtain the general inference function by stating:

$$\hat{r}_{ij}=\sigma\left(W_2 \cdot \operatorname{ReLU}\left(W_1\left[z_i, \alpha_i\right]+b_1\right)+b_2\right) \tag{9}$$

where W_1, W_2 and b_1, b_2 are network parameters; $\sigma(\cdot)$ is the sigmoid function; $[z_i, \alpha_i]$ indicates feature splicing to cognitive states.

3.1.4 Performance comprehensive evaluation and feedback layer

Aiming to convert the results of multi-featured cognitive diagnosis into a comprehensive assessment of students' achievement in civic education, the MCRD-IEEM model outputs a layer of achievement called the comprehensive evaluation and feedback layer, which also offers tailored pedagogical feedback suggestions for the teachers and the system. This layer addresses not only the computation of final scores but also the thorough study of students' cognitive structure, level of ability mastery, and affective state to attain interpretive assessment of learning effects.

First of all, with the following fundamental formula, this layer calculates the score based on the students' ability vector α_i and their behavioural and emotional characteristics vector z_i acquired from the cognitive diagnosis layer using a linear weighting model.

$$S_i=\lambda_1 \cdot \sum_{k=1}^{n} w_k \cdot \alpha_{ik}+\lambda_2 \cdot f_b\left(z_i^{(b)}\right)+\lambda_3 \cdot f_e\left(z_i^{(e)}\right) \tag{10}$$

where S_i is the general performance of student i, α_{ik} is the mastery of the k^{th} cognitive dimension, and w_k is the weight of each competency dimension; $f_b(\cdot)$ and $f_e(\cdot)$ are the quantitative functions of the behavioural and affective states, and λ_1, λ_2, λ_3 are the fusion coefficients, which satisfy that the sum of the three is one.

Apart from that, the system creates a tailored feedback report based on performance and competency that incorporates: mastered knowledge points, poor cognitive dimensions, aberrant behavioural cues and risk warnings. Not only does the feedback enable students to reflect on themselves, but it also gives teachers the foundation to vary their education. It consists in graphical visuals, language summaries, and teacher recommendations (Philipsen et al., 2019).

By means of this layer of design, the MCRD-IEEM model achieves a multi-dimensional comprehensive assessment of students' performance in civic education, so strengthening the practicality and intelligence of the model, and offers technical support for the building of a digital, exact and personalised civic education support system.

By use of four hierarchical modules, the MCRD-IEEM model builds a diagnostic system for students' performance in civic and political education with a clear structure, rigorous logic and complementary functions. Realising the whole process of modelling from the original behavioural data to the cognitive state portrayal, each module advances from the bottom data perception to the high-level intelligent reasoning, then to the achievement output and personality feedback, which totally reflects the comprehensive application value of multi-feature fusion and cognitive diagnostic technology in the digital scenario of civic and political education.

3.2 System performance evaluation metrics

Starting from four dimensions, this paper chooses representative and specific assessment indexes to measure them, so ensuring that the MCRD-IEEM model achieves an effective balance between intelligibility and practicality in order to systematically evaluate the performance of the model in the task of diagnosing the performance of civic education.

First, area under curve (AUC) was selected as the assessment indicator for diagnostic accuracy, which is used to evaluate the differentiation ability of the model in predicting the correctness of students' answers. The higher the AUC value, the more effective the model is in differentiating between mastery and non-mastery students, which makes the model more reliable in cognitive diagnosis modelling (Chen et al., 2020).

Second, knowledge consistency rate (KCR) is utilised as an indicator in the dimension of cognitive explanatory power to check whether the model output of students' knowledge mastery level corresponds with the actual teaching assessment and teachers' perspective (He et al., 2023). Reflecting the pedagogical interpretability and trustworthiness of the model diagnostics, this indicator is based on the comparison between the teacher annotation data and the model output.

Third, learning gain rate (LGR) is selected as a metric, i.e., the extent of increase in students' performance or competency mastery level following application of the model proposals, for the efficacy of tailored feedback. The difference between pre-test and post-test scores allows one to determine LGR, therefore representing the intervention effect of tailored feedback in actual learning environments (Lin, 2025).

At last, the dimension of system response efficiency chooses average response time (ART) as a performance indicator to assess the computational timeliness of the model in handling certain student diagnostic demands (Wang et al., 2018). One of the main determinants of the feasibility of the practical use of the model is this indicator, which directly affects the system deployment and real-time feedback capacity.

By means of the aforementioned four particular indications, the MCRD-IEEM model may be fully assessed in terms of accuracy, interpretability, feedback efficacy and system efficiency, so offering a quantitative basis for next experimental validation and optimisation.

4 Experiment and evaluation

4.1 Introduction to the dataset

Originally published by the Even Platform Education Foundation in Taiwan, the experimental data chosen for this study originates from Junyi Academy Online Learning Activity Dataset, which actually documents students' online learning experience. This paper chooses a subset of the questions with features such logical reasoning and situational judgement and aggregates them with the question-answering behaviour data to build multimodal input features, which are used for the training and evaluation of the model, so meeting the demand for cognitive modelling in the civic education scenario.

Table 1 lists the major fields in the dataset together with their explanations:

This dataset offers a suitable behavioural basis and knowledge mapping relationship for cognitive diagnostic modelling, therefore supporting the validation of the MCRD-IEEM model in actual online learning environments.

Table 1 Main fields of the Junyi Academy Online Learning Activity Dataset

Field name	*Description*
user_id	Unique identifier for each student
problem_id	Unique identifier for each problem/question
timestamp	Timestamp of the student's response
correct	Whether the answer is correct (1 = correct, 0 = incorrect)
elapsed_time	Time spent on answering the problem (in milliseconds)
problem_sequence	Position of the problem within the session sequence
hint_count	Number of times the student requested hints before answering
retry_count	Number of times the student retried after incorrect attempts
knowledge_tag	Knowledge point or tag associated with the problem (for Q-matrix usage)

4.2 Experimental design and comparison models

Combining multi-model comparison with feature ablation analysis allowed the experimental design to be carried out in order to fully evaluate the performance of the proposed multi-feature cognitive diagnostic model, MCRD-IEEM, in the task of diagnosing students' performance in civic education. The three main experimental goals are:

1 to evaluate the relative advantages of the model in several algorithm categories

2 to investigate the contribution of multimodal features to the model performance

3 to confirm the prediction accuracy and resilience of the proposed model on real data.

To ensure the reliability and reproducibility of the experimental results, we conducted statistical significance tests in our experiments and used random seeds and cross-validation methods. Specifically, we set random seeds in each experiment to ensure consistency in data division and model training. In addition, we used a five-fold cross-validation method to divide the dataset into five subsets and used one of the subsets as the test set and the remaining four as the training set in each experiment. With this approach, we can effectively evaluate the performance of the model and ensure the statistical significance of the results.

Covering conventional cognitive diagnostic approaches, classical machine learning algorithms, deep learning models, multi-feature fusion frameworks, this experiment chooses many typical models for comparison:

DINA, or deterministic input, noisy 'and' gate, model. The DINA model assumes that the students' mastery of each knowledge point is deterministic and there could be some noise in the process of responding questions, therefore modelling their knowledge mastery state (Paulsen and

Valdivia, 2022). A baseline approach in the field of cognitive diagnostics, it is mostly utilised to deduce students' knowledge mastery based on their question-answering data.

Based on the assumption that students' answering behaviour is influenced by their potential ability and the difficulty of the topics, IRT is a probabilistic statistical model for analyses the relationship between students' performance on different topics and their possible ability, which has a strong explanatory and theoretical foundation. Students' academic level and aptitude are often assessed using it.

Many educational data analysis projects benefit from the standard supervised learning technique SVM. Effective handling of both linear and nonlinear classification problems, SVM divides samples by determining the best hyperplane in a high-dimensional space. In this work, students' answer results are classified using SVM to forecast their knowledge point mastery.

By building several decision trees and voting on their outcomes, RF is an integrated learning strategy that increases the accuracy and stability of classification models. Highly fault-tolerant and with good interpretability, RF is consequently extensively applied in education for student behaviour analysis and performance prediction.

Comprising several fully connected layers able to manage nonlinear relationships in input data, multilayer perceptron (MLP) is a fundamental feed-forward neural network model. This work uses MLP as a benchmark model for deep learning methods to capture the intricate interaction between student behavioural data and their academic performance.

Able to manage temporal correlations in student answer data, deep knowledge tracing (DKT) model is an RNN-based student knowledge tracing technique. Through the approach, DKT learns the learning process of variously timed pupils to forecast their future learning patterns. Particularly in online learning situations, this model performs really well in educational data.

Graph-based knowledge tracing (GKT): GKT is an advanced model ideal for representing knowledge structures in civic education as graph convolutional network (GCN) allows GKT to efficiently capture the relational patterns of students' knowledge point mastery and merges graph theory with deep learning.

Combining Bayesian knowledge with student behavioural characteristics is the model Bayesian knowledge tracing with behavioural embedding (BKT + BE). Apart from inferring students' knowledge mastery using the conventional Bayesian network, the model adds multimodal information including students' emotions and behaviours, so enhancing the prediction capacity and personalised recommendation capability of the model.

Designed especially to address the fusing of multimodal data, multimodal deep fusing network (MDFN) is a deep learning system. With great adaptability and accuracy, the model can combine several elements in the students' learning process and assist to identify possible influences on their academic performance by jointly learning many data sources (e.g., behavioural data, learning progress, emotional feedback, etc.).

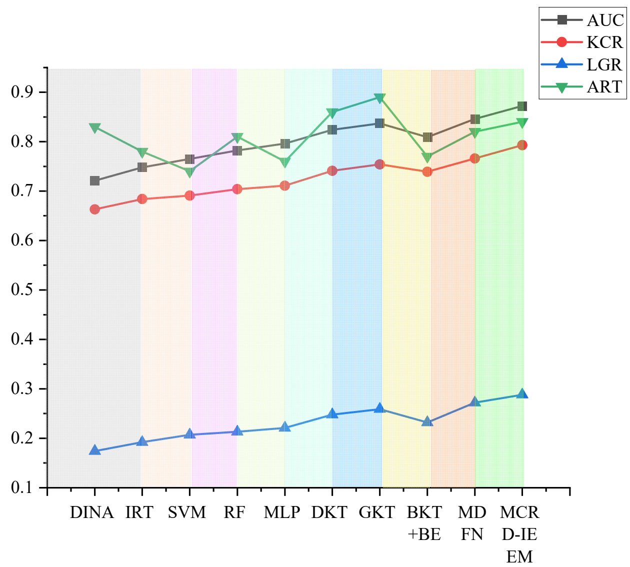
To evaluate the performance of the model and ensure the reliability of the results, we used training set/test set division in our experiments. Specifically, we randomly divided the dataset into training and test sets in the ratio of 80% training set and 20% test set. This division ensures the generalisation ability of the model on unseen data. During model training, we use the training set to train the model and evaluate the model's performance on the test set. To further ensure the stability and reliability of the results, we also performed a five-fold cross-validation, where the dataset is divided into five subsets, and each experiment uses one of the subsets as the test set and the remaining four subsets as the training set. In this way, we were able to evaluate the performance of the model more comprehensively.

4.3 *Experiment 1: validation of model effects*

This experiment is to fully validate the general efficiency of the proposed multi-featured cognitive diagnostics model MCRD-IEEM in the job of performance prediction in civic education. By means of a comparison with several mainstream models, the experiment assesses its diagnostic capacity and practical application value in handling multidimensional data of pupils. All models were trained and evaluated in the same dataset and experimental context, and a five-fold cross-validation was applied for performance evaluation so as to guarantee the scientificity and fairness of the experiment.

Figure 2 displays the experimental findings.

Figure 2 Comparative experimental performance of each model with different indicators (see online version for colours)



The MCRD-IEEM model suggested in this study performs better than the other comparative models based on the experimental data, particularly in AUC (0.872), KCR

(0.793) and LGR (0.288), which are considerably better than the other four assessment criteria. This implies that the model can more precisely assist the cognitive diagnosis task in civic education and is more suited to recognise students' knowledge mastery level, modelling knowledge consistency, and spotting learning gains.

On the other hand, conventional models as DINA and IRT are rather weak in performance, particularly in the LGR measures, which only reach 0.174 and 0.192 respectively, thereby demonstrating their limited capacity to recognise changes in students' learning effects. While conventional machine learning techniques like SVM and RF have somewhat raised the accuracy, their capacity to represent intricate features is still limited. Conversely, DKT and GKT based on deep learning exhibit improved performance and their benefits in temporal modelling and graph structure understanding, particularly the KCR of GKT approaches 0.754, which is near to the level of the model in this research.

With AUCs of 0.846 and 0.809 respectively, MDFN and BKT+BE models also show good potential in multimodal information modelling; yet, their KCR and LGR are still somewhat low compared to MCRD-IEEM. MCRD-IEEM integrates cognitive path analysis and embedded expression learning based on multi-feature cognitive modelling, therefore improving the accuracy and stability of diagnosis. precision and stability, therefore confirming its practical worth in the process of intelligent assessment of civic education.

4.4 *Experiment 2: multi-feature fusion effect analysis*

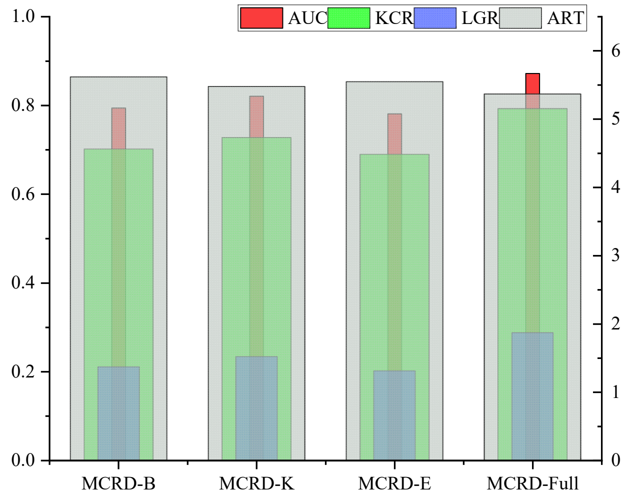
This research intends to investigate the impact of several feature dimensions on model performance by means of control variables, respectively, so verifying the efficacy of the MCRD-IEEM model in multi-feature fusion by omitting or merging the inputs alternately. The model input features specifically fall into three categories: behavioural features (e.g., click records, video viewing duration); knowledge features (e.g., answer correctness, mastery probability); and emotional feedback features (e.g., learning attitude scores, emotional tendency labels). Set up for comparison are the four model versions listed below:

- MCRD-K inputs knowledge features alone
- MCRD-B inputs just behavioural traits
- MCRD-E inputs of emotional feedback features only
- MCRD-Full inputs of all three kinds of features (i.e., the whole MCRD-IEEM model).

Figure 3 display the experimental results.

MCRD-Full (0.872) much exceeded all single-feature models on the AUC measure. Among them, MCRD-K (0.821) performs the best; knowledge mastery status is the fundamental basis of performance diagnostic; while the models of MCRD-B (0.794) or MCRD-E (0.781) perform weakly, both of them nevertheless give effective complements. MCRD-Full increases the AUC by 6.2% by combining the three types of features, compared with the ideal single-feature model, MCRD-K, therefore confirming the need of cooperative modelling of multimodal data to improve prediction accuracy.

Figure 3 Experimental results of multi-feature fusion effect (see online version for colours)



Regarding KCR, MCRD-Full (0.793) increases 8.9% over MCRD-K (0.728), meaning that the inclusion of behavioural trajectories and emotional feedback can help to improve the consistency between diagnosis results and real teaching evaluation. For instance, the fluctuations in students' responses under severe emotional stress could indicate cognitive blindness; MCRD-Full, on the other hand, records such events using emotional aspects, therefore guiding the diagnosis closer to teachers' dynamic observation of the students' learning state.

The LGR of MCRD-Full (0.288) in the LGR dimension is 23.1% higher than that of MCRD-K (0. 234), so stressing the strengthening power of multi-feature fusion on the efficacy of tailored intervention. Particularly, the overlay study of behavioural features (e.g., low homework submission rate) and emotional attributes (e.g., persistent anxiety state) precisely identifies high-risk pupils and suggests focused tutoring tactics, so improving posttest results.

Although multidimensional data is included in MCRD-Full, its system response time (ART) (5.37 seconds) is rather optimised when compared to MCRD-B (5.62 seconds). While the complementary character of multimodal features reduces the number of model iterations and achieves a balance between efficiency and accuracy, this implies that principal component dimensionality reduction and parallelised computation essentially relieve the computational burden of feature redundancy.

All things considered, experiment 2 confirmed the value of multi-feature fusion in the diagnosis of student performance and further demonstrated the benefits of the MCRD-IEEM model in multi-dimensional data processing and collaborative modelling, so offering a more complete technical support for the evaluation of personalised civic education.

5 Conclusions

5.1 Summary and limitations of the study

This work proposes an intelligent assessment model – MCRD-IEEM – that combines multi-modal features such behavioural data, knowledge mastery state and emotional feedback, etc. It also concentrates on the theme of diagnosing students' performance in civic education based on multi-feature cognitive diagnosis in the digital perspective. The model's four layers help to improve the interpretability and flexibility of the outcomes in addition to raising the diagnostic accuracy.

The Junyi Academy Online Learning Activity Dataset indicates that the experimental section is meant to be compared with the conventional model and examine the impact of feature fusion; the evaluation indices are AUC, KCR, LGR, and ART. The results confirm that the MCRD-IEEM beats the comparison model in the four dimensions and that the multimodal feature fusion with the conventional model may be applied to raise the diagnosis accuracy. It confirms in the evaluation of civic education the efficiency of multimodal feature fusion and cognitive-driven modelling. This study offers a technical road for thorough assessment of students' learning situation and tailored intervention as well as empirical evidence for the intelligent upgrading of civic and political education.

This study has made significant advances in diagnosing students' performance in civic education through a multi-feature cognitive diagnosis from a digital perspective and has proposed an original MCRD-IEEM model. However, there are certain limitations that need to be addressed in future research. First, the dataset used in this study is primarily derived from specific online learning platforms, which may limit the model's generalisability and its applicability across various educational environments. Second, although the MCRD-IEEM model demonstrates strong performance in tests, its complexity leads to increased computational costs and reduced interpretability. Balancing the complexity, accuracy, and interpretability of the model for practical applications remains a challenge. Additionally, the model may struggle to manage nonlinear and unstructured relationships.

Furthermore, this study mostly used quantitative indicators in evaluating the performance of the model, which, although reflecting the performance of the model from several angles, might not be able to fully capture the multidimensional performance of students in civic education. At last, this study neglected to adequately account for in the experimental design the long-term consequences of educational interventions.

5.2 Directions for follow-up research

Future studies can be broad in the following ways to help to overcome the limits of current one: to increase the generalisability of the model, the first is to investigate its adaptability and generalisability in several educational environments and cultural settings.

The second objective is to explore methods for retaining or enhancing the accuracy and interpretability of the model while simultaneously simplifying its structure and reducing computation costs.

Third, we aim to provide innovative evaluation tools and approaches to more comprehensively assess students' performance in political and ideological education, encompassing several dimensions, including cognition, emotion and behaviour.

Fourth, doing long-term follow-up research to evaluate the model's long-term impact on political and ideological literacy of pupils.

Future studies should also take into account how to more successfully combine the model with current educational technology and platforms. This will help to accomplish tailored teaching and counselling. By means of these research orientations, the scientific, pragmatic and intelligent level of the performance of ideological and political education can be enhanced even more.

In addition, to increase the generalisability of the model, future research will explore its adaptation and generalisation to different educational settings and cultural contexts. For example, there may be significant differences in students' motivation, affective expressions, and learning strategies across cultures, all of which may affect the performance of the model. Through these efforts, we hope to make the MCRD-IEEM model more widely applicable to the assessment of citizenship education worldwide.

It is worth noting that potential risks and ethical issues must be fully considered when using multimodal data for student assessment. Student data privacy is of paramount importance because multimodal data contains detailed information about students' personal behaviour, affective feedback and learning process, and if these data are mishandled or leaked, it will result in serious privacy violations for students. Therefore, the collection, storage and use of data must meet strict privacy protection standards and require informed consent from students. At the same time, the issues of bias and fairness should not be ignored. Multimodal data may produce unfair assessment results due to data sources, sample bias or algorithm design, e.g., certain groups of students may be misjudged as underperforming due to unbalanced data characteristics. Therefore, measures need to be taken to eliminate potential bias during model design and data processing to ensure assessment fairness. In addition, the application of AI in education must be responsible. The purpose of educational assessment is to help students develop and grow, rather than simply categorising or ranking their performance, and the development and application of AI models should have the core objectives of promoting educational equity and supporting students' personalised development, while avoiding undue psychological pressure or negative impacts on students.

Declarations

The author declares that she has no conflicts of interest.

References

Amin, H., Pratama, Y. and Amin, A.H. (2023) 'Revitalizing Ibn Khaldun's theory of Islamic education for the contemporary world', *AL-ISHLAH: Jurnal Pendidikan*, Vol. 15, No. 3, pp.4010–4020.

Belchior, R.F. and Lyons, R. (2022) 'An exploration of changing student entrepreneurial motivators – a longitudinal analysis', *International Journal of Entrepreneurial Behavior & Research*, Vol. 28, No. 1, pp.151–181.

Burbules, N.C., Fan, G. and Repp, P. (2020) 'Five trends of education and technology in a sustainable future', *Geography and Sustainability*, Vol. 1, No. 2, pp.93–97.

Castelo, S., Rulff, J., McGowan, E., Steers, B., Wu, G., Chen, S., Roman, I., Lopez, R., Brewer, E. and Zhao, C. (2023) 'Argus: visualization of AI-assisted task guidance in AR', *IEEE Transactions on Visualization and Computer Graphics*, Vol. 30, No. 1, pp.1313–1323.

Chen, F., Cui, Y. and Chu, M-W. (2020) 'Utilizing game analytics to inform and validate digital game-based assessment with evidence-centered game design: a case study', *International Journal of Artificial Intelligence in Education*, Vol. 30, pp.481–503.

Du, W. and Ma, X. (2021) 'Probing what's behind the test score: application of multi-CDM to diagnose EFL learners' reading performance', *Reading and Writing*, Vol. 34, No. 6, pp.1441–1466.

Griffith, P.B., Doherty, C., Smeltzer, S.C. and Mariani, B. (2021) 'Education initiatives in cognitive debiasing to improve diagnostic accuracy in student providers: a scoping review', *Journal of the American Association of Nurse Practitioners*, Vol. 33, No. 11, pp.862–871.

Hananto, A.R., Musdholifah, A. and Wardoyo, R. (2024) 'Identifying student learning styles using support vector machine in Felder-Silverman model', *Journal of Applied Data Sciences*, Vol. 5, No. 3, pp.1495–1507.

He, J., Liu, Y., Ran, T. and Zhang, D. (2023) 'How students' perception of feedback influences self-regulated learning: the mediating role of self-efficacy and goal orientation', *European Journal of Psychology of Education*, Vol. 38, No. 4, pp.1551–1569.

Lee, Y. (2019) 'Estimating student ability and problem difficulty using item response theory (IRT) and TrueSkill', *Information Discovery and Delivery*, Vol. 47, No. 2, pp.67–75.

Lee, Y., Moon, G.G. and Kwon, Y-K. (2019) 'Implementing liberal arts education in the era of the fourth industrial revolution: lessons and implications for Korea's higher education policy', *International Review of Public Administration*, Vol. 24, No. 4, pp.282–294.

Li, H. (2025) 'Multicultural data assistance mining analysis for ideological and political education in smart education platforms using artificial intelligence', *Wireless Networks*, Vol. 31, No. 1, pp.567–581.

Lin, K-H. (2025) 'Project-based learning in financial literacy education: effects on learning outcomes and motivation across cognitive styles', *Advances in Management and Applied Economics*, Vol. 15, No. 3, pp.1–3.

Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascarán, J. and Fernández-Leal, Á. (2023) 'Human-in-the-loop machine learning: a state of the art', *Artificial Intelligence Review*, Vol. 56, No. 4, pp.3005–3054.

Paulsen, J. and Valdivia, D.S. (2022) 'Examining cognitive diagnostic modeling in classroom assessment conditions', *The Journal of Experimental Education*, Vol. 90, No. 4, pp.916–933.

Philipsen, B., Tondeur, J., Roblin, N.P., Vanslambrouck, S. and Zhu, C. (2019) 'Improving teacher professional development for online and blended learning: a systematic meta-aggregative review', *Educational Technology Research and Development*, Vol. 67, pp.1145–1174.

Sharma, A. and Mansotra, V. (2019) 'Deep learning based student emotion recognition from facial expressions in classrooms', *International Journal of Engineering and Advanced Technology*, Vol. 8, No. 6, pp.4691–4699.

Tedre, M., Toivonen, T., Kahila, J., Vartiainen, H., Valtonen, T., Jormanainen, I. and Pears, A. (2021) 'Teaching machine learning in K–12 classroom: pedagogical and technological trajectories for artificial intelligence education', *IEEE Access*, Vol. 9, pp.110558–110572.

Velagaleti, S.B., Choukaier, D., Singh, S., Kaur, J., Dubey, A., Mujoo, S., Tolani, K., Bhatia, R. and Singh, R. (2024) 'Utilizing emotion analysis for suicide prediction and mental health detection in students with deep learning', *International Journal of Intelligent Systems and Applications in Engineering*, Vol. 12, pp.729–738.

Vittorini, P. and Galassi, A. (2023) 'rDSA: an intelligent tool for data science assignments', *Multimedia Tools and Applications*, Vol. 82, No. 9, pp.12879–12905.

Wang, S., Zhang, S., Douglas, J. and Culpepper, S. (2018) 'Using response times to assess learning progress: a joint model for responses and response times', *Measurement: Interdisciplinary Research and Perspectives*, Vol. 16, No. 1, pp.45–58.

Xu, T., Wu, X., Sun, S. and Kong, Q. (2023) 'Cognitive diagnostic analysis of students' mathematical competency based on the DINA model', *Psychology in the Schools*, Vol. 60, No. 9, pp.3135–3150.

Zheng, Y., Xu, Z. and Wang, X. (2021) 'The fusion of deep learning and fuzzy systems: a state-of-the-art survey', *IEEE Transactions on Fuzzy Systems*, Vol. 30, No. 8, pp.2783–2799.