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Construction of a Multi-Objective Optimization Labor Education Course Model Based on Fuzzy Cognitive Orientation

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Abstract This study focuses on the application of fuzzy cognitive diagnostic techniques in the design and optimization of labor education curriculum, and proposes a cognitive diagnostic framework for KSCD by constructing a cognitive model integrating fuzzy cognitive diagnosis with a multilevel scoring Q matrix, combined with a deep neural network approach. The study used empirical analysis to verify the validity of the model, and elementary school students had the highest probability of mastering labor problem solving ability (A7) (0.701±0.294), while labor knowledge (A2) and labor values (A1) were relatively weak (mean values of 0.505 and 0.522, respectively). Labor habits (A6) showed the greatest individual differences (SD=0.319), and the probability of mastering labor emotion regulation strategies (A3) was lower than labor attitudes. Finally, the stratified teaching strategy and dynamic remedial mechanism are proposed to provide theoretical basis and practical path for the precise implementation of labor education.

Index Terms labor education, fuzzy cognitive diagnosis, Q matrix, deep neural network, KSCD model

I. Introduction

Labor education is an important content of the current social education system, is an important part of the comprehensive development of moral, intellectual, physical, aesthetic and laborious education system, with the value of moral, intellectual, physical and aesthetic comprehensive education [1], [2]. In recent years, many national ministries of education have issued a series of documents on strengthening labor education, clearly put forward the labor education into the whole process of talent training [3]. Therefore, accurately grasping the significance of the times of labor education under the concept of curriculum, strengthening the effectiveness of labor education, and cultivating students' labor literacy is a due course of action for the development and change of the times, and is also the proper meaning of cultivating social builders and successors who are all-rounded in morality, intelligence, physical fitness, aesthetics and physical strength [4]-[6].

However, many schools ignore the educational value of labor education, limiting the design of labor education curriculum to purely handcraft classes and a single labor education base, or directly ignoring its educational value, treating labor education as leisure and entertainment after school, or even as a means of punishment after students make mistakes, leading to a series of problems such as primary school students' contempt for labor, unwillingness to work, and disrespect for workers [7]-[9]. In addition, the labor education curriculum is judged only by whether students' labor passes or fails, ignoring the existence of the cognitive gray scale of students' skill acquisition, and due to the diversity of students' interests, the existing types of labor are difficult to meet students' individual needs, further highlighting the shortcomings of the curriculum design [10]-[12].

In this paper, the development of cognitive diagnostic technology is firstly sorted out, focusing on explaining the structure of each cognitive diagnostic model. Based on the requirements of the new curriculum, we innovatively design a labor program for elementary school students. A cognitive model of labor literacy with 7 key attributes is constructed, and a Q-matrix with the progressive features of school grades is developed. A variety of cognitive diagnostic models were fitted and tested, and the KSCD model, which has the best performance, was used to reveal the weaknesses of students' labor knowledge acquisition. Based on the empirical data, a tiered intervention strategy is proposed to provide methodological support for the precise implementation of labor education.

II. Individualized teaching based on fuzzy cognitive diagnosis

II. A. Cognitive diagnosis

Cognitive diagnosis aims to reveal and understand the cognitive state of learners by observing their learning behaviors and measuring their mastery of specific knowledge concepts, so as to promote their comprehensive development in a targeted manner and realize learner-centered personalized education. The key task of cognitive diagnosis is to accurately assess the cognitive state of learners to support self-regulated learning. This subsection will introduce the classical theoretical functions of traditional cognitive diagnosis and deep cognitive diagnosis research based on deep learning methods.

II. A. 1) Traditional cognitive diagnosis

The Classical Test Theory (CTT) of traditional educational measurement evaluates learners through overall scores, but its parameter estimation relies too much on learner samples, and the reliability estimation accuracy is not high. In response to these limitations, Item Response Theory (IRT) takes into account the learner's cognitive level and the question parameters. In IRT, "Item" refers to the question and "Item Response" refers to the learner's response to the question. IRT mainly uses logistic regression functions for modeling, which can be divided into single-parameter models, two-parameter models and three-parameter models according to different parameters. The single-parameter model only considers the difficulty of knowledge concepts, while the two-parameter model adds the problem discrimination on this basis, while the three-parameter model adds guess parameters on the basis of the two-parameter model. The existing deep cognitive diagnostic modeling is mainly based on the interaction functions of two-parameter models, such as DIRT, NCD and KSCD. The two-parameter IRT function is defined as follows:

$$P\left(x_{ij}=1 \mid \theta_i, \beta_j, \eta_j\right)=\frac{1}{1+e^{-D\eta_j(\theta_i-\beta_j)}} \tag{1}$$

where P is the predicted value of learner i answering correctly on topic j, θ_i is the latent trait of learner i, β_j is the difficulty of knowledge concepts included in topic j, η_j is the differentiation level of topic j, and D is a constant. When D is taken to be 0.1702, the probability density of the function differs from the other basic form of IRT, the normal shoulder curve, by less than 0.01, so D generally takes the value of 1.702 (or 1.7).

II. A. 2) Deep cognitive diagnosis

In deep cognitive diagnostic modeling research, the two-parameter IRT interaction function has certain advantages in terms of both model prediction performance and interpretability.The DIRT model mines the textual information of the questions through multiple neural networks, and inputs the obtained question features into the two-parameter IRT interaction function to predict the learner's response accuracy.The NCD model is based on the deep neural network, and defines a class of MIRT interaction function that can automatically fit the complex interactions between the learner and the questions. The NCD model is further based on deep neural networks and defines a MIRT-like interaction function that can automatically fit the complex interactions between learners and questions, which is defined as follows, and the model is shown in Fig. 1.

$$x_{ij}=Q_j \circ (\alpha_i-\beta_j)\times \eta_j \tag{2}$$

$$y_{ij}=\sigma\left(W_3\sigma\left(W_2\sigma\left(W_3x_{ij}^T+b_1\right)+b_2\right)+b_3\right) \tag{3}$$

where y_{ij} is equivalent to the probability of answering correctly P, which represents the predicted value of learner i answering correctly on topic j. Q_j is the expert-labeled topic-knowledge concept association matrix, and α_i is equivalent to the potential trait θ_i of learner i in Equation (1), which indicates the mastery level of learner i on the knowledge concept. σ is the sigmoid activation function, and W and b are the trainable weights and bias parameters, respectively.

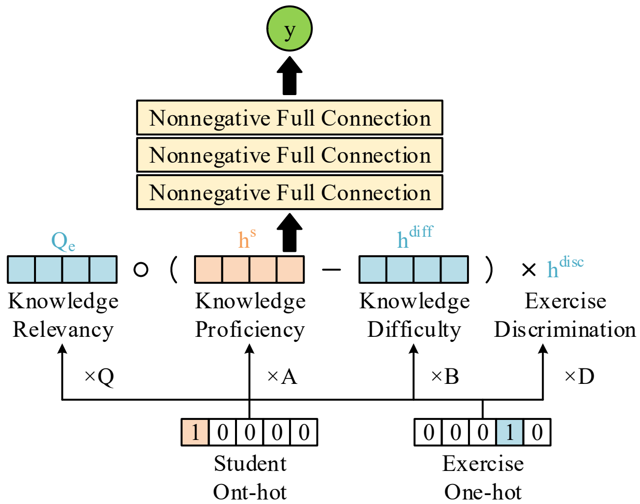

Figure 1: NCD model

The interaction function of NCD avoids the high expert design cost and gives the framework some extensibility. In the extended model of NCD, the Neurocognitive Diagnosis with Textual Content Enhancement (CNCD-F) model, the first layer of the interaction function is defined as follows, and the new modules compared to the NCD model are shown in Figure 2.

$$x_{ij} = Q_j \circ \left(\alpha_i - \left(\beta_j \| F_j\right)\right) \times \eta_j \tag{4}$$

where F_j is the topic text feature, the CNCD-F model enhances the diagnostic ability of the model by introducing the topic text feature vector spliced with the knowledge concept difficulty vector so that the interaction function can take into account the text information of the topic in the interaction between the learner and the topic.

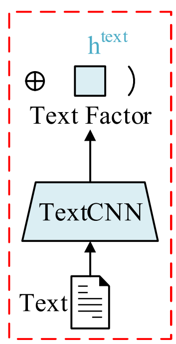

Figure 2: The feature extraction module of the topic text of the CNCD-F model

The KSCD framework further introduces the knowledge concept relationship based on the NCD framework, and defines a new interaction function based on Equation (2) to get the learner's mastery level of non-interactive knowledge concepts.

II. B.Fuzzy Cognitive Diagnostic Process in Personalized Instruction

Combined with the framework of personalized teaching and fuzzy cognitive diagnosis, this study introduces the process of fuzzy cognitive diagnosis in personalized teaching, and the specific process is shown in Figure 3. In the process of personalized teaching, students are tested and submitted on the system, the system collects and stores students' answer data, fuzzy cognitive diagnosis diagnoses students' knowledge status according to students' answer data and test questions-knowledge points Q matrix, and uses Markov chain Monte Carlo algorithm to estimate parameters, including students' latent characteristics θ_e, difficulty b_{ek} and discrimination a_{ek}, test question error rate s and guess rate g. The first layer is the potential characteristics of students, and the fuzzy cognitive diagnosis assumes that each student e has a potential feature θ_e, and believes that the potential characteristics affect the skill mastery of students. The second level is the student's knowledge point mastery d_{ek}, which is determined by the potential feature θ_e, the difficulty b_{ik} and the discrimination a_{ik}, and the knowledge point mastery degree is a continuous value between 0 and 1, which provides a basis for personalized remedial teaching. The third level is the student's mastery of the test question η_{ej}, the subjective question and the objective question mastery degree are modeled differently, the student must master all the knowledge points examined by the objective question before it is possible to answer the test question, however, as long as the student masters one of the knowledge points examined by the subjective question, it is possible to answer part of the test question correctly, therefore, the mastery degree of the objective question conforms to the "connection" hypothesis, and the subjective question mastery degree conforms to the "compensatory" hypothesis. Combined with the test question-knowledge point Q matrix, the objective questions are modeled by fuzzy intersection, and the subjective questions are modeled by fuzzy merger. The fourth layer is the true score of the answer, that is, the probability that the student will answer the test question correctly, and the error rate and guessing rate of the student's answer to the test question are integrated on the basis of the mastery of the test question, and the error refers to the student's mastery of the test question but the wrong answer, and guessing that the student has not mastered the test question but answered it correctly, and there are two situations of correct answering, that is, the student has mastered the test question and has no mistake or the student has not mastered the test question but answered the question correctly by guessing, and the student has completed the remedial learning. The system predicts the recommended test questions for students according to their true scores in the recommended test questions, so as to avoid students from feeling cognitive load due to the difficulty of the test questions.

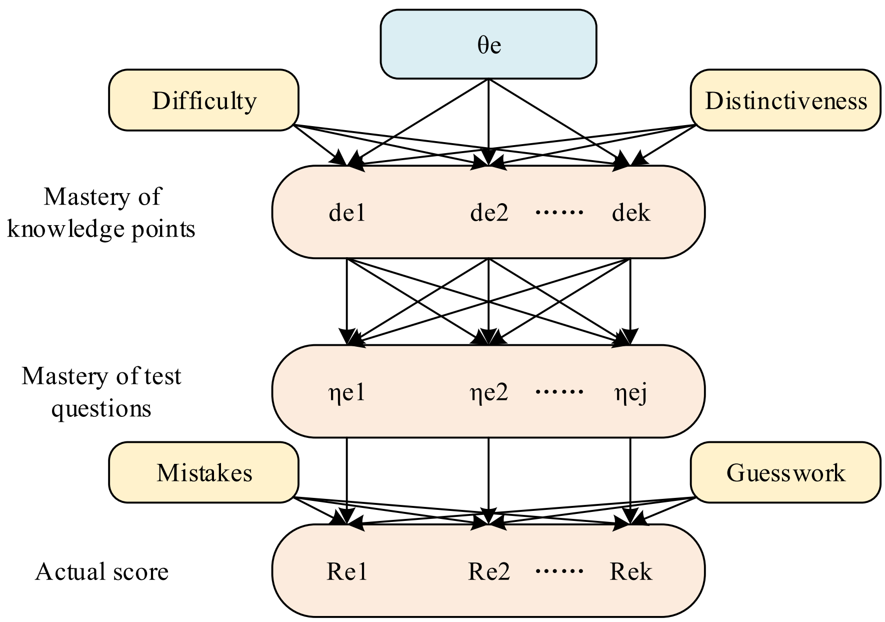

Figure 3: The process of fuzzy cognitive diagnosis in personalized teaching

On blurring the level of mastery of test questions. All the knowledge points examined in the test questions together determine the level of mastery of the test questions. The common roles of knowledge points on objective and subjective questions are associative and compensatory, respectively. The linkage type assumes that students must master all the knowledge points examined in the question if they want to answer the question correctly; the compensation type assumes that students may partially answer the question as long as they have mastered any of the knowledge points examined in the question. In general, objective questions have standardized answers that require students to master all the knowledge points examined in the question in order to answer the question correctly. Therefore, the fuzzy cognitive diagnosis assumes that the common role of knowledge points in the objective questions is linkage type, the degree of mastery of the objective questions is the intersection of the mastery of all the knowledge points examined in the test; subjective questions are generally scored according to the steps of the answer, the students, even if they do not have a full grasp of all the knowledge points examined in the test question, may also be able to answer a part of the answer correctly, the more knowledge points mastered, the higher the score of the answer, if the student masters that the test question to examine the If students master all the knowledge points examined in the test question, they may answer the test question completely correctly.

Therefore, the fuzzy cognitive diagnosis assumes that the common effect of the knowledge points on the subjective questions is compensatory, and the mastery of the subjective questions is the concatenation of the mastery of all the knowledge points examined in the test question. The fuzzification of students' mastery of the test question is shown in Figure 4, where student e1 is in the common area of $k1$, $k2$, $k3$, indicating that the student has mastered all the knowledge points examined in the objective question and has completely mastered the question, and student e2 has partially mastered, completely mastered, and not mastered at all $k1$, $k2$, $k3$, and has mastered the objective question to the extent of 0, respectively; Student e1, who partially mastered, did not master at all, and fully mastered $k1$, $k2$, and $k3$, respectively, indicating that the student might have gotten some of that test question right, and student e2, who did not master $k1$, $k2$, and $k3$ at all, had a level of mastery of 0 on that subjective question, and was unlikely to have gotten the test question right.

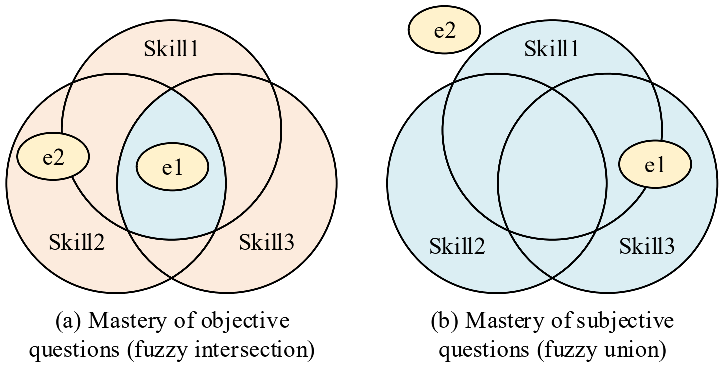

Figure 4: Fuzzing of students' mastery of test questions

Given a test-question-knowledge-points Q matrix with m knowledge points, the mastery level of student e on topic j, η_{ej}, and the mastery level of an objective question, η_{ej}, is given in the following formula:

$$\eta_{ej} = u \cap_{1 \le k \le K, q_{jk}=1} (k) \tag{5}$$

The formula for Subjective Mastery η_{ej} is shown below:

$$\eta_{ej} = u \cup_{1 \le k \le K, q_{jk}=1} (k) \tag{6}$$

In the above formula, K is the number of knowledge points examined in test question j, $q_{jk} = 1$ means that test question j examines knowledge point k, otherwise it does not, and u_k is the degree of knowledge point mastery.

The formula for fuzzy intersection and fuzzy concatenation is as follows:

$$(A \cap B)(x) = \min(A(x), B(x)) \tag{7}$$

$$(A \cup B)(x) = \max(A(x), B(x)) \tag{8}$$

Equation (7) (8) can be interpreted in this way: the degree of mastery of the objective questions is equal to the degree of mastery of the worst knowledge point among all the knowledge points examined in that test, and the degree of mastery of the subjective questions is equal to the degree of mastery of the best knowledge point among all the knowledge points examined in that test. A subjective question examines $k1$, $k2$, $k3$ three knowledge points, the degree of mastery of knowledge points are 0.1, 0.7, 0.9, according to fuzzy and formula to get the degree of mastery of the subjective question is 0.9, which is deviating from the actual situation. To solve this problem, the R-FuzzyCDF model uses the arithmetic mean to calculate the students' mastery of subjective questions, and the formula for the students' mastery of subjective questions is redefined as:

$$\eta_{ej} = \frac{\sum u_{1 \le k \le K, q_{jk}=1} (k)}{\sum_{k=1}^{K} q_{jk}} \tag{9}$$

In the above formula, $\sum u_{1\le k\le K, q_{jk}=1}(k)$ is the cumulative sum of the mastery level of all the knowledge points examined in the test question j, and $\sum_{k=1}^{K} q_{jk}$ is the number of knowledge points examined in that test question. From equation (9), the mastery level of subjective questions of A test question is $(0.1, 0.7, 0.9)/3 = 0.57$, so we can conclude that if the gap between students' mastery level of each knowledge point examined in the subjective questions is relatively large, it is not reasonable enough to calculate the mastery level of the test question by using arithmetic averaging, but it is not as effective as the fuzzy cognitive diagnosis by using fuzzy and calculating the mastery level of the subjective questions But compared with the fuzzy cognitive diagnosis using fuzzy and calculating the mastery level of subjective questions, it is better. In order to get a more reasonable mastery level of subjective questions, Liu Jia used the geometric mean algorithm with the following formula:

$$\eta_{ej} = \sqrt[\sum_{k=1}^{K} q_{jk}]{\prod_{k=1}^{K} \rho_{ek}} \tag{10}$$

Among them,

$$\rho_{ek} = \begin{cases} 1, & q_{jk} = 0 \\ d_{ek} q_{jk}, & q_{jk} = 1 \end{cases} \tag{11}$$

$$d_{ek} = \begin{cases} 0.01, & d_{ek} = 0 \\ d_{ek}, & d_{ek} \neq 0 \end{cases} \tag{12}$$

The value of η_{ij} is a continuous value between 0 and 1. If $\eta_{ij} = 1$, it means that the student has completely mastered all the knowledge points examined in the question, and the value of η_{ij} increases as the student's mastery of the knowledge points increases. The geometric mean is multiplied together, and if the student's mastery of a knowledge point in a subjective question is 0, the geometric mean formula yields that the student's mastery of the subjective question is also 0. However, the subjective question is scored according to the student's response steps, and even if the student has mastered only one knowledge point examined in the test question, he or she may have done a part of the question correctly, so, if the student has not mastered a knowledge point of the test question at all, the mastery level of the point will be set to 0.01. The mastery level of A test question is $\sqrt[3]{0.1*0.7*0.9} = 0.40$ from Eq. (10), and the use of geometric mean algorithm can portray the mastery level of students on the subjective questions more reasonably.

III. Design of labor projects based on the new curricula

(1) Focusing on life to enhance students' interest in labor

Students are generally not interested in daily chores and production labor, and they think that complex production labor and service labor are troublesome, coupled with academic pressure, parents take the initiative to undertake the necessary daily labor and production labor for their children and other phenomena, resulting in the general lack of students' labor ability and awareness.

Therefore, this paper designs a labor project for students in the “Little Labor Master” micro-video production contest, which allows students to observe the labor masters around them around daily life labor, production labor and service labor. The subjects can be parents, ordinary workers, folk artists, etc., or students themselves. Through personal experience and on-site realization, students can form a correct view of labor, learn to respect ordinary workers, feel the excellent traditional culture and craftsmanship, develop a sense of innovation, enhance the interest in labor and practical ability, and become a new generation of people who know, know and love labor.

(2) Stimulate students' interest in labor by focusing on problems

Knowledge and experience gained through problem-based learning are easier for students to accept and understand. For the boarding school at the beginning or end of the period students have to move their luggage from home to school or from school to home, I guide the students to jointly design the campus service labor, such as “love to help the group” campus volunteer labor project, the purpose is to let the students help each other in the service labor to feel the alumni love, the love of fellow students, so that the students in the process of campus volunteer service to understand the labor of the campus, the students will be able to understand the work of the students. The purpose is to let students feel the alumni love and fellow students' love in the process of mutual help and service, to let students understand the value and meaning of labor in the process of volunteer service, to stimulate students' interest and desire for labor, to implement the cultivation of labor literacy, to transmit the new social civilization and to promote the overall development of human beings.

IV. Fuzzy cognitively oriented labor education curriculum design

With the advancement of the new round of basic education reform, labor education has been incorporated into the core category of the human education system, but its curriculum design generally faces two major bottlenecks: one is that the traditional teaching mode is difficult to meet the cognitive heterogeneity of students' needs, and the other is the lack of scientific quantitative assessment of the complex structure of labor literacy. This study constructs a cognitive model of labor education based on the fuzzy cognitive diagnosis theory and combined with the deep learning method.

IV. A. Constructing a cognitive model of labor literacy

IV. A. 1) Extraction of Key Cognitive Attributes

This paper test sample from province A, the sample includes 4752 elementary school students in which, 2581 boys and 2171 girls. The labor literacy of primary school students was comprehensively analyzed from psychology, pedagogy and related fields, the concept of labor literacy of elementary school students was defined, and the main cognitive attributes of labor literacy of primary school students were analyzed. The cognitive model of elementary school students' labor literacy is then constructed based on relevant literature on labor education and labor literacy as well as national policies. Finally, the cognitive diagnostic scale of elementary school students' labor literacy is formed.

Labor concepts are gradually formed in the process of actual labor, including the cognition and overall concepts of labor, individuals engaged in labor, and the fruits of labor, as well as the basic attitudes and emotions generated on this basis. Therefore, labor value (A1) is the core goal of labor education. In addition, labor literacy of primary school students should be examined from two aspects: labor emotion regulation strategy (A3) and labor attitude (A4). Labor attitude is the motivation for elementary school students to implement labor behaviors. Elementary school students' labor values emphasize the evaluation and cognition of labor itself, i.e., the attention, understanding and recognition of labor. Elementary school students' labor emotion regulation strategy is concerned with helping elementary school students maintain a positive emotional experience in the labor process. Elementary school students' labor attitudes, on the other hand, are the psychological and cognitive behavioral tendencies of elementary school students when they are engaged in labor activities, which are often externalized into individual behavioral manifestations.

Labor ability is both the result of the cultivation of labor education and the support for the conduct of labor education at the same time. This paper focuses on exploring the potential qualities of elementary school students' labor literacy, which is mainly studied from the cognitive level. Therefore, we need to focus on two aspects of labor competence: labor knowledge and labor operation cognition. Labor knowledge involves the individual's understanding and knowledge of labor tasks, while labor operation cognition is the individual's ability to understand and apply labor practices, including cognitive activities such as observation, thinking, decision-making, and innovation in the labor process. To sum up, only by mastering labor knowledge (A2) and labor operation cognition (A5) can primary school students comprehensively improve the level of labor literacy and lay a solid foundation for future personal development and social contribution.

Good labor habits (A6) can enable primary school students to develop a careful and conscientious way of working, thus enhancing their observation and awareness of problem identification. Elementary school students should be able to solve problems in the areas of life service and practice independently or collaboratively in labor practice, and accumulate experience and improve problem-solving ability from it (A7), which is also proposed in the curriculum standard, and elementary school students should be encouraged to exercise independent problem-solving ability.

Therefore, combining the teaching requirements of the curriculum standards for labor education, the contents of the textbooks and the collation of literature, and through in-depth discussions with frontline teachers, this paper finally combines the values of elementary school students' labor (A1), elementary school students' knowledge of labor (A2), elementary school students' strategies for regulating their labor emotions (A3), elementary school students' attitudes to labor (A4), elementary school students' cognitive knowledge of labor practices (A5), elementary school students' habits of labor (A6) and Seven attributes such as elementary school students' labor problem solving ability (A7) were identified as the key attributes for the cognitive diagnosis of elementary school students' labor literacy.

IV. A. 2) Evidence-based modeling for Q-matrix calibration

Evidence models are used to reveal the underlying characteristics and behavioral patterns of a student model through detailed analysis of the student's answers and responses. An evidence model consists of 2 components, the rules of evidence, which are essentially grading rules or scoring criteria that are used to determine the criteria for student performance or quality of work. The measurement model, on the other hand, refers to the relationship between the student model variables and the values taken, i.e., how the student receives the appropriate score by responding to the Elementary Student Labor Literacy Cognitive Diagnostic Scale. The relationship between student performance behaviors and scoring criteria can be clarified by developing rules of evidence and measurement models. Response formats and measurement criteria will vary from item to item.

After identifying the attributes and their hierarchical relationships, it is necessary to create a Q-matrix as a blueprint for scale development to guide the development of the items.The Q-matrix describes the relationship between the test items and the cognitive attributes being measured, and guides how the test items will measure specific cognitive attributes. In a test, the number of attributes or combinations of attributes measured by the items is limited. Assuming that a scale measures a total of K attributes, there are 2K-1 possible item-attribute combination models (excluding questions that do not measure any attributes). However, due to the hierarchical relationship between attributes, some attributes must be predicated on other attributes, and some attribute combinations cannot exist. Therefore, before building the Q-matrix, the adjacency and reachability matrices of the hierarchical relationships between attributes must first be determined. In a quiz, only items that all satisfy the inter-attribute relationships shown in the A matrix or R matrix are consistent with the cognitive attribute hierarchical relationships of the quiz. Secondly, the typical item assessment pattern can be inferred from the attribute hierarchy relationships. Typical item assessment model is based on the hierarchical relationship between attributes to ensure that all test items are logical, while the establishment of Q matrix becomes a key part.

In this paper, there are seven key attributes of elementary and middle school students' labor literacy, and the ideal mastery pattern can be derived based on the R matrix, and the Q matrix of the cognitive diagnostic scale of elementary students' labor literacy is shown in Table 1. The Q matrix in Table 1 strictly follows the attribute hierarchy, in which items 1 to 10 cover different combinations of attributes, for example, item 1 measures six attributes, A1, A2, A4, A5, A6, A7, at the same time, reflecting the design needs of composite cognitive tasks.

Table 1: Q matrix of cognitive diagnostic scales

Item	A1	A2	A3	A4	A5	A6	A7
1	1	1	0	1	1	1	0
2	1	1	0	1	0	0	1
3	1	1	1	1	1	0	1
4	1	1	1	0	1	1	0
5	1	1	0	0	0	1	0
6	0	0	1	1	0	0	0
7	1	0	1	0	1	0	1
8	1	1	1	0	1	1	1
9	1	0	1	0	0	1	0
10	0	1	1	1	0	0	0
Number of visits	8	7	7	5	5	5	4

Multilevel scoring is used in this paper, and fitting tests for multiple cognitive diagnostic models, including the DIRT model, will be conducted subsequently. In order to fully explore the information of multilevel scoring items, the Qc matrix is therefore added on top of the Q matrix. Through multilevel scoring, the evaluator can score for different levels of mastery, thus more accurately reflecting the subject's performance at each level. The traditional Q matrix is to judge the subjects into two levels of non-mastery and mastery, while the idea of the multilevelized Q matrix is to judge the subjects into which level of the attribute is not mastered and specifically mastered, so it can provide richer and more detailed information, and the diagnosis of the subjects is more valuable and guiding significance.

This paper involves 2 types of multiple-choice and fill-in-the-blank questions. The matrix position corresponding to the subject's level of response is marked as 1, otherwise as 0. Elementary school students' labor literacy is divided into different levels of mastery, and each level corresponds to specific cognitive requirements and abilities. Different school segments correspond to different mastery levels, with school segment 1 corresponding to level 1 and school segment 2 corresponding to level 2. The Qc matrix of the Labor Literacy Cognitive Diagnostic Scale for Elementary School Students is shown in Table 2, which further refines the attribute mastery levels and reflects the progression of school segments.

Table 2: Qc Matrix of Cognitive Diagnosis Scale

	Item	Cat	A1	A2	A3	A4	A5	A6	A7
1	1	1	1	0	0	0	0	0	0
2	1	1	1	0	0	0	0	0	0
3	2	1	1	1	0	0	0	0	0
4	2	2	1	1	0	0	0	0	0
5	3	1	1	1	1	0	0	0	0
6	3	2	1	1	1	0	0	0	0
7	4	1	1	0	1	1	0	0	0
8	4	2	1	0	1	1	0	0	0
9	5	1	1	1	1	1	0	0	0
10	5	2	1	1	1	1	0	0	0
	Item	Cat	A1	A2	A3	A4	A5	A6	A7
11	6	1	1	1	1	1	1	0	0
12	6	2	1	1	1	1	1	0	0
13	7	1	1	1	1	1	1	1	0
14	7	2	1	1	1	1	1	1	0
15	8	1	1	1	1	1	1	1	1
16	8	2	1	1	1	1	1	1	1
17	9	1	1	1	1	1	1	1	1
18	9	2	1	1	1	1	1	1	1
19	10	1	1	1	1	1	1	1	1
20	10	2	1	1	1	1	1	1	1

The combination of multilevel scoring and attribute multileveling can provide more detailed and comprehensive information in a test or assessment. By assessing multiple attributes and their different levels, a more accurate picture of the subject's ability and performance can be obtained. This combination helps to assess different aspects of ability and characteristics in depth, providing a greater basis for individualized assessment. The quizzes in this paper have been revised by experts in the field through several workshops and have good reliability and validity. The internal consistency coefficients of each question booklet of the quiz are higher than 0.9, the difficulty of the questions is between 0.6 and 0.7, and the differentiation is greater than 0.4, which is in line with the quality requirements of large-scale quizzes. Systematically trained raters graded students' responses, and the scoring criteria were refined through expert discussion and pre-assessment, with multiple-choice questions scored 0 and 1, and fill-in-the-blank questions scored up to a maximum of 6 points on a multilevel scale. Based on the recommendations of existing studies on the scoring of subjective questions in cognitive diagnostic tests, the present study converted the multilevel scoring to 0 and 1 scoring, with full scores counted as 1 and other scores recorded as 0.

IV. B. Cognitive diagnostic model fit test

The different alternative models DIRT, NCD, CNCD-F and KSCD were fit tested and the best model was selected based on the fit of each model. The fitting results of different cognitive diagnostic models are shown in Table 3, the KSCD model-2LL value is 3902731, which is significantly lower than the DIRT and NCD models, and the AIC and BIC values are also better than the other models. According to MADres and MADcor, the KSCD model fits better than the other models. Although the MX2 indicator shows that the CNCD-F model is better, its p(MX2) value is close to the critical value and its SRMSR (0.024) is higher than that of the KSCD model (0.013), which suggests that there is a certain systematic bias in the CNCD-F model. Combining the above fitting indexes, the KSCD model has a better fit.

Table 3: Fitting Results of different cognitive diagnostic models

	-2LL	AIC	BIC	MX2	p(MX2)	MADcor	MADres	SRMSR
DIRT	3972424	3972883	4002764	2294.164	0.0325	0.047	0.804	0.047
NCD	3972186	3972536	4001867	2893.194	0.0362	0.033	0.811	0.041
CNCD-F	3924614	3924282	3983637	1937.286	0.0475	0.021	0.245	0.024
KSCD	3902731	3902211	3927541	2204.184	0.0469	0.016	0.196	0.013

In addition to the fitting comparison of the quiz as a whole, this paper also performs the fitting analysis of each item separately to determine the fitting of different models to specific items, and the RMSEA results of the items of different models are shown in Table 4. The item-level RMSEA analysis further verified the stability of the KSCD model, with an average RMSEA of 0.007, significantly lower than that of 0.029 for the DIRT model, and all items had an RMSEA of less than 0.05, which was in line with the requirements for the accuracy of cognitive diagnostic models.

Table 4: RMSEA results of different model items

Item	DIRT	NCD	CNCD-F	KSCD
1	0.033	0.027	0.015	0.007
2	0.028	0.021	0.018	0.005
3	0.031	0.024	0.017	0.008
4	0.026	0.026	0.014	0.005
5	0.035	0.023	0.016	0.006
6	0.031	0.024	0.017	0.007
7	0.027	0.023	0.015	0.009
8	0.025	0.024	0.016	0.006
9	0.031	0.025	0.014	0.008
10	0.027	0.021	0.017	0.004
Mean value	0.029	0.024	0.016	0.007
Standard deviation	0.019	0.015	0.008	0.004

The relationship between the cognitive attributes in this study is complex, and by combining the results, the KSCD model should be chosen to carry out the analysis.

IV. C. Cognitive Attribute Mastery Probability Results

Applying the KSCD model for cognitive diagnostic analysis, the probability of mastery on each cognitive attribute of labor literacy among elementary school students in the study sample was obtained as shown in Table 5. Elementary school students had the highest probability of mastery in labor problem solving ability (A7) (0.701 ± 0.294), while labor knowledge (A2) and labor values (A1) were relatively weak (mean values of 0.505 and 0.522, respectively). Standard deviation analysis showed that labor habits (A6) had the largest individual differences (SD=0.319), which may be influenced by both family practice opportunities and the effect of school curriculum implementation. The mastery probability of labor emotion regulation strategies (A3) was lower than that of labor attitudes, suggesting that the emotional education module needs to strengthen contextualized design. The degree of dispersion of the probability of mastery of each attribute suggests that the design of the labor curriculum should pay attention to tiered teaching strategies, especially the implementation of compensatory interventions for attributes with low probability of mastery (e.g., A1, A2).

Table 5: Mastery Probability of Cognitive Attributes

Cognitive attribute	Mean value	Standard deviation
A1	0.522	0.297
A2	0.505	0.311
A3	0.592	0.298
A4	0.614	0.306
A5	0.622	0.283
A6	0.628	0.319
A7	0.701	0.294

V. Conclusions and strategies

V. A. Conclusion

In this study, we reconstructed the labor education curriculum system through fuzzy cognitive diagnostic technology and designed a fuzzy cognitive oriented labor education curriculum.

The results of the fitting test show that the KSCD model-2LL value is 3902731, which is significantly lower than the DIRT and NCD models, and the AIC and BIC values are also better than the other models. According to MADres and MADcor, the KSCD model fits better than the other models. Although the MX2 metric shows that the CNCD-F model is better, its p(MX2) value is close to the critical value and its SRMSR (0.024) is higher than that of the KSCD model (0.013). Combining the above fitting indicators, the KSCD model has a better fit. The item-level RMSEA analysis further verified the stability of the KSCD model, with an average RMSEA of 0.007, which was significantly lower than that of the DIRT model (0.029), and the RMSEA of all the items was less than 0.05, which was in line with the requirement of the accuracy of the cognitive diagnostic model.

Applying the KSCD model for cognitive diagnostic analysis, elementary school students had the highest probability of mastering labor problem solving ability (A7) (0.701 ± 0.294), while labor knowledge (A2) and labor values (A1) were relatively weak (mean values of 0.505 and 0.522, respectively). Standard deviation analysis showed that labor habits (A6) had the largest individual differences (SD=0.319), which may be influenced by both family practice opportunities and the effect of school curriculum implementation. The probability of mastery of labor emotion regulation strategies (A3) was lower than that of labor attitudes, suggesting that the emotional education module needs to be strengthened with contextualized design.

V. B. Strategies

The optimization of the labor education curriculum needs to be combined with the in-depth integration of cognitive science and educational practice, and a systematic improvement path should be constructed from the four aspects of curriculum design, teaching implementation, technical support, and evaluation system.

At the level of curriculum design, a hierarchical and progressive curriculum framework should be established based on the cognitive attributes of labor literacy. By clarifying the hierarchical relationship among the core attributes of labor values, labor knowledge, and labor habits, curriculum modules covering basic, developmental and challenging objectives should be designed. For example, for students in the lower level, the focus is on the immersive cultivation of labor attitudes and values, and the emotional connection is established through life tasks, such as family labor practices and campus responsibilities; while in the upper level, the complex objectives of knowledge integration and problem solving ability should be strengthened, and interdisciplinary projects should be designed to promote cognitive transfer and the development of higher-order thinking.

At the level of teaching implementation, a dynamic diagnosis and personalized intervention mechanism should be built. Based on the fuzzy cognitive diagnosis technology, the diagnostic model identifies the weaknesses of students' cognitive attributes and generates hierarchical teaching objectives and remedial programs. For example, for groups with weak labor values, contextualized reflection tasks, such as vocational experience logs and labor ethics case studies, can be embedded to strengthen emotional identity.

At the technical support level, intelligent adaptation of cognitive diagnosis and teaching resources should be promoted. By constructing a dynamic question bank system, the cognitive attribute labels are associated with the topic characteristics to realize the precise push and dynamic adjustment of test questions. For example, based on the results of students' cognitive diagnosis, adaptive generation of practice questions containing specific combinations of attributes can reduce ineffective cognitive load.

At the level of evaluation system, it is necessary to establish a long-term mechanism of multiple synergies. The tripartite linkage between home, school and society can form a closed loop of labor education: the family side can track habit formation through daily labor records and reflection logs; the school side can generate personalized growth files based on cognitive diagnostic data and dynamically adjust teaching strategies; and the social side can incorporate real-life scenarios such as volunteering and production practice into the scope of evaluation, and strengthen the transfer of literacy skills through social authentication.

The above strategies can effectively promote the transformation of the labor education curriculum from experience-oriented to scientific and personalized by empowering precise teaching with cognitive diagnostic technology, driving the internalization of literacy through life situations, and optimizing the learning path through a dynamic feedback mechanism.

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