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Research on the Construction of Business Administration Professional Curriculum System Based on Learning Path Mining Algorithm under Digital Talent Cultivation Mode

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Abstract Digital transformation has a profound impact on higher education, and the training of business administration professionals faces new challenges. The demand of enterprises for business administration talents has undergone structural changes, requiring digital literacy and innovation ability. This study constructs a curriculum system for business administration majors based on learning path mining algorithm under digital talent cultivation mode. Methodologically, the traditional DINA model is improved, reaction time parameters are introduced, and a reparameterized DINA model is established; a core literacy assessment framework containing cognitive model construction, Q matrix establishment, data collection, and diagnostic output is designed; potential knowledge states are identified through clustering analysis, and learning paths are portrayed. The results show that for the test of 379 business administration students, the average score is 12.665, the probability of mastering organization management (A1) reaches 0.9, and human resource management (A4) is only 0.4; clustering analysis yields 8 categories of knowledge states, with KS3 accounting for 30.08% as the most; 4 complete learning paths are identified, with path 2 covering 226 people accounting for 59.6%. The conclusion shows that the improved cognitive diagnostic model can effectively identify the differences in students' knowledge mastery, and the learning path mining provides the basis for personalized teaching; accordingly, it proposes the constructive strategies of reconstructing the curriculum system, preparing the syllabus, and realizing the theoretical-practical docking to push forward the reform of digital talent cultivation for business administration majors.

Index Terms Digital Talent Cultivation, Cognitive Diagnostic Model, Learning Path Mining, Business Administration Major, DINA Model, Curriculum System Construction

I. Introduction

Entering the second decade of the 21st century, the industrial wave led by the new scientific and technological revolution has put forward higher requirements for talent cultivation, and the cause of Chinese higher education is facing unprecedented challenges [1]. In the face of increasingly complex social problems, colleges and universities urgently need to break down disciplinary barriers, integrate interdisciplinary professional knowledge, and promote deep integration between majors. Traditional majors should not only keep the right and innovation, but also classify and promote, according to the characteristics of their respective majors, to establish a sound system of comprehensive development of students, academics, and disciplines as a whole, and to realize the high-quality and high-level development of liberal arts education [2]-[4]. To achieve this strategic task, it is necessary to hold on to the key element of the curriculum system, continue to promote the updating of education and teaching content, and cultivate thick-based, complex new-age talents with the integration of emerging interdisciplinary disciplines and curricula [5]. The business administration program in colleges and universities is an important channel for training entrepreneurs, managers and business leaders, and its curriculum system is of great significance for promoting the development of the digital economy, promoting innovation and entrepreneurship, and improving the management level [6]. In the digital era, enterprises and managers need to have more digital, networked and intelligent capabilities, which need to be effectively cultivated and enhanced in college education [7], [8]. Therefore, we explore the issues of the curriculum system of business administration in colleges and universities under the digital background from both theoretical and practical aspects, with a view to providing useful guidance and reference for business administration education in colleges and universities.

Since the late 1960s, a large number of research results have emerged for the problem of learning path planning methods, including learning path mining algorithms based on evolutionary algorithms, learning path mining algorithms based on graphs, learning path mining algorithms based on data mining, learning path mining algorithms based on neural networks, and so on [9]-[12]. These results, to some extent, solve the learning path planning problem. It has been shown that a reasonably ordered sequence of learning resources has a facilitating effect on learners' learning process and learning effect [13]. For example, literature [14] utilized the new techniques of process mining and log frames to assess the effectiveness of learning paths and measure students' adherence, demonstrating the applicability of the techniques in online courses and showing that adherence is positively correlated with student performance. Literature [15] used an inductive mining algorithm to assess self-regulated learning skills in an e-learning course, and the model was able to mine the differences between the learning processes of passing and failing students to indicate learning paths for failing students. Literature [16] proposed a model-based learning path mining framework for identifying appropriate learning paths for learning groups in e-learning environments, while solving the problem of efficient student learning, and verified the effectiveness of the approach through teaching experiments with actual learners. Literature [17] used a multi-objective optimization model based on a meta-heuristic algorithm to develop a knowledge-based recommender system that is capable of mining personalized learning paths for students based on their background and career goals.

Literature [18] describes an open source learning analytics application (LeMo), stating that LeMo is capable of collecting and analyzing learner activity data from various platforms and applying algorithms for learning path mining. Literature [19] proposes a learning path mining method that combines topic scores and learner interest scores for online learning environments, which enables personalized learning for students and effectively improves learner engagement and course relevance. Literature [20] systematically describes learning path mining techniques and algorithms utilizing open educational resources, details the three steps of learning path mining (concept extraction, relationship mapping, and path creation), and improves the existing methods to meet the ever-changing learner needs. Literature [21] constructed a learning path mining model by analyzing the network formed by the interactions between students and the learning management system, and used deep learning to classify learning paths, thus achieving high accuracy prediction in predicting student performance. The above studies on learning path mining provide a feasible path for the construction of business administration professional curriculum system in the digital era [22]. However, most of the research results are still confined to research-oriented projects under ideal conditions, and the practical application in education and life still has certain limitations, and there is a lot of room for improvement in the development of this field [23].

The era of digital economy puts forward new requirements for business administration talents, who not only need to master traditional management theories, but also need to have digital thinking and innovative entrepreneurial ability. In the process of cultivating business administration professionals, higher education institutions are faced with the problems of insufficient teaching evaluation accuracy, lack of learning path planning, and outdated curriculum system. Cognitive diagnostic theory provides a new perspective for educational measurement and evaluation, which can deeply analyze students' cognitive structure and knowledge mastery status. DINA model, as a typical cognitive diagnostic model, has been widely used in the field of educational evaluation, but the traditional model only takes into account the results of the answers and ignores the process data such as response time. Learning path mining technology can discover the development law of students' knowledge state and provide support for personalized teaching design. Business administration majors are involved in various fields such as organization management, marketing, financial management, etc. The knowledge system is complex, and the learning process of students presents non-linear characteristics. Existing research focuses on the teaching reform of a single course and lacks systematic research from the perspective of the overall curriculum system. Under the background of digital transformation, the reconstruction of business administration professional curriculum system has become an inevitable trend. Based on the cognitive diagnosis theory, this study improves the DINA model by introducing the reaction time parameter, and constructs the assessment method of students' core literacy under the digital talent cultivation mode. By conducting cognitive diagnostic tests on business administration students, we obtain data on their knowledge mastery status. Cluster analysis technology is used to determine the categories of potential knowledge states, and learning paths are drawn based on the inclusion relationship between knowledge states. Finally, based on the diagnosis results and learning paths, we propose a strategy for constructing the curriculum system of business administration majors to realize the precise alignment between the teaching content and the cultivation objectives.

II. Improvement of the cognitive diagnostic model

The DINA model is a commonly used cognitive diagnostic model [24]. In this chapter, reaction time will be added to improve the traditional DINA model, and the improved reparameterized DINA model will be proposed.

Adding response time information as auxiliary information in cognitive diagnosis and using it in conjunction with response results can obtain more accurate diagnostic information, and a joint model that combines two types of data, response results and response time, is cited below.

II. A.Reparameterized DINA model

Let Y_{ni} be the result of the n nd person's response to the i rd question, the relationship between the attribute and the result of the response can be expressed in the DINA model as:

$$P(Y_{ni}=1)=g_i+(1-g_i-s_i)\prod_{k=1}^{k}\alpha_{n_k}^{q_{ik}} \tag{1}$$

Among them, $P(Y_{ni}=1)$ represents the probability that the n nd person answers the i rd question correctly, g_i and s_i respectively represent the guess probability and mistake probability of the i th question, and $1-g_i-s_i$ is the discrimination degree of the question. α_{nk} indicates whether the n th person has the k th attribute. If the n th person masters the k th attribute, it is $\alpha_{nk}=1$; otherwise, it is $\alpha_{nk}=0$. Q is a $I\times K$ -order matrix, where q_{ik} indicates whether the i th question tests the k th attribute. If the i th question tests the k st attribute, then $q_{ik}=1$; otherwise, $q_{ik}=0$. Thus, matrix Q builds a bridge between the observable and unobservable cognitive states of students.

Reparameterize $P(Y_{ni}=1)$ by first reparameterizing the two parameters g_i and s_i in the influence Y_{ni}, i.e:

$$\gamma_i=H(g_i) \tag{2}$$

$$\delta_i=H(1-s_i)-H(g_i) \tag{3}$$

where $H(x)$ denotes the Logit transform, also known as the log-odds transform, in the specific form of $H(x)=\ln(\frac{x}{1-x})$. Combining Eqs. (2)(3), then Eq. (1) can be changed to [25]:

$$H(P(Y_{ni}=1))=\gamma_i+\delta_i\prod_{k=1}^{k}\alpha_{n_k}^{q_{ik}} \tag{4}$$

Eq. (4) is also known as the reparameterized DINA model, where the probability of a subject mastering an attribute is:

$$H(P(\alpha_{nk}=1))=\tau_k\theta_n-v_k \tag{5}$$

where $P(\alpha_{nk}=1)$ is the probability that the n nd person masters the k rd attribute, τ_k, v_k is the slope parameter and the intercept parameter, respectively, θ_n represents the general ability of the n th person, and a higher value of θ_n implies that the probability that the subject masters the corresponding attribute is higher.

II. B.Reaction time modeling

Let T_{mi} be the reaction time of the n nd person answering the i rd question, and its lognormal reaction time model is:

$$\ln T_{ni}=\beta_i-\omega_n+\varepsilon_{ni},\varepsilon_{ni}\sim N(0,\sigma_{\varepsilon_{ni}}^2) \tag{6}$$

where $\ln T_{ni}\sim N(\mu_i-\omega_n,\sigma_{\varepsilon_{mi}}^2)$, T_{mi} are the reaction times of the n rd person answering question i, β_i denotes the time intensity parameter of question i, and ω_n denotes the speed parameter of the n th person. The use of a lognormal reaction time model here allows the distribution of reaction times to be converted to a more symmetrical form.

In the hierarchical modeling framework, it is assumed that the question parameters of the DNIA model with the inclusion of reaction times follow a three-dimensional normal distribution:

$$X_i = \begin{pmatrix} \beta_i \\ \gamma_i \\ \delta_i \end{pmatrix} \sim N\begin{pmatrix} \mu_\beta \\ \mu_\gamma, \Sigma_1 \\ \mu_\delta \end{pmatrix} \tag{7}$$

Equation (7) gives the relationship between the topic parameters in the DINA model, and the error term ε_{ni} in the lognormal reaction time model is not included in χ_i, which is an independent distribution.

Similarly, it is assumed that the parameters on personnel in the DNIA model with additive reaction times obey a two-dimensional normal distribution:

$$\begin{pmatrix} \omega_n \\ \theta_n \end{pmatrix} \sim N\begin{pmatrix} \mu_\omega \\ \mu_\theta \end{pmatrix}, \Sigma_2 \Bigg), \Sigma_2 = \begin{pmatrix} \sigma_\omega^2 & \rho_{\omega\theta}\sigma_\omega\sigma_\theta \\ \rho_{\omega\theta}\sigma_\omega\sigma_\theta & \sigma_\theta^2 \end{pmatrix} \tag{8}$$

Thus, the DNIA model for the addition of reaction time is constituted by Eqs. (1) to (8).

The prior distributions of the topic parameters are set as follows:

$$\begin{gathered} \mu_\beta \sim N(-2.197, 2), \mu_\gamma \sim N(4.394, 2) I(\mu_\gamma > 0), \\ \mu_\delta \sim N(3, 2), \Sigma_1 \sim W^{-1}(R, 3) \end{gathered} \tag{9}$$

where the prior distribution specifying β, γ, δ is used to reparameterize the DINA model, W^{-1} denotes the inverse Wishart distribution, and R is a three-dimensional unit matrix.

The prior distributions for the personnel parameters are set as follows:

$$\begin{pmatrix} \omega_n \\ \theta_n \end{pmatrix} \sim N\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \Sigma_2 \Bigg) \tag{10}$$

To satisfy identifiability, let the variance of ω_n be 1. Then $\Sigma_2 = \Delta\Delta'$, where $\Delta = \begin{pmatrix} 1 & 0 \\ \varphi & \psi \end{pmatrix}$, Δ' is the conjugate transpose of Δ, $\varphi \sim N(0,1), \psi \sim \Gamma(1,1)$.

The prior distributions of the attribute parameters are set as follows:

$$\tau_k \sim N(0,4) I(\tau_k > 0), v_K \sim N(0,4) \tag{11}$$

III. Methodology for assessing the core literacy of students in the digital talent training model

The implicit nature of core literacy determines the level of core literacy possessed by learners, which must be diagnosed and inferred with the help of their external performance in activity tasks. In this chapter, we will combine the improved DINA model with the reaction time in this paper to propose a method for assessing students' core literacy under the digital talent cultivation mode, and the specific implementation process links are shown in Figure 1.

III. A. Cognitive modeling of disciplinary domains

The cognitive model of a subject area defines the cognitive attributes of subject core literacy, subject knowledge and subject ability and the hierarchical structure between them, which is the prerequisite and foundation for carrying out cognitive diagnosis. The construction of the cognitive model of a subject domain often requires the participation of experts in the subject domain to determine the goals and contents of cognitive diagnosis for the domain based on the combing of existing research literature. Each node in the cognitive model represents a cognitive component or task type, and each edge represents the hierarchical structure between cognitive components or task types.

III. B. Test Item Preparation and Q Matrix Establishment

Under the guidance of the cognitive model of subject domains, test items suitable for different cognitive attributes and their hierarchical structures need to be compiled to realize the diagnosis and classification of learners with different cognitive states. In order to ensure a high rate of correct diagnosis and identification, test items should be designed to cover each cognitive attribute as much as possible, and the same cognitive attribute should be measured as many times as possible by multiple test items. Using the associations established between cognitive attributes and test items (activity tasks or test questions), a binary correlation matrix (also known as Q-matrix) is formed with cognitive attributes as columns and test items as rows [26]. In the Q-matrix, a 1 indicates that a cognitive attribute was measured by the test item, and a 0 indicates that the cognitive attribute was not measured.

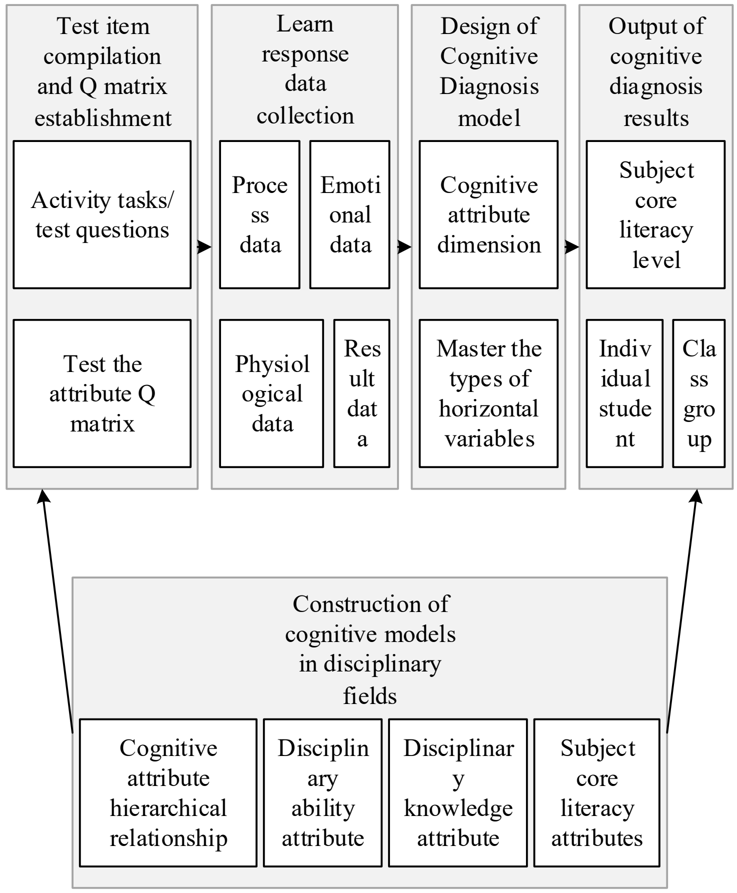

Figure 1: Core literacy assessment framework based on cognitive diagnosis

III. C. Learning response data collection

Under the technology-rich environment, the real-time data collected on students' learning responses have become more comprehensive and diversified, including both outcome data after the completion of the responses. These outcome and process data together constitute the chain of evidence of the cognitive diagnostic test, which on the one hand provides a basis for cross-evidence to ensure the accuracy of the cognitive diagnostic test, and on the other hand provides support for the design of improved intervention programs based on the cognitive diagnostic results.

III. D. Cognitive diagnostic output

With the cognitive model of subject domain, test attribute matrix and learning response data as the information input, the cognitive diagnosis results can be output after processing by the cognitive diagnosis model. For the cognitive diagnostic results, on the one hand, we can explain and analyze the performance attributes of different individuals or groups of subjects from the perspective of test scores, and on the other hand, we should also visualize the core literacy performance of the subjects under the digital talent cultivation mode from the perspective of core literacy embedded in the cognitive model of the subject domain.

IV. Diagnostic analysis of learning assessment of digital talent development model

In this chapter, we will adopt the methodology proposed in the previous chapter for measuring students' core literacy in the digital talent development model, using cognitive diagnosis to measure and cognitively analyze students' learning and evaluate them with precise feedback.

IV. A. Subjects of study

The assessment selected 182 first-year students majoring in business administration in a university in Sichuan Province. In the second half of the academic year of 2024, the digital talent cultivation model was adopted to carry out the teaching of business administration courses, and the students were tested after completing all the new courses. The number of paper test papers issued was 379, and 379 valid test papers were returned.

IV. B. Analysis of the overall results of the assessment

The descriptive statistical analysis of the scores of each item and the total scores of all subjects was performed using Excel software. The full score of the quiz paper was 27 points, and the mean score of all subjects was 12.665 with a standard deviation of 7.075.The specific results are shown in Table 1. Among them, the mean scores of questions 1-3 were all above 0.8, indicating that most of the subjects had mastered the basic knowledge of quadratic equations. The mean scores of questions 9-13 were not half of the total scores of the corresponding items, which was related to the difficulty of the questions. This is due to the difficulty of the questions, and the multi-stage scoring system, in which subjects could not proceed to the next step until they had successfully completed the previous step, also contributed to the low mean scores for questions 9-13. Overall, there was some variation in the total scores of the subjects, and the overall scores of the questions were moderate.

Table 1: Descriptive analysis of test papers

Title	Full score	Average value	standard deviation	Variance	Minimum value	Maximum value
T1	1	0.942	0.24	0.049	0	1
T2	1	0.891	0.297	0.094	0	1
T3	1	0.907	0.294	0.096	0	1
T4	1	0.774	0.432	0.169	0	1
T5	1	0.729	0.431	0.184	0	1
T6	1	0.62	0.485	0.232	0	1
T7	1	0.515	0.494	0.259	0	1
T8	2	1.276	0.816	0.655	0	2
T9	3	1.419	1.243	1.552	0	3
T10	3	1.496	1.259	1.602	0	3
T11	4	1.7	1.812	3.289	0	4
T12	4	0.906	1.384	1.944	0	4
T13	4	0.49	1.178	1.393	0	4
Total score	27	12.665	7.075	49.33	0	27

For the overall analysis of teaching assessment, the maximum a posteriori probability estimation (MAP) method was chosen to categorize students' cognitive mastery patterns by subject alpha of the improved DINA model in this paper. If the probability of mastering an attribute is greater than 0.6, the attribute is recognized as having been mastered; if the probability is less than 0.4, the attribute is recognized as not having been mastered; if the probability of mastering an attribute ranges from 0.4 to 0.6, further judgment is required. The probability of students' cognitive attribute mastery is shown in Figure 2, in which A1~A7 correspond to the knowledge points of organization management, marketing, financial management, human resource management, strategic management, operation management and innovation and entrepreneurship management, respectively. As can be seen from the figure, the mastery probability of A1 is as high as 0.9, and the mastery probabilities of A2, A3, and A5 are all greater than 0.6, indicating that most of the students' knowledge mastery belongs to the middle to upper level. The probability of mastering the remaining three attributes is lower than 0.5, and the probability of mastering A4, an attribute of human resource management, is only 0.4, which indicates that students do not have a sufficient mastery of the concepts related to human resource management, and teachers need to strengthen the focus on the explanation. Among them, attribute A7 has the worst mastery, and the associated attribute A6 also has a low mastery. A6 and A7 are related to operation management and innovation and entrepreneurship management, which need to be internalized and absorbed on the basis of students' understanding of theories. This also reflects that students' comprehensive application ability and knowledge transfer ability should be fully examined in the teaching of business administration courses.

Overall, the core literacy assessment method of students in digital talent cultivation mode proposed in this paper, which chooses to join the improved DINA model of reflecting time to realize the cognitive diagnostic test of business administration professional course knowledge, can not only help teachers grasp the whole teaching classroom situation from a macroscopic point of view, fully understand the proportion of students' overall cognitive mastery mode, break through the teaching key points, adjust the teaching plan in time and promote students to internalize the knowledge structure, but also provide a reference for teachers to individualize remediation and tracking teaching.

Promote students to internalize the structure of knowledge, but also for teachers to personalized remediation of students, tracking teaching to provide reference.

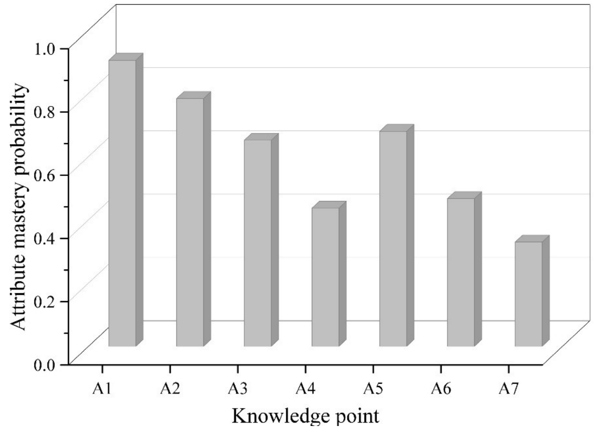

Figure 2: The probability of students' cognitive attribute mastery

V. Pathways of study in business administration programs

Learning paths are the sequences of different learning knowledge or skills based on students' cognitive development process in content learning. Cognitive diagnosis based learning data assessment is an effective implementation method, which can give clearer learning paths and visualized evaluation feedback to the teaching mechanism of assessment for learning. In the teaching process, both teachers and learners have the vision of full coverage of learning; however, in actual teaching, students often fail to master multiple attributes at the same time, at this time, in order to help subsequent learning, and in-depth analysis of the potential value behind the assessment data based on cognitive diagnostics, to solve the problems in teaching and learning, and to further help students to plan the learning path, which can optimize the role of cognitive diagnostics and assessment data. This chapter will analyze the potential value behind the assessment data obtained from cognitive diagnosis, solve the problems in teaching, and further help students plan learning paths, so as to optimize the role of cognitive diagnosis and assessment data.

In this chapter, we will portray the learning path of business administration majors, including three parts: determining the potential knowledge state based on cluster analysis; portraying the learning path; and describing the learning path.

V. A. Potential Knowledge State Determination Based on Cluster Analysis

This study utilized SPSS software to conduct an exploratory cluster analysis of the estimated probability of attribute mastery by students. Through continuous exploration of the clustering values, when the input clustering value of 8 is given, if there is a slight change or no change at all in the clustering centers, it indicates that convergence has been achieved. Therefore, after conducting cluster analysis on the probability of attribute mastery, the determined clustering value is category 8. Convergence was achieved because there were no variations or only minor variations in the cluster centers. When the iteration is 4, the minimum distance between the initial centers is 1.549 to obtain the final clustering value. Considering that the probability of attribute mastery and the mastery mode involved in this study are all based on the analysis of R software, the MAP method is still followed, with 0.5 as the judgment criterion. If it is greater than 0.5, it is determined that the attribute has been mastered and marked as 1; if it is less than 0.5, it is not mastered and marked as 0. The attribute mastery mode after clustering is specifically shown in Table 2. In cognitive diagnosis, the potential knowledge state of an individual subject can be derived from the attribute mastery pattern and classified and analyzed. This study classified the actual attribute mastery patterns of all students and obtained eight types of attribute mastery patterns. Given that the actual attribute mastery mode of the students is 1100011 and the mastery status of attribute A2 is 0, which is in an unmastered state, then the students cannot master attributes A4, A5, A6 and A7. Therefore, the actual potential knowledge status of this group should be 1100000. Similarly, it can be concluded that the actual potential knowledge state of the subject with the attribute mastery mode of 0110100 should be 0110100. The actual potential knowledge state of the subjects with the attribute mastery mode of 1101110 should be 1101100.

Table 2: Attribute mastery pattern after clustering

-	1	2	3	4	5	6	7	8
A1	1	1	1	1	1	0	1	1
A2	1	1	1	1	1	1	1	1
A3	1	1	1	0	0	1	0	1
A4	1	1	0	0	0	0	1	0
A5	1	0	1	0	1	1	1	1
A6	1	0	0	1	1	0	1	0
A7	1	1	0	1	0	0	0	1
Number of attributes	7	5	4	3	4	3	5	5

In this study, the students' actual attribute mastery patterns were corresponded to the potential knowledge states one by one and numbered, from which the potential knowledge states (KS) of all the subjects were obtained as shown in Table 3. As can be seen from the table, first of all, from the clustering of the actual mastery mode corresponding to the potential knowledge state of the categorization statistics, all the knowledge attributes have not mastered the KS6 has 9 people, is the smallest number of people in all categories; the largest number of people is the mastery of the mode of 111,100 KS3, amounting to 114 people; followed by mastery of four knowledge attributes of the number of people in the KS7 is 72 people. Secondly, from the point of view of the number of attributes mastered, KS2, KS7 and KS8 have actually mastered 5 knowledge attributes. At the same time, the number of people belonging to the clustering pattern of KS2 and KS7 are both 50 or more, while the number of people belonging to the pattern of KS8 is slightly higher, accounting for 14.51% of the total number of people. In terms of the categorization ratio, 30.08% of the students' mastery patterns were attributed to KS3, which lacked the corresponding understanding and application of the attributes of A4, A6 and A7, while the percentages of students with potential knowledge statuses of 0000000 and 1111111 were 2.37% and 2.90% respectively, i.e., the least and the most ideal mastery statuses showed a normal distribution, which indicates that the test questions have a certain This shows that the test questions have a certain degree of differentiation which can play a role in meeting the expected screening.

Table 3: Statistical results of knowledge state

Numbering	Potential knowledge state	The actual attribute mastery mode	Number of attributes	Number of persons classified	Classification ratio
KS1	1111111	1111111	7	11	2.90%
KS2	1111001	1111001	5	52	13.73%
KS3	1110100	1110100	4	114	30.08%
KS4	1100000	1100011	2	37	9.76%
KS5	1111100	1111100	5	29	7.65%
KS6	0000000	110100	0	9	2.37%
KS7	1101100	1101110	4	72	19.00%
KS8	1110101	1110101	5	55	14.51%

V. B. Carving out learning paths

Learning paths can be well adapted to the needs of teachers and students, according to students for cognitive diagnostic test data analysis to design a suitable path, so that students have a sequential, logical, hierarchical area to complete the content of the corresponding path nodes, gradually to the state of all all the attributes are mastered. There is a containment relationship between different knowledge states, taking the potential knowledge states KS4 and KS5 as an example, as shown in Figure 3. From the above figure, we can see that KS3, the mastery knowledge state, is smaller than KS5 (KS3≦KS5).

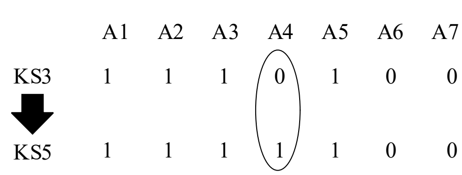

Figure 3: Path characterization

Because KS5 has mastered attribute A4 on top of having mastered attributes A1, A2, A3, and A5; and KS4 has not mastered attribute A4, but only A1, A2, A3, and A5, this indicates that there exists a containment-containment relationship between the two knowledge states of KS3 and KS5. That is, KS3 (1110100) ⊆ KS5 (1111100), then there exists a learning path of KS3 → KS5. The path KS6 → KS4 → KS3 → KS5 → KS1 can be obtained in this way. Since KS8 (1110101) also contains all the knowledge states in KS3 (1110100), there can also be a path from KS3 to KS8 as follows: KS6→KS4→KS3→KS8→KS1. By such a subordinate method and so on, we can get the path diagram as shown in Figure 4.

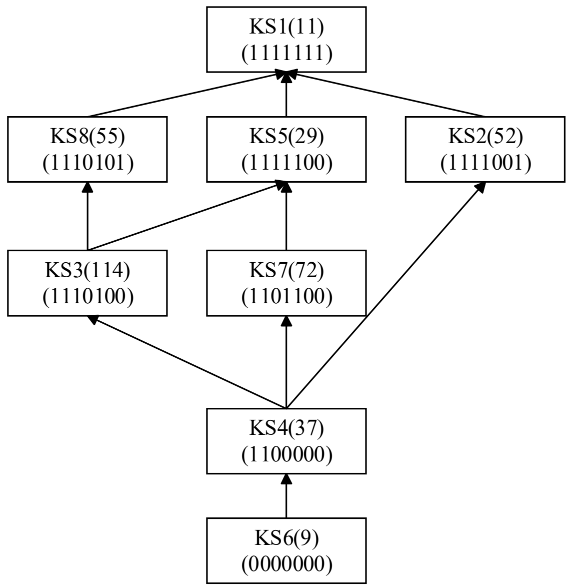

Figure 4: Path diagram

V. C. *Describe the learning path*

From the path diagram in the previous section, it can be clearly seen that there are complete 4 learning paths from the case of not mastering all the examined knowledge attributes to the case of mastering all the examined knowledge attributes, in which the longest learning path includes 5 potential knowledge statuses after clustering, and the shortest learning path includes 4 potential knowledge statuses after clustering. Counting the number of potential knowledge states in each path, we can get the distribution of the number of students in these 4 complete learning paths, as shown in Table 4. From the table, it can be seen that the number of students in learning path 2 is the largest, with 226 students, accounting for 59.6% of all subjects, and the number of students in learning path 3 is the smallest, with the number of 109 students.

Table 4: The distribution of the number of students in the learning path

Path number	The process of learning path	Number of people
1	KS6→KS4→KS3→KS5→KS1	200
2	KS6→KS4→KS3→KS8→KS1	226
3	KS6→KS4→KS2→KS1	109
4	KS6→KS4→KS7→KS5→KS1	158

VI. Strategies for constructing a curriculum system for the business administration program

This chapter will combine the results of the diagnostic analysis of the learning assessment of the digital talent cultivation mode above with the portrayed learning path of the business administration professional courses, and put forward the ideas and strategies for the construction of the curriculum system of the business administration professional courses under the digital talent cultivation mode.

(1) Reformulate the teaching program and syllabus of business administration majors.

The traditional professional curriculum system of business administration has been unable to meet the demand for high-quality business administration talents of enterprises nowadays. Therefore, it is necessary to re-construct the curriculum system of business administration and prepare the teaching program and syllabus of business administration according to the characteristics and development trend of different industries, in order to cultivate business administration talents with rich professional knowledge and practical experience.

(2) Reconstruct the curriculum according to the requirements of business administration majors.

Existing business administration courses may not match with the demands of various industries, so it is necessary to reconstruct the courses to improve students' professional quality and practical ability, so that they can better adapt to the demands of different industries and deliver excellent management talents to enterprises.

(3) Realize the effective connection between theoretical courses and practical courses of business administration majors.

At present, there is a split between the theoretical courses and practical courses of business administration in some colleges and universities, and it is necessary to realize the effective docking of the two. Teachers can adjust the teaching content, teaching methods and teaching evaluation. At the same time, they can introduce actual cases and industry experience in the theoretical courses, combine theoretical knowledge with practical problems, and require students to analyze and solve practical problems with theoretical knowledge; in the teaching of practical courses, they should strengthen theoretical guidance and academic guidance, and organize students to participate in actual engineering projects.

VII. Conclusion

The construction of the curriculum system of business administration under the digital talent cultivation mode needs to be supported by scientific assessment methods and path planning. The improved DINA model with the addition of reaction time significantly improves the accuracy of cognitive diagnosis. Among the seven core knowledge attributes, the mastery rate of organizational management is up to 90%, while the mastery rates of human resource management and innovation and entrepreneurship management are 40% and less than 30%, respectively, which reflects the imbalance of students' knowledge structure. Cluster analysis identifies 8 typical knowledge states, in which KS3 students mastering 4 attributes are the most numerous, accounting for 30.08% of the total number of students, and students with complete mastery and complete lack of mastery are characterized by normal distribution. Learning path mining found 4 main paths, and the second path covered 59.6% of students, revealing the universal law of knowledge acquisition. Based on the results of the assessment, the construction of the curriculum system of business administration should focus on three key strategies: rewriting the teaching program and curriculum outline to adapt to the digital demand; reconstructing the professional curriculum according to the industrial demand and strengthening the weak knowledge areas; and realizing the effective docking between theoretical courses and practical courses to enhance the comprehensive application ability of students. Through the organic combination of precise diagnosis, path optimization and system reconstruction, the study promotes the overall improvement of the quality of business administration talent training.

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