Dynamic Assessment of Knowledge to Ability Transformation for College Students

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Abstract: In the environment of talents orientation, the formation of high-quality and complex abilities is of great significance to students. However, with the continuous expansion of the curriculum system, the dual pressures of knowledge fragmentation and knowledge generalization has greatly weakened students' knowledge structure. It results in problems of being comprehensive and diverse more than refine. In this paper, we focus on matching of expected output of teaching and personnel demand. Through a precise matrix matching of training objectives and training programs, which can dynamically evaluate and improve the students' performance via achievement of expected output. The improved assessment based on such matrix and can establish a high-quality training system and improve the long-term competitiveness of college students.

Keywords: Dynamic assessment; Curriculum system; Ability matrix; Knowledge structure

1. INTRODUCTION

Output-based education can clearly focus on the key points of the education system, allocate teaching resources, plan teaching processes, improve evaluation systems, and organize education systems, thereby ensuring that students gain substantial competitiveness in their future careers [1-2]. It enables students to achieve corresponding expected results, rather than just having quantitative advantages in knowledge acquisition. Therefore, for the entire education system, teaching models, teaching methods, and teaching tools are all teaching means, not the ultimate goal. The purpose of teaching is to achieve specific abilities for students based on their future career development needs. The design of the teaching system is a completely ex post facto driven activity [3].

The teaching process should be based on the structure of vocational needs and the needs of national economic development. It needs to plan the abilities and goals that students should achieve upon graduation, as well as their levels. Then, based on the abilities and goals of students, a reasonable teaching roadmap should be designed, and teaching resources should be allocated. Teaching plans and programs should be formulated. Finally, through appropriate teaching modes,

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teaching methods, and evaluation methods, students should be guaranteed to accumulate knowledge according to the teaching plan, and transform knowledge into abilities, and ultimately achieve corresponding goals [4].

Whether knowledge can be transformed into ability depends on the matching between knowledge and ability in the teaching system. Even if the OBE teaching mode is used and the target ability and corresponding teaching system are designed, if the matching between knowledge and ability is poor, it is difficult to achieve the established output goal, and it is easy to fall into two extreme states, either overemphasizing basic theoretical teaching and learning theory for the sake of learning theory, or overemphasizing internship practice and taking "usefulness" as the standard, relegating the cultivation of high-level applied talents to the cultivation of skilled workers [5]. This is the crux of the problem that both teachers and students of technology application-oriented majors are deeply troubled by.

2. MODEL

2.1Knowledge-ability target achievement coefficient matrix

Firstly, we changed the parallel correspondence between curriculum and knowledge and ability to a vertical correspondence, that is, we no longer emphasize the dual correspondence between curriculum content and knowledge and ability, but regard ability and knowledge as a whole with inherent connections [6]. From the perspective of teaching, curriculum only needs to meet certain knowledge target requirements, and there is no need to propose ability target requirements in the curriculum. Different knowledge depths and abilities have a certain progressive relationship. Assuming that the credit of curriculum M_i^C is M_i^P, the corresponding knowledge vector is M_i^K, where the superscript C represents the variable as the course identification, the subscript i is the corresponding course number, and the subscript j is the corresponding knowledge number. The vector $M_i^K = (M_{i,1}^K, M_{i,2}^K, \dots, M_{i,n_i}^K)$, $M_{i,j}^K$ represents the knowledge corresponding to curriculum M_i^C, and n_i represents the number of knowledge points in curriculum M_i^C. The relationship between knowledge vector M_i^K and the ability vector M_i^D forms a knowledge-ability target achievement coefficient matrix. Similar to the knowledge vector, the ability vector $M_i^D = (M_{i,1}^D, M_{i,2}^D, \dots, M_{i,m_i}^D)$, where $M_{i,j}^D$ represents the ability corresponding to the course M_i^C. All courses belonging to the same ability group have the same corresponding M_i^D, and m_i represents the number of ability targets for the course M_i^C. For i, n, m, n_i, m_i defined in the set of natural numbers, the knowledge-ability target achievement coefficient matrix is defined as follows:

$$M_i^{K\to D} = \begin{pmatrix} M_{i,1,1}^{K\to D} & \cdots & M_{i,1,m_i}^{K\to D} \\ \vdots & \ddots & \vdots \\ M_{i,n_i,1}^{K\to D} & \cdots & M_{i,n_i,m_i}^{K\to D} \end{pmatrix},$$

$$s.t. \sum_{n=1}^{n_i} M_{i,n,m_i}^{K\to D} \le M_i^P \ \forall\, m \le m_i$$

$$
\begin{aligned}
& \sum_{n=1}^{n_i} M_{i,n,m_i}^{K\to D} = M_i^P \ \exists\ m_i^* \le m_i \\
& \sum_{n=1}^{n_i}\sum_{m=1}^{m_i} M_{i,n,m}^{K\to D} \le M_i^P * m_i * \rho \\
& M_{i,n,m}^{K\to D} \ge 0 \ \exists\ n \le n_i, m \le m_i
\end{aligned} \tag{1}
$$

Where ρ is the adjustment factor. There is a correlation between knowledge and ability, rather than a simple relationship of presence or absence, so that the contribution of knowledge to ability can be determined based on the score. For any ability, the contribution of knowledge is either positive or zero.

The condition $\sum_{n=1}^{n_i} M_{i,n,m_i}^{K\to D} \le M_i^P \ \forall\ m \le m_i$ indicates that in any course, for any ability, the total contribution of knowledge that contributes to its formation cannot exceed the credit of the course, so that the upper limit of the maximum contribution of knowledge can be horizontally compared in the course. This can avoid the problem of excessive contribution of knowledge due to various human factors in some courses. The constraint condition indicates that for any course, regardless of its credit, the sum of the contribution of knowledge to any ability in each credit is bounded by the credit; for courses with the same credit, the upper bound is consistent, and for courses with different credits, the upper bound is proportional to the credit.

This also reflects the meaning of the upper limit of the knowledge capacity of credits, that is, the credits of a course are constrained by the maximum contribution of knowledge to ability in the course. When a low-credit course cannot accommodate a large amount of knowledge, it is manifested as the sum of knowledge contributions to certain abilities exceeding the number of credits, and thus the number of credits for the course should be increased or the number of knowledge points in the course should be reduced. This can avoid injecting a large amount of knowledge into students in a smaller-scale course, preventing a teaching process that is extensive but not refined.

The condition $\sum_{n=1}^{n_i} M_{i,n,m_i}^{K\to D} = M_i^P \ \exists\ m_i^* \le m_i$ indicates that for any course, there is at least one ability whose total contribution to the knowledge that contributes to its formation reaches the credit of the course, thus allowing the lower limit of the maximum knowledge contribution to be compared horizontally across courses. This can avoid the problem of insufficient knowledge contribution due to various human factors in some courses. The constraint condition indicates that for any course, regardless of its credit, there is at least one ability $M_{i,m_i^*}^{D}$ in each credit, and the corresponding sum of knowledge contribution is exactly equal to the credit. We call this ability the characteristic ability corresponding to the course. A course has at least one characteristic ability. For courses with the same credit, the sum of knowledge contributions to any characteristic ability remains consistent. For courses with different credits, the sum of knowledge contributions to any characteristic ability is proportional to the credit. This also reflects the lower limit meaning of the credit's knowledge capacity, that is, the credit of a course is constrained by the knowledge contribution to the characteristic ability in the course.

When a high-credit course covers only a small amount of knowledge, it is manifested as the fact that even after completing all the corresponding knowledge, no ability can meet the credit requirement of the course, which means that too many credits or too little knowledge are covered. The number of credits for the course should be reduced, or the knowledge points in the course should be increased. This avoids the situation where insufficient knowledge points are taught in a large-scale course, and the teaching process needs to be filled up with other methods.

The condition $\sum_{n=1}^{n_i}\sum_{m=1}^{m_i} M_{i,n,m}^{K\to D} \le M_i^P * m_i * \rho$ indicates that for any course, the total contribution of knowledge to all abilities is subject to the dual constraints of credit and ability. This condition constrains the balance and depth of knowledge, avoids the phenomenon of too many knowledge difficulties in the course, and provides horizontal comparison between different ability vectors. The constraint indicates that for any course, there is an upper bound on the total contribution of knowledge to ability.

If a course has more characteristic abilities (or abilities with higher knowledge contribution), it indicates that the course focuses on cultivating characteristic abilities, and other ability cultivation should be relatively weakened; on the other hand, if a course has fewer characteristic abilities, it indicates that the course is relatively average in terms of ability cultivation. At the same time, as each course has at least one characteristic ability related to the course, there is no problem of excessive knowledge dispersion for any course. The more characteristic abilities, the more concentrated the ability cultivation of the course, and vice versa. The more characteristic abilities, the smaller the average contribution of knowledge to non-characteristic abilities, and the greater the difference between its contribution to characteristic ability. The following table lists the maximum average contribution value of knowledge to non-characteristic abilities per unit credit under different numbers of knowledge items and ability items.

2.2Dynamic Matrix Update

The response result matrix $A_i^{K\to D}$ of the course M_i^C is

$$\mathrm{A}_i^{K\to D} = \begin{bmatrix} A_{i,1,1}^{K\to D} & \cdots & A_{i,1,m_i}^{K\to D} \\ \vdots & \ddots & \vdots \\ A_{i,n_i,1}^{K\to D} & \cdots & A_{i,n_i,m_i}^{K\to D} \end{bmatrix} \tag{2}$$

The corresponding adjustment matrix is

$$\mathrm{Z}_i = \frac{1}{\phi_i n_i \mu_i} Q^{-1}(n_i) \tag{3}$$

In which, there is

$$Q(n_i) = \begin{bmatrix} N_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & N_{m_i} \end{bmatrix} \tag{4}$$

$$\mu_i = \max_v \sum_{u=1}^{n_i} \frac{1}{\phi_i n_i} Q^{-1}(n_i)\,[u, v] \tag{5}$$

The improvement technique for the knowledge-ability target achievement coefficient matrix is

$$\widetilde{M}_i^{K\to D} = (1-\beta_i) M_i^{K\to D} + \beta_i A_i^{K\to D} Z_i \tag{6}$$

where β_i is the learning parameter of the course M_i^C, and the larger β_i is, the greater the improvement.

3. EVALUATION OF TEACHING EFFECTS

Based on the evaluation of learning, we used homogeneity evaluation as an additive mechanism for peer evaluation, in an attempt to overcome some of the problems caused by dual-line peer evaluation [7]. The basic principle is that under the influence of the dual-line mechanism, the greater the difference between the evaluation results of the explicit and implicit mechanisms, the less effective the evaluation. If we construct a homogeneity matrix for evaluation and superimpose its results on the explicit mechanism evaluation results, we can solve the above problems to some extent. The evaluation mechanism we designed is as follows.

Suppose the structure design of the course M_i^C is M_i^S (the structure design can correspond to the class hours, or to other knowledge-related organizational structures), where the superscript S represents that the variable is the course structure identification, and the subscript i is the corresponding course number. The vector $M_i^S = (M_{i,1}^S, M_{i,2}^S, \dots, M_{i,h_i}^S)$, $M_{i,h}^S$ represents the structural elements corresponding to the course M_i^C, and h_i represents the number of structural elements of the course M_i^C. According to the OBE teaching method, the course should have the following structure: knowledge matching matrix $M_i^{S\to K}$.

$$M_i^{S\to K} = \begin{pmatrix} M_{i,1,1}^{S\to K} & \cdots & M_{i,1,n_i}^{S\to K} \\ \vdots & \ddots & \vdots \\ M_{i,h_i,1}^{S\to K} & \cdots & M_{i,h_i,n_i}^{S\to K} \end{pmatrix},$$

$$s.t. \textstyle\sum_{h=1}^{h_i} M_{i,h,n}^{S\to K} = 1, \forall\, n \le n_i \tag{7}$$

where $M_{i,h,n}^{S\to K}$ represents the maximum structure-knowledge matching score, which is the highest score that can be achieved when students and teachers complete the structural element $M_{i,h}^S$ to produce the target knowledge output $M_{i,n}^K$. Assuming that the matching achievement coefficient matrix given by the evaluator is $B_i^{S\to K}$.

$$B_i^{S\to K} = \begin{pmatrix} B_{i,1,1}^{S\to K} & \cdots & B_{i,1,n_i}^{S\to K} \\ \vdots & \ddots & \vdots \\ B_{i,h_i,1}^{S\to K} & \cdots & B_{i,h_i,n_i}^{S\to K} \end{pmatrix},$$

$$s.t.\ \ 0 \le B_{i,h,n}^{S\to K} \le 1, \forall\, h \le h_i, n \le n_i \tag{8}$$

Therefore, the actual structure is as follows-knowledge matching score.

$$\widetilde{M}_i^{S\to K} = \begin{pmatrix} M_{i,1,1}^{S\to K} B_{i,1,1}^{S\to K} & \cdots & M_{i,1,n_i}^{S\to K} B_{i,1,n_i}^{S\to K} \\ \vdots & \ddots & \vdots \\ M_{i,h_i,1}^{S\to K} B_{i,h_i,1}^{S\to K} & \cdots & M_{i,h_i,n_i}^{S\to K} B_{i,h_i,n_i}^{S\to K} \end{pmatrix} \tag{9}$$

If viewed from the perspective of each structural element $M_{i,h}^S$, the actual amount of knowledge it implements should be

$$\widetilde{M}_{i,h\to}^{S\to K} = \textstyle\sum_{n=1}^{n_i} M_{i,h,n}^{S\to K} B_{i,h,n}^{S\to K} = M_{i,h,}^{S\to K} (B_{i,h,}^{S\to K})' \tag{10}$$

Where $M_{i,h,}^{S\to K} = (M_{i,h,1}^{S\to K} \quad \cdots \quad M_{i,h,n_i}^{S\to K})$ represents the maximum structure-knowledge matching score for the structural element $M_{i,h}^S$. $B_{i,h,}^{S\to K} = (\,B_{i,h,1}^{S\to K} \quad \cdots \quad B_{i,h,n_i}^{S\to K})$ represents the evaluator's assessment of the achievement coefficient for the structural element $M_{i,h}^S$ in relation to the target knowledge, and $\widetilde{M}_{i,h\to}^{S\to K}$ represents the evaluator's overall contribution level assessment for the structural element $M_{i,h}^{S}$.If viewed from the perspective of each target knowledge $M_{i,n}^{K}$, its total implementation level should be:

$$\widetilde{M}_{i,\to n}^{S\to K} = \sum_{h=1}^{h_i} M_{i,h,n}^{S\to K} B_{i,h,n}^{S\to K} = (M_{i,,n}^{S\to K})' B_{i,,n}^{S\to K} \tag{11}$$

Among them, $M_{i,,n}^{S\to K} = \left(M_{i,1,n}^{S\to K} \quad \cdots \quad M_{i,h_i,n}^{S\to K}\right)'$ is the maximum structural element score vector of the target knowledge $M_{i,n}^{K}$. $B_{i,,n}^{S\to K} = (\,B_{i,1,n}^{S\to K} \quad \cdots \quad B_{i,h_i,n}^{S\to K})$ is the evaluation of the achievable coefficient of the target knowledge $M_{i,n}^{K}$ in each structural element by the evaluator, and $\widetilde{M}_{i,\to n}^{S\to K}$ is the overall achievement level evaluation of the target knowledge $M_{i,n}^{K}$ by the evaluator.

When the information of typical evaluators is sufficient and completely rational, the evaluation of structural element $M_{i,h}^{S}$ for target knowledge $M_{i,n}^{K}$ can maintain consistency in multiple evaluations. That is to say, regardless of the evaluation environment presented to the evaluator, the score given by the evaluator for the contribution of given structural element $M_{i,h}^{S}$ in target knowledge $M_{i,n}^{K}$ must equal $\widetilde{M}_{i,h_i,n_i}^{S\to K}$. However, this does not guarantee the fairness of the evaluation itself. According to the existence of the dual-line mechanism described earlier, students may be influenced by many factors when evaluating the role of structural elements in knowledge, resulting in lack of accuracy (such as whether the teacher often tells jokes, whether the exam gives the scope and answer in advance, etc.). Therefore, we assume that under the following three conditions: (1) the evaluator needs to conduct two evaluations at sufficiently long intervals, (2) a different framework is provided for each evaluation, and (3) the first evaluation cannot be corrected based on the second evaluation. The evaluation is non-perfectly rational, and a correction factor q_i^l is constructed accordingly.

$$q_i^l = \frac{\left|\sum_{h=1}^{h_i} \widetilde{M}_{i,h\to}^{S\to K} - \sum_{n=1}^{n_i} \widetilde{M}_{i,\to n}^{S\to K}\right|}{n_i} \tag{12}$$

The correction factor q_i^l can be used as a measure of internal consistency for typical evaluators, and as a reliability weight to help teachers improve structural elements, better complete teaching tasks, and achieve teaching goals. When $q_i^l \to +\infty$, it indicates that the typical evaluator tends to be completely internally consistent. The larger q_i^l, the better the consistency of the typical evaluator. The interval time should usually be greater than one week.

4. Behavioral Outcome

4.1Interation Based on Behaviror

According to the principle of availability heuristic in behavioral economics, people tend to evaluate the probability of events based on the ease of memory or recall of event instances [8]. The availability heuristic will increase the weight or probability of instances that are easy to remember or recall in the evaluation, or exaggerate their role, while reducing the weight or probability of instances that are difficult to remember or recall, or exaggerate their role. For a specific event, such as the structural element $M_{i,h}^{S}$ mentioned above, if the first evaluation is a near event evaluation (i.e., the time interval between the occurrence or presentation of the structural element is not far), then the near event will inevitably have a significant impact on the evaluator's evaluation score; while the second evaluation is a far event evaluation, the influence of the structural element on the evaluation will be less significant. The reason why the interval between the two evaluations should be greater than one week is precisely the result of considering the above factors. The iterative result is listed in table 1.

4.2Converged Matrix Result

Table 1 Table Type Styles

Knowledge	Ability						
	$M_{i,1}^D$	$M_{i,2}^D$	$M_{i,3}^D$	$M_{i,4}^D$	$M_{i,5}^D$	$M_{i,6}^D$	$M_{i,7}^D$
$M_{i,1}^K$	0.11	0.11	0.08	0.15	0.07	0.03	0.08
$M_{i,2}^K$	0.17	0.11	0.11	0.18	0.10	0.08	0.19
$M_{i,3}^K$	0.01	0.07	0.01	0.07	0.16	0.18	0.15
$M_{i,4}^K$	0.12	0.16	0.12	0.06	0.09	0.20	0.09
$M_{i,5}^K$	0.01	0.03	0.09	0.07	0.13	0.07	0.01
$M_{i,6}^K$	0.06	0.15	0.16	0.14	0.04	0.07	0.03
$M_{i,7}^K$	0.19	0.04	0.08	0.08	0.18	0.16	0.11
$M_{i,8}^K$	0.19	0.18	0.11	0.08	0.13	--	0.14
$M_{i,9}^K$	0.03	0.01	0.10	0.05	0.17	0.14	0.20
$M_{i,10}^K$	0.01	0.13	--	0.14	0.11	0.14	0.07
Total	0.88	0.98	0.86	1.02	1.17	1.08	1.07

According to the preference theory of behavioral economics, when people do not have obvious preferences, they are easily influenced by the framework effect, such as the presentation of the problem or other signals that help determine the valuation, which will help people make choices quickly. Therefore, if there is a significant difference between the frameworks of the two evaluations, the evaluator will be influenced by the framework effect and focus on the framework guidance.

At the same time, according to the confirmation bias theory, people have a strong tendency to seek information that may confirm their current beliefs rather than information that makes them rethink, and they also tend to interpret new information as supporting their current beliefs. In the two evaluations mentioned above, the first evaluation comes first, so it is impossible to avoid the evaluator using the information from the first evaluation to revise the second evaluation. The only way to minimize this natural revision is to increase the time interval between the two evaluations and use different frame information. If it is allowed to revise the result of the first evaluation after the second evaluation, the evaluator will inevitably change the first evaluation based on the information they have recently held, which means that the evaluator will not objectively rethink and face the first evaluation independently, but simply enhance their beliefs based on the easily searchable information, the second evaluation that just happened, and revise the first evaluation accordingly, making the time interval and frame effect differences ineffective.

5. CONCLUSIONS

Unreasonable evaluations are all unreasonable exaggerations of negative evaluations. After weighting with the correction factor, the exaggerated magnitude decreases, meaning that the impact of the unreasonable evaluation decreases. Therefore, in any case, after weighting with the correction factor, the weight of the unreasonable evaluation will be significantly reduced, thereby alleviating the impact of the unreasonable evaluation. The correction factor weighting has a significant elimination effect on unreasonable evaluations, which can be used to avoid excessive or undue evaluations by evaluators due to factors other than teaching to a certain extent.

Even in the competency-oriented teaching model, there are still problems in matching knowledge learning and ability development. This paper focuses on the dilemma of knowledge and ability matching in technology applied majors. It is found that under the output-oriented model, there are still characteristics of weak overall ability structure, vague ability cognition, and unclear knowledge-driven characteristics. Based on this, corresponding improvement strategies are proposed.

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