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PAPER

Enhancing Educational Design Capabilities through Interactive Mobile and Adaptive Learning Platforms: An Empirical Study

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ABSTRACT

With the continuous advancement of educational technology, interactive mobile and adaptive learning platforms are playing an increasingly important role in the field of education. This is particularly evident in the development of educational design skills among education students, as these platforms showcase their unique value. Educational design capability is a crucial skill for education students, directly related to the quality of designing and implementing future teaching activities. Traditional methods of education often fail to fully consider individual student differences, resulting in inadequate cultivation of personalized capabilities. This study aims to explore and achieve precise cultivation of educational design capabilities in education students through interactive, mobile, and adaptive learning platforms. This paper first reviews the current application of interactive mobile and adaptive learning platforms to cultivate educational design capabilities. It highlights deficiencies in existing research methods related to personalized matching and recommendation system design. To address these deficiencies, this study proposes a new set of adaptive matching methods. These methods include capability characteristic recognition based on competitive advantage thinking, the construction of individual strength models, as well as matching calculation, and decision-making scheme optimization using the projection decision method and the Hungarian method. Additionally, the study designs a learning project recommendation algorithm based on explicit ratings to enhance the accuracy and personalization of learning project recommendations. The application of these methods not only enhances the educational design capabilities of education students but also provides new theoretical support and practical guidance for the development of interactive, mobile, and adaptive learning platforms.

KEYWORDS

interactive mobile, adaptive learning platform, educational design capability, individual strength model

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1 INTRODUCTION

With the advancement of technology, including the rise of interactive mobile technologies, and the evolution of educational models, adaptive learning platforms have emerged as a pivotal area of development in the modern educational ecosystem [1, 2]. These platforms, by offering personalized learning paths and leveraging the capabilities of mobile technologies for on-the-go access, not only enhance learning efficiency but also strengthen students' professional skills [3]. In education, the capacity for educational design—encompassing the skills to efficiently design, implement, and evaluate teaching activities—is a critical competency for students, embodying innovative and entrepreneurial abilities [4–6]. Traditional education models often fail to adequately address individual student differences and align capabilities, highlighting the significant potential of adaptive learning platforms enhanced with interactive mobile technologies in fostering students' educational design skills [7].

The importance of research into adaptive learning platforms is underscored by their ability to deliver customized content tailored to the unique characteristics and learning needs of each student, thereby effectively nurturing their educational design skills [8–11]. The integration of interactive mobile technologies within these platforms introduces a highly personalized learning environment for education students through data analysis, instant feedback, and intelligent recommendations, facilitating the development of educational design capabilities [12, 13]. The exploration and application of such platforms not only encourage personal development but also drive innovation in educational methodologies, elevating both the quality and efficiency of education.

Previous studies on adaptive learning platforms have predominantly focused on general skill enhancement, with a lack of in-depth investigations into specific domains such as educational design capabilities. Moreover, existing approaches often lack a dynamic optimization mechanism to accurately align students with learning projects, thus failing to maximize the benefits of individual strengths and learning preferences. This leads to a lack of precision and personalization in the recommendations provided by these systems [14–17]. Thus, refining matching algorithms and recommendation strategies in adaptive learning platforms, particularly those incorporating interactive mobile technologies, is crucial for enhancing educational design skills [18–20].

This study aims to develop a series of adaptive learning project matching and recommendation methods to enhance the educational design capabilities of students in the field of education. It begins by identifying the characteristic competencies in educational design among students, using competitive advantage thinking to construct models of individual strengths. The study then applies the projection decision method for precise matching of students to learning projects, with the Hungarian method employed to optimize the decision-making for matching outcomes. Furthermore, it introduces a learning project recommendation algorithm that utilizes explicit ratings. This algorithm is designed to suggest projects that align with the educational design capability enhancement objectives of different student groups. This study aims to enhance the educational design skills of education students and provide a fresh perspective on adaptive learning platform theory and practice. This will enhance the scientific rigor and effectiveness of educational training models.

2 ADAPTIVE MATCHING FOR EDUCATIONAL DESIGN SKILL ENHANCEMENT

The core advantage of adaptive learning platforms lies in their ability to provide customized learning content and paths based on the individual needs and learning progress of students. For education students, enhancing their educational design capabilities is not just about mastering theoretical knowledge; more importantly, it involves applying theory to practice and designing innovative and effective educational plans. This paper focuses on enhancing the educational design skills of education students. It aims to achieve optimal alignment between student capabilities and learning projects through the development and examination of adaptive matching methods. This, in turn, enhances learning efficiency and quality. Figure 1 illustrates the research framework for the adaptive matching method for learning projects.

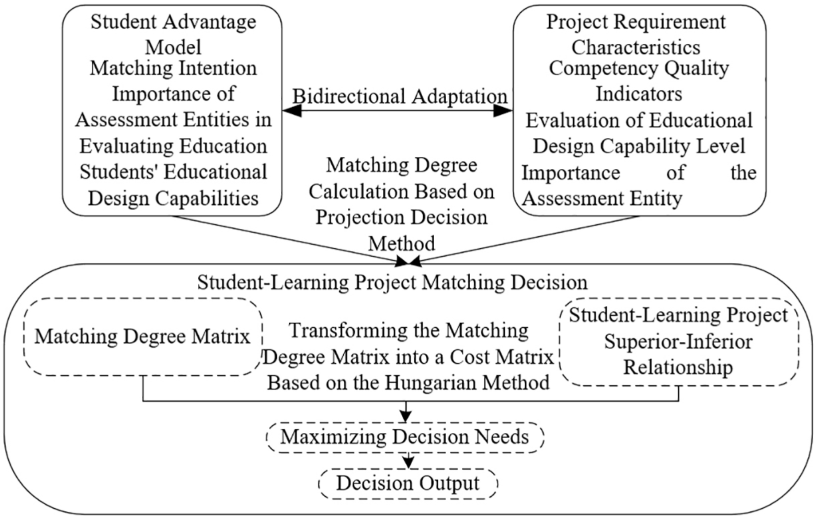

Fig. 1. Research framework for adaptive matching method of learning projects

2.1 Identifying competencies in educational design projects

After identifying the various competency quality indicators set $Y = \{y_1, y_2, ..., y_c\}$ needed by education students for various types of educational design capability enhancement learning projects, this paper uses this indicator set as the foundation for preparing the survey questionnaire. For the educational design capability enhancement learning project u, assuming that the educational design capability level evaluation matrix required for education students on each competency quality indicator is represented by N_u^h, the expression is as follows:

$$N_u^h = \begin{bmatrix} N_{u11}^h & N_{u12}^h & \cdots & N_{uc1}^h \\ N_{u21}^h & N_{u22}^h & \cdots & N_{uc2}^h \\ \cdots & \cdots & \cdots & \cdots \\ N_{uL1}^h & N_{uL2}^h & \cdots & N_{uLc}^h \end{bmatrix} \tag{1}$$

Further derivation leads to the expression for enhancing the required superior competency features N_u^h for the educational design capability in the learning project.

$$Q_u^h = \begin{bmatrix} Q_{u11}^h & Q_{u22}^h & \cdots & Q_{uc1}^h \\ Q_{u21}^h & Q_{u22}^h & \cdots & Q_{uc2}^h \\ \cdots & \cdots & \cdots & \cdots \\ Q_{uL1}^h & Q_{uL2}^h & \cdots & Q_{uLc}^h \end{bmatrix}_{u=1,2,\ldots,v} \tag{2}$$

For the u type of educational design capability enhancement learning project, the importance of L evaluators can be determined through the following calculation:

$$\eta_u^h = \left[\eta_{u1}^h, \eta_{u2}^h, \ldots, \eta_{ut}^h, \ldots, \eta_{uL}^h\right] \tag{3}$$

The superior competency features required by education students for the i type of educational design capability enhancement learning project can be calculated as follows:

$$Q_u^{h*} = \left[Q_{u1}^{h*}, Q_{u2}^{h*}, \ldots, Q_{uc}^{h}\right]^* \cdot \left[\sum_{T=1}^{L} \eta_{ut}^h Q_{ut}^h \sum_{T=1}^{L} \eta_{uT}^h Q_{ut}^h, \ldots, \sum_{T=1}^{L} \eta_{uTC}^h Q_{uTC}^h\right] \tag{4}$$

Combining the aligned intentions of education students and the assessment of their educational design capabilities by universities, we identify a group O of education students who may be suitable for the v type of educational design capability enhancement learning project, considering them as the subjects to be evaluated. Using the indicator set $Y = \{y_1, y_2, \ldots, y_c\}$ of the v types of educational design capability enhancement learning projects as a standard, V assess evaluate the educational design capability level of the k-th evaluated educational student on each indicator. This assessment results in obtaining the educational design capability evaluation matrix N_k^e for educational students, which is represented by the following expression:

$$n_k^e \begin{bmatrix} n_{k11}^e & n_{k22}^e & \cdots & n_{k1c}^e \\ n_{k21}^e & n_{k22}^e & \cdots & n_{k2z}^e c \\ \cdots & \cdots & \cdots & \cdots \\ n_{kV1}^e & v_{kV2}^e & \cdots & v_{kVc}^e \end{bmatrix} \tag{5}$$

Further, the superior feature Q_k^e of the k-th education student to be matched in educational design capability can be obtained through data processing:

$$Q_k^e = \begin{bmatrix} Q_{k11}^e & Q_{k22}^e & \cdots & Q_{k1c}^e \\ Q_{k21}^e & Q_{k22}^e & \cdots & Q_{k2c}^e \\ \cdots & \cdots & \cdots & \cdots \\ Q_{kV1}^e & Q_{kV2}^e & \cdots & Q_{kVc}^e \end{bmatrix}_{k=1,2,\ldots,o} \tag{6}$$

For the k-th evaluated educational student, the importance of V evaluators can be calculated as follows:

$$i_k^e = \left[i_{k1}^e, i_{k2}^e, \ldots, i_{ks}^e, \ldots, i_{kV}^e\right] \tag{7}$$

The superior feature in educational design capability of the k-th evaluated education student can be calculated using the following expression:

$$Q_k^{e*} = \left[Q_{k1}^{e*}, Q_{k2}^{e*}, \ldots, Q_{kc}^{e*}\right] \cdot \left[\sum_{s=1}^{V} i_{1ks}^e Q_{1ks}^e \sum_{s=1}^{V} i_{2ks}^e Q_{2ks}^e, \ldots, \sum_{s=1}^{V} i^e\right] \tag{8}$$

2.2 Measurement of matching degree between students and learning projects

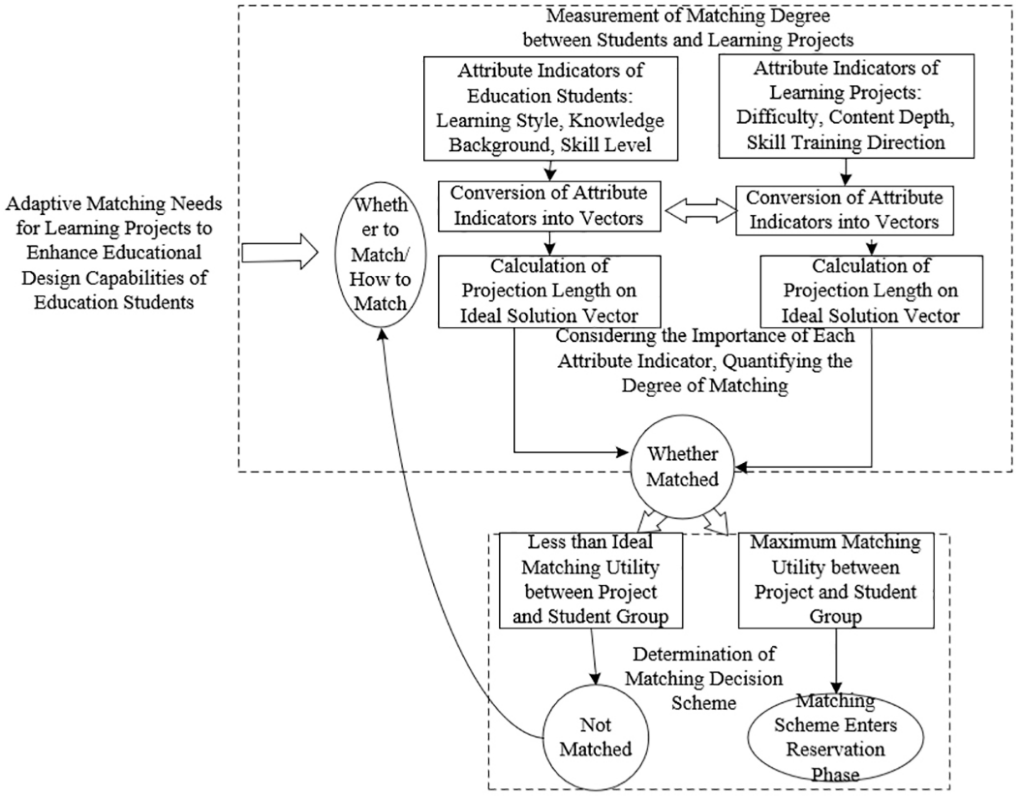

Fig. 2. Matching mechanism between students and learning projects

In the context of adaptive learning platforms, each educational student and learning project can be viewed as a complex entity with multiple attribute indicators. These indicators include the student's learning style, knowledge background, skill level, as well as the project's difficulty, content depth, skill training direction, etc. This paper employs the projection decision method to calculate the degree of match between education students and projects aimed at enhancing educational design capabilities. This method converts attribute indicators into vectors and calculates their projection length on the ideal solution vector, quantifying the degree of matching. This simplifies the decision-making process. This method also considers the importance of each attribute indicator, making the final decision more precise and objective.

Figure 2 illustrates the matching mechanism between students and learning projects. The basic idea of using the projection decision method in this paper is to initially establish the educational design capability indicators of education students and the competency indicators of learning projects, thus creating the fundamental framework for evaluation. Then, each indicator is weighted according to its significance in enhancing educational design capabilities, ensuring the specificity and differentiation of the evaluation process. Subsequently, by constructing the optimal solution vector, the attribute indicator vectors of students and learning projects are compared with it, and the projection length is calculated. This value reflects the similarity and adaptability between the students and the learning projects. Finally, these projection values provide a quantifiable and comparable index of the degree of matching, offering a scientific foundation for designing and optimizing personalized learning paths on adaptive learning platforms. Specifically, suppose two vectors $Q_k^{e*} = \eta = (\eta_1, \eta_2, \ldots, \eta_l)$ and $Q_u^{h*} = \lambda = (\lambda_1, \lambda_2, \ldots, \lambda_l)$, let $Q_k^{e*} = \eta = (\eta_1, \eta_2, \ldots, \eta_l)$, the magnitude of vector η is expressed as $\left|Q_k^{e*}\right| = \left|\eta\right| = \sqrt{\Sigma_{k=1}^{l} \eta_k^2}$. Then the angle between Q_k^{e*} and Q_u^{h*} can be calculated as follows.

$$COS(Q_k^{e*} = \eta, Q_u^{h*} = \lambda) = \frac{\sum_{k=1}^{l} \eta_k \lambda_k}{\sqrt{\sum_{k=1}^{l} \eta_k^2} \cdot \sqrt{\sum_{k=1}^{l} \lambda_k^2}} \tag{9}$$

Suppose the projection of η on λ is represented by two vectors $Q_k^{e*} = \eta = (\eta_1, \eta_2, \ldots, \eta_l)$ and $Q_u^{h*} = \lambda = (\lambda_1, \lambda_2, \ldots, \lambda_l)$. Typically, the larger the value of $W(Q_k^{e*})$, the greater the projection of Q_k^{e*} on Q_u^{h*}, indicating that Q_k^{e*} and Q_u^{h*} are closer. If λ is a positive ideal solution, the higher the $W(Q_k^{e*})$ value, the closer it is to the ideal solution, indicating a stronger match between Q_k^{e*} and Q_u^{h*}. Assuming that the superior features of all education students' educational design capabilities are represented by $Q_k^{e*} = \eta$, and the superior features of the competency of different types of educational design capability enhancement learning projects are represented by $Q_u^{h*} = \lambda$, then it follows that:

$$W(Q_k^{e*} = \eta) = \frac{\sum_{k=1}^{l} \eta_k \lambda_k}{\sqrt{\sum_{k=1}^{l} \eta_k^2} \cdot \sqrt{\sum_{k=1}^{l} \lambda_k^2}} \cdot \sqrt{\sum_{k=1}^{l} \eta_k^2} \cdot = \frac{\sum_{k=1}^{l} \eta_k \lambda_k}{\sqrt{\sum_{k=1}^{l} \lambda_k^2}} \tag{10}$$

Let the matching degree of the educational design capability competitive feature structure between education student k and educational design capability enhancement learning project u be represented by x_{uk}, where $u = 1,2,\ldots v$; and $k = 1,2,\ldots o$. He matrix is as follows:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{o1} \\ x_{21} & x_{22} & \cdots & x_{o2} \\ \cdots & \cdots & \cdots & \cdots \\ x_{v1} & x_{v2} & \cdots & x_{vo} \end{bmatrix} \tag{11}$$

2.3 Determination of student-learning project matching decision scheme

Adaptive learning platforms face the challenge of aligning a variety of educational design projects aimed at enhancing capabilities with a diverse group of students. The challenge lies in how to fairly and effectively allocate learning resources to ensure that each student receives the most suitable learning opportunities for enhancing their capabilities. The Hungarian method is a classic combinatorial optimization algorithm that can find the most efficient matching scheme in many-to-many matching problems. In this study, the Hungarian method helps the adaptive learning platform optimize the matching between students and learning projects, ensuring an optimal or near-optimal allocation result, even when the number of students and projects is unequal.

The basic idea of this method is to use the Hungarian method for optimized allocation after obtaining the matrix of educational design capability and learning project matching degrees. First, using the matching degree matrix obtained through the projection decision method, we determine the relative superiority and inferiority relationships between students and learning projects. Suppose the number of educational design capability enhancement learning projects is represented by V and the number of education students by O, then when $V<O$, construct (O-V) educational design capability enhancement learning projects to form an $O*O$ matrix. When $V>O$, construct (V-O) educational students to form an $O*O$ matrix. Next, through the algorithmic process of the Hungarian method, the matching problem between students and projects is transformed into an optimization problem. The goal is to find a matching scheme that maximizes the total matching degree. This process involves converting the similarity degree matrix into a cost matrix and then determining the optimal allocation within this cost matrix. Suppose the matching degree calculation matrix is represented by X, and the model for the maximization of decision needs is represented by $X = [x_{11}\ x_{12} \dots x_{1o}\ x_{12}\ x_{22} \dots x_{2o} \dots \dots \dots \dots\ x_{v1}\ x_{v2} \dots x_{vo}]$. When arranging educational projects e_k to educational design capability enhancement learning project h_u, then $A_{uk} = 1$; when not arranging educational projects e_k to enhance students' educational design capabilities, h_u, then $A_{uk} = 0$. The expression for the objective function is as follows:

$$MAX\ c = \sum_{u=1}^{v} \sum_{k=1}^{o} X_{uk} A_{uk} \tag{12}$$

The objective function represented by the above formula characterizes the maximum total utility needed for all educational students to complete all v educational design capability enhancement learning projects. $X_{uk} = 1$ represents the maximum total effect obtained by arranging the k-th student to complete the u-th learning project, and the square matrix composed of $X_{uk} = 1$, $u = 1, 2, \dots, v$, $k = m, 2, \dots, o$ is represented by X. The following constraints apply:

$$s.t = \sum_{u=1}^{v} A_{uk} = 1, u = 1, 2, v. \tag{13}$$

$$\sum_{k=1}^{o} A_{uk} = 1, k = 1, 2, \dots, o \tag{14}$$

3 ADAPTIVE RECOMMENDATION FOR EDUCATIONAL DESIGN PROJECTS

In the context of adaptive learning platforms, improving the educational design skills of students in the field of education is crucial objective. The key to achieving this goal lies in effectively to recommending learning projects that are suitable for the students' level and needs. This paper proposes an adaptive recommendation method to ensure that students can access and participate in learning experiences that best promote their professional growth. This recommendation method can match the most suitable educational design capability enhancement learning projects based on students' current ability levels, learning progress, personal preferences, and learning objectives. This not only improves the level of personalization in learning and student satisfaction but also enhances learning efficiency through precise matching, reduces resource waste, and thereby improves the overall quality of education and teaching effectiveness.

This method involves specifically analyzing the educational design capabilities of education students and the learning needs and preferences of similar groups. Through the adaptive recommendation algorithm, the most suitable enhancement learning projects are personalized and recommended for each student. It requires collecting and analyzing extensive data about student performance and group preferences, and then using this data to train the recommendation model, enabling it to identify the most suitable learning resources for individual students. The assumptions this method needs to meet include the contribution of group preferences to improving the accuracy of recommendations and maintaining individual differences within the group on common preference attributes. These conditions establish design principles for the adaptive recommendation system: it should capture the general needs and trends of educational students while also focusing on and respecting each student's individualized learning preferences.

The adaptive learning platform first needs to calculate the performance scores of educational students in various educational design capability enhancement learning projects. This can be assessed through a comprehensive evaluation of various data points, such as student interactions in the project, the quality and quantity of tasks completed, and test results. These scores reflect the students' capabilities and potential areas for improvement in specific educational design fields, serving as a foundation for personalized matching recommendations. Suppose the preference list for different attributes within the group I of education student i is represented by $\{F_1, F_2 \ldots F_l\}$, where l is the number of attributes. Then, the attention weight list for different attributes is represented by $X = \{\beta_1, \beta_2 \ldots \beta_l\}$, where $\beta_u = F_u / \Sigma_{u=1}^{l}$. The preference list for different attributes of education student i is represented by $F_u = \{f_1, f_2 \ldots f_l\}$, where l is the number of attributes. Then, the attention weight list for different attributes can be represented by $X = \{\alpha_1, \alpha_2 \ldots \alpha_l\}$, where $\alpha_u = f_u / \Sigma_{u=1}^{l} f_u$. The following formula provides the score calculation for student i in the educational design capability enhancement learning project u:

$$O(i,u) = \sum_{j=1}^{J} (\lambda\beta_j + \alpha_j) \sum_{m=1}^{l} o_{i,j,1} w_{u,j,m} \tag{15}$$

For each attribute value of a learning project, the platform will calculate its similarity with the target attribute values of the student's educational design capabilities. A high similarity indicates that the project's attributes closely match the student's target attributes, thus increasing the likelihood of enhancing the student's capabilities in that area. Suppose the attention weight to different attributes by the group of education students i is represented by λ. The probability of education student i taking U attribute value on attribute j is represented by $O_{i,j,1}$, and the preference list for the same attribute of education student i is represented by $\{t_1, t_2 \ldots t_v\}$, where v represents the number of attribute values. Then $O_{i,j,1} = t_m / \Sigma_{u=1}^{v} t_u$. The formula below represents the similarity $w_{u,j,1}$ of the attribute value taken by educational design capability enhancement learning project u on attribute j to the U attribute value on target attribute j, where the value taken by the project u on attribute j is represented by $a_{j,u}$, and the U value on target attribute j is represented by $a_{j,1}$:

$$w_{u,j,m} = \frac{a_{j,u} \times a_{j,m}}{\sqrt{a_{j,u}^2 \times a_{j,m}^2}} \tag{16}$$

If attribute j cannot be quantified, then when the value of educational design capability enhancement learning project on attribute j is 1, $w_{u,j,1} = 1$; when the value of educational design capability enhancement learning project on attribute j is not 1, $w_{u,j,1} = 0$. Finally, the adaptive recommendation system will compare the attribute values of the learning projects with the attention weights assigned by the student group and score and rank all learning projects. This process combines the absolute level of attribute values with the influence of group preferences, ensuring that the recommended projects not only meet the individual development goals of the student but also satisfy the general needs and preferences within the group. Ranking the educational design capability enhancement learning projects $O(i,u)$ from high to low, the system will recommend a series of best-matching educational design capability enhancement learning projects for each student based on the ranking results. These suggestions, based on individual capability assessments and group attention weights, aim to provide students with the learning resources most likely to enhance their educational design capabilities.

4 RESULTS AND ANALYSIS

Analyzing the competitive feature matching degree data shown in Table 1, we can observe the matching degree between various teams and various learning projects. The numerical value of the matching level indicates the degree of alignment between the educational design capability features of the team working on a specific learning project and the competitive features of that project. A higher value indicates a better match. In the table, it can be noticed that team B5 has the highest matching degree of 0.148 in project A3, which is the highest among all team-project pairings, indicating that team B5 matches project A3 exceptionally well. Similarly, team B3 has a high matching degree of 0.145 in project A5. These high matching degree values indicate that the method described in this paper can effectively identify teams and learning projects exhibit strong synergy. This synergy reflects a good alignment between the educational design capabilities and the competitive features of the learning projects. On the other hand, the matching degree of team B2 with project A6 is 0.121, which is one of the lower values in the table, indicating that team B2 will not achieve the optimal learning effect on project A6. Combining these data, the method proposed in this paper effectively reveals the degree of matching between various teams and different learning projects, offering data support for adaptive learning recommendations for educational students. Through precise calculations of competitive feature matching degrees, combined with individual strength models and optimization algorithms, efficient matching can be achieved. Moreover the quality of matching can be further enhanced through optimized decision schemes.

Figure 3 illustrates the performance of a specific explicit rating-based learning project recommendation algorithm across various attention weight values in relation to diversity, coverage, recall rate, and accuracy. Different weight values represent the varying degrees of influence of different attributes of educational design capabilities on the recommendation results. As shown in the graph, with the increase in attention weights, diversity initially increases to 0.71 and then gradually decreases. Under moderate weights (0.2–0.8), the recommendation system can maintain a high level of diversity. Thus, it suggests that by moderately valuing various attributes of educational design capabilities, the system can recommend a variety of learning projects to students. The coverage rate continuously decreases with the increase in weight, dropping from 0.54 to 0.35. This implies that when certain attributes are emphasized, the recommendation system tends to suggest a few specific learning projects, thus limiting the coverage of the entire project library. The recall rate peaks at 0.13 when the weight is between 0.2 and 0.4 then stabilizes, and begins to decline when the weight reaches 1. This suggests that moderate weights help improve the system's ability to recommend relevant projects to students, but weights that are too high or too low reduce the recall rate. Accuracy first rises and then peaks at 0.37 when the weight is 0.4, subsequently declining with the increase in weight. This indicates that appropriate weights can improve the accuracy of recommendations, but excessively high weights can lead to a decrease in accuracy. This occurs when the system becomes overly fixated on specific attributes, neglecting other equally important factors. Overall, the recommendation algorithm proposed in this paper demonstrates good performance in managing various attention weights, particularly excelling in diversity and accuracy at moderate weight levels. This indicates that the algorithm works best in balancing different attributes of educational design capabilities, and excessively high or low weights affect the quality of the recommendation results.

Figure 4a illustrates the impact of various recommendation schemes on the proportion of improvement in the educational design capabilities of education students when suggesting different numbers of learning projects. This ratio is based on a specific evaluation method used to measure the enhancement of students' educational design capabilities following the completion of recommended learning projects. It can be observed that as the number of recommended learning projects increases, the proportion of improvement in educational design capabilities for all four recommendation schemes exhibits an upward trend. The recommendation scheme in this paper has improved from 0.488 to 0.546. It not only starts at a higher level than other schemes but also demonstrates a more significant increase when recommending multiple projects, particularly achieving the highest improvement ratio when recommending five projects. Overall, the recommendation scheme in this paper demonstrates superior performance across various recommendation quantities, especially showing more significant capability improvement as the number of recommendations increases. This is because the scheme in this paper considers more comprehensive factors in recommendations, such as the student's personal abilities, preferences, and the relevance and complementarity of learning content.

Figure 4b illustrates the variance in educational design capability improvement among education students under various recommendation schemes based on different numbers of recommended learning projects. Variance is used in statistics to quantify the dispersion of data distribution. A higher variance indicates greater uncertainty in students' capability improvement, while a lower variance suggests more consistent capability improvement. The variance of the recommendation scheme in this paper has increased from 0.21 to 0.275. This trend indicates that as more project recommendations are provided, the differences in capability improvement among students also increase. This is because the recommendation scheme in this paper focuses more on personalized matching, leading to more significant differences in capability improvement among different students. Overall, the recommendation scheme in this paper initially exhibits higher variance, suggesting that even with a limited number of recommendations, the scheme can offer more personalized suggestions. As the number of recommendations increases, the further rise in variance indicates that the system can maintain or even enhance personalization with multiple recommendations.

Table 2 presents the comparison results of four distinct adaptive recommendation methods based on accuracy, recall rate, coverage, and diversity. According to the data in the table, the recommendation method in this paper has an accuracy of 0.3654, which is higher than the other three methods. This suggests that this method can more accurately recommend projects that users will like. This is one of the most critical performance indicators of a recommendation system because higher accuracy typically leads to an improved user experience. In terms of recall rate, the performance of this paper's recommendation method is 0.1147, slightly lower than the project-based recommendation scheme's 0.1236, but higher than the collaborative filtering recommendation scheme's 0.1138. A lower recall rate indicates that some relevant projects have not been recommended. In terms of coverage, this paper's recommendation method leads with a result of 0.5249, indicating that this method can consider a broader range of projects when making recommendations, thus providing a richer selection. In terms of diversity, this paper's recommendation method scores 0.6879, significantly outperforming other methods. It shows that this method can offer a more diverse and extensive range of projects in the recommendation list, helping to meet the varied needs of different users. Overall, the recommendation method described in this paper demonstrates excellent performance in accuracy, coverage, and diversity. Although there is a shortfall in the recall rate, overall, this method demonstrates its effectiveness in considering key performance indicators of recommendation systems, particularly in delivering accurate and varied recommendations. This can enhance the user experience and meet the personalized learning needs of different students.

Table 1. Matching students' degree with learning projects

Matching Degree	Project A1	Project A2	Project A3	Project A4	Project A5	Project A6
Team B1	0.123	0.132	0.141	0.128	0.142	0.123
Team B2	0.124	0.127	0.127	0.131	0.136	0.121
Team B3	0.118	0.135	0.123	0.142	0.145	0.137
Team B4	0.123	0.126	0.142	0.141	0.131	0.124
Team B5	0.124	0.141	0.148	0.142	0.142	0.128
Team B6	0.126	0.142	0.135	0.131	0.140	0.123
Team B7	0.121	0.136	0.141	0.135	0.145	0.131
Team B8	0.127	0.121	0.136	0.145	0.142	0.127
Team B9	0.128	0.137	0.132	0.142	0.128	0.123
Team B10	0.123	0.141	0.145	0.143	0.145	0.134

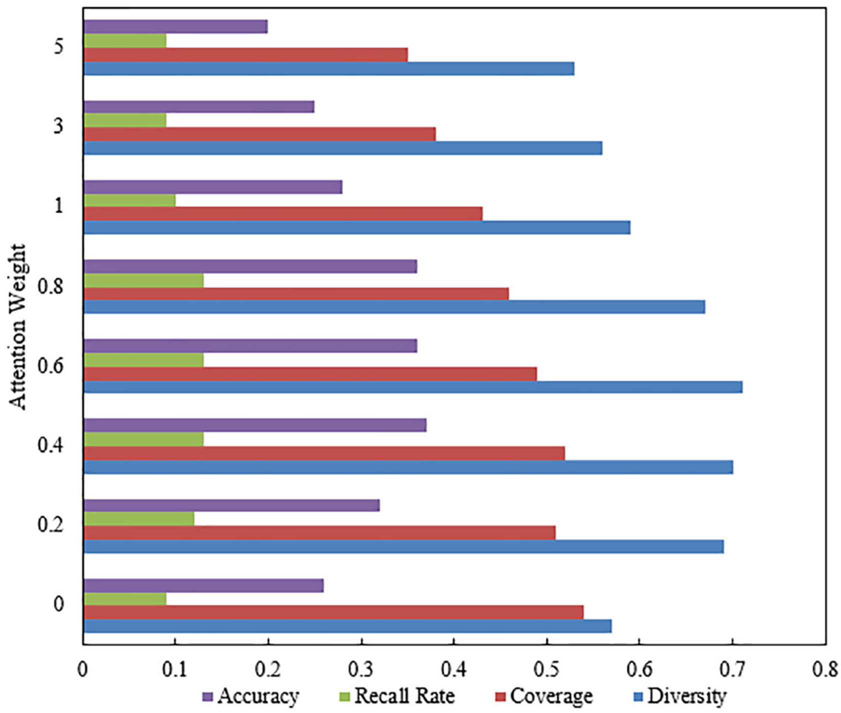

Fig. 3. Model performance comparison under various attention weight values

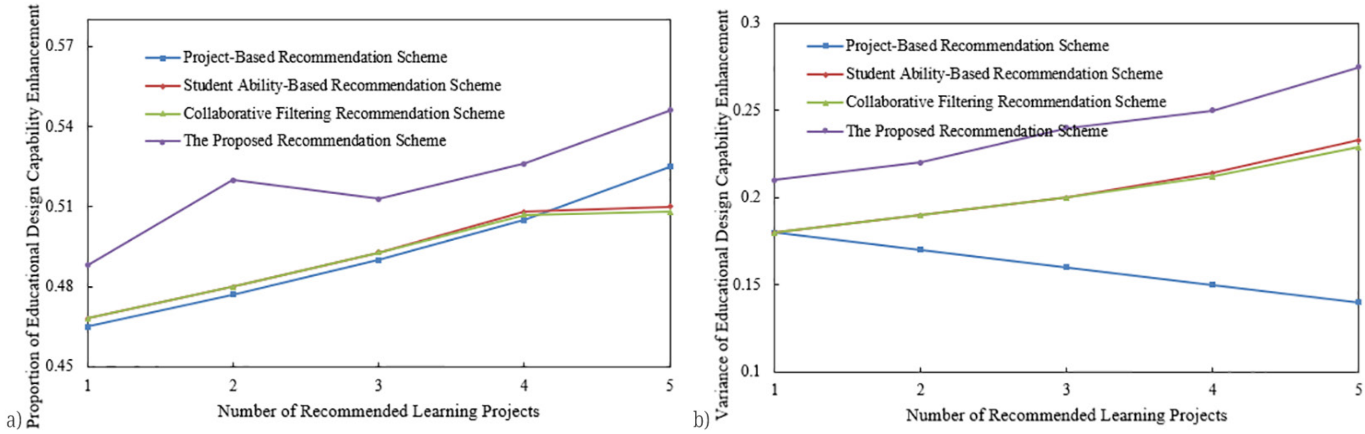

Fig. 4. Comparison of educational design capabilities of education students

Table 2. Comparison of adaptive recommendation method performance for different learning projects

Method	Accuracy	Recall Rate	Coverage	Diversity
The Proposed Recommendation Method	0.3654	0.1147	0.5249	0.6879
Project-Based Recommendation Scheme	0.3287	0.1236	0.5231	0.5826
Student Ability-Based Recommendation Scheme	0.2159	0.1158	0.4789	0.5413
Collaborative Filtering Recommendation Scheme	0.3368	0.1138	0.5135	0.5789

5 CONCLUSION

This paper focuses on designing and implementing an adaptive learning project recommendation method to enhance the educational design capabilities of education students. The emphasis is on providing personalized learning resource recommendations based on the ability characteristics and group preferences of education students, thus more effectively supporting and promoting the development of students' professional abilities. In this research, an adaptive recommendation algorithm considering individual and group characteristics is proposed. The experimental results show that the recommendation method in this paper outperforms other comparative recommendation methods in several key performance indicators, specifically reflected in:

1. The method proposed in this paper surpasses project-based, student ability-based, and collaborative filtering recommendation schemes in accuracy. This indicates that it can more precisely identify and recommend learning projects that are of interest to students.
2. Although in some *Top-N* recommendation scenarios, the recall rate of the method in this paper is slightly lower than the student ability-based recommendation scheme, its recall rate shows a higher growth rate as the recommendation list lengthens, demonstrating its effectiveness in covering user interest points.
3. The method proposed in this paper performs well in both coverage and diversity, meaning it can recommend a wide range of projects to users while maintaining the diversity of the recommendation list.

4. By considering the various attributes of education students' educational abilities and the importance of group preferences, the method outlined in this paper can offer personalized recommendations for different user groups.
5. The method proposed in this paper demonstrates the highest recall rate in all Top-N recommendation tests, particularly in shorter recommendation lists. This suggests that it is capable of offering high-quality recommendations even within constrained recommendation spaces.

Therefore, the adaptive learning project recommendation method proposed in this paper has a high accuracy and coverage rate. While maintaining recommendation diversity, it also upholds a high recall rate in recommendation lists of varying lengths, showcasing its effectiveness in personalized recommendations. This method integrates individual learning abilities and group preferences, offering precise recommendations for enhancing the educational design capabilities of learning projects for education students. This promotes students' professional growth and learning efficiency. These features make the recommendation method outlined in this paper highly valuable in practical educational scenarios.

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