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A recommendation system for effective learning strategies: An integrated approach using context-dependent DEA

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ABSTRACT

Universities have been focusing on increasing individualized training and providing appropriate education for students. The individual differences and learning needs of college students should be given enough attention. From the perspective of learning efficiency, we establish a clustering hierarchical progressive improvement model (CHPI), which is based on cluster analysis and context-dependent data envelopment analysis (DEA) methods. The CHPI clusters students' ontological features, employs the context-dependent DEA method to stratify students of different classes, and calculates measures, such as obstacles, to determine the reference path for individuals with inefficient learning processes. The learning strategies are determined according to the gap between the inefficient individual to be improved and the individuals on the reference path. By the study of college English courses as an example, it is found that the CHPI can accurately recommend targeted learning strategies to satisfy the individual needs of college students so that the learning of individuals with inefficient learning processes in a certain stage can be effectively improved. In addition, CHPI can provide specific, efficient suggestions to improve learning efficiency comparing to existing recommendation systems, and has great potential in promoting the integration of education-related researches and expert systems.

1. Introduction

Education is a national priority, and students, as the main players in education, deserve more attention. To change China's traditional educational pattern, we should satisfy the individual needs of students and provide more suitable education. The *Outline of National Education and Reform Medium- and Long-term Plan* states that "Higher education should care about each student, promote each student's active and lively development and provide a suitable education for each student". The *Overall Plan to Promote the Construction of World-Class Universities and First-Class Disciplines* announced by the State Council in 2015 also advocated strengthening the individual training of students and comprehensively improving the quality of students. Not only in China but also in the United States, Britain and other countries, the importance of individualized learning of students is increasing (Waldrip et al., 2014).

However, many students still encounter great learning difficulties. These difficulties are mainly reflected in the failure to achieve the desired results, despite their best efforts. According to the student engagement theory, for students with similar mental level and teaching conditions, the arrangement of personal engagement in learning activities, such as time allotment, targeted training and learning strategy formulation, is considered to be of more importance than raw engaging time and effort of learning (Christenson et al., 2012). Excluding intellectual and cognitive factors, most of the low academic achievements is due to the inappropriate arrangement of students' investment in learning. In addition, due to the lack of effective guidance and scientific recommendations, many students do not know how to adjust learning

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efforts to improve learning achievements. As the main part of education and teaching, students are closely related to the quality of higher education (Jill, 2006). How to fully consider the individual differences and learning needs of students and then recommend corresponding learning resources and learning strategies, is not only of great practical significance and practical requirements, but also worth academic attention.

Expert systems, due to their good interpretability and adaptability, have been widely used in various research aspects of education (Nydahl,1992), and have shown good performance in tasks such as student assessment (Natek & Zwilling, 2010) and student advising (Nambiar & Dutta, 2010) However, the certain distance between theoretical research and practical application of expert systems still deserves to be considered. In order to expand the usage of expert systems in education and achieve the application of advanced, effective methods, a systematic, well-organized research framework with specific input–output process and solid purpose is needed. Based on the requirements of learning quality improvement, the research method and applicability of expert systems are capable.

To further enhance the effect of personalized learning and enrich the accuracy of learning path recommendations, we make personalized recommendations for learning strategies based on improvements in learning efficiency. The efficient learning can enhance students' sense of learning achievement and learning motivation. If they are in an inefficient learning state for a long time, students will lose their interest in learning, especially when students do not receive personalized advice, loneliness and frustration can lead to less motivation and lower achievement (Kaklauskas et al., 2012). Currently, research on student learning efficiency is mainly divided into qualitative and quantitative approaches. Qualitative research based on pedagogy and psychology is more common (Omoda-Onyait et al., 2013), focusing on the investigation of influencing factors of learning efficiency in quantitative research. However, studying influencing factors is not enough. Determining how to improve the learning efficiency is more important. To satisfy those actual needs, we proposed a recommendation system that is based on student learning efficiency to improve learning achievement. Unlike the current mainstream systems, the personality recommendation system is based on student performance and preferences, thus could be better understood and operated for students.

Based on data envelopment analysis (DEA) and clustering methods, we recommend learning strategies to improve learning efficiency for students. A recommendation system named the clustering hierarchical progressive improvement (CHPI) model is established. The CHPI model can be used to analyse the learning efficiency level of every student. Combined with the learning habits of other efficient classmates, it can also provide effective learning suggestions for individuals with inefficient learning processes. Problems such as cold start, high model complexity, and long running time can be avoided in online learning recommendation systems. To evaluate the effectiveness of the CHPI model, the English course of the University of Science and Technology in Beijing was employed as an example for experiments.

Compared to the existing research, the contribution of our proposed model to the particular field mainly lies in three parts:

(1) We provide a new framework of recommendation system for students to achieve personalized learning and make improvements on study. The cluster method together with the DEA-based optimization model are applied to fulfil students' personalized needs and provide suggestions on learning methods
(2) The concept of learning efficiency based on context-dependent DEA is introduced to measure and evaluate students' learning status, and multiple indexes are defined in order to form the optimized learning path for a particular student.
(3) Combined with empirical research results, the proposed CHPI model has been proven to be appliable in learning strategy recommendation on the basis of learning process datasets. The integration and modularization of the model provides a new vision for the combination of expert systems and education related tasks.

The remainder of this article is arranged as follows: Section 2 provides a literature review of the related studies of our works. Section 3 introduces the theoretical basis and principles of the CHPI model; Section 4 verifies the validity of the CHPI model by examples; Section 5 summarizes the research.

2. Literature review

2.1. Relevant studies on personalized learning

The current research focus in the field of personalized learning seeks to determine how to fully utilize students' learning process data. The study of the learning system developed in combination with big data technology has achieved an excellent response and effect. Omoda et al. (2013) and Bhattacharya et al. (2012) used a questionnaire to design the basic requirements framework for personalized learning, which can track students' learning patterns and provide real-time feedback during the interaction between students and e-learning systems. Wu & Ma (2010) provided a personalized knowledge requirements model based on the concept map and knowledge-flow ontological approaches to fulfil a company's knowledge needs. Su (2017) proposed an adaptive learning path recommendation system in the context of learning style based on an interpretive structural model. Overall, the assessment of student characteristics acts as the basis of personalized learning, and the efficiency of which matters in obtaining a view of the recent learning conditions of a particular student.

In view of this, researchers aim to improve the performance of student assessment algorithms to make further contributions to personalized learning. Cluster algorithms are commonly used to classify students according to different standards such as personal attributes, learning styles, and learning needs. López et al. (2012) proposed a cluster based method to predict the final marks in a university course on the basis of forum data, and proved the effectiveness of Expectation-Maximisation (EM) clustering algorithm in this task. Shovon & Haque (2012) developed a hybrid procedure based on Decision Tree and Data Clustering that enables academicians to predict students' GPA. Singh et al. (2011) dealt with the extraction and analysis of faculty performance of management disciplined from student feedback using clustering and association rule mining techniques. Overall, the feasibility and efficiency of clustering methods in personalized learning have been proven, and further investigations still need to be explored and put into practice.

2.2. Systematized learning recommendation

With the development of online learning platforms and the advent of the era of big data, the problem of information overload is severe. The use of traditional methods to effectively process massive amounts of learning process data is difficult. Some studies have begun to help users make decisions in complex information environments using recommendation systems to satisfy the personalized needs of students (Nabizadeh et al.,2020). The results show the efficiency of recommendation systems to satisfy the personalized needs of students.

As the recommendation system has the advantages of discovering user preferences, real-time feedback, accurate personalized recommendation, and facilitating transactions, it is employed in e-commerce, web recommendations, music software, news and many other fields. Considering the ease of collection and analysis of data, the application of recommendation systems in education is based on online learning. The main directions are online learning resource recommendations, course recommendations (Zhou et al., 2018), and learning path recommendations (Su, 2017). Recommending learning methods based on student characteristics (Koren et al., 2009; Labib et al., 2017), etc. Currently, the techniques currently applied in recommendation systems include the collaborative filtering-based recommendation system, the matrix factorization-based recommendation system, the K-Nearest Neighbour (KNN)-based recommendation system, the neural network-based recommendation system, the knowledge map-based recommendation system, the ontology-based recommendation system and so on. The analysis of their advantages, disadvantages, main contributions of their applications and related researches are summarized in Table 1.

According to the summary, existing education oriented recommendation systems still have limitations and shortages in practical applications:

- The collaborative filtering-based recommendation system and matrix factorization-based recommendation system have the advantages of simple concepts and high accuracy but there are also problems such as cold start and data sparsity. Although ontology-based recommendations and neural network-based recommendations in current learning recommendation systems can solve these problems, shortcomings that are greatly affected by the dataset may exist, including complex training processes and long training time. How to achieve acceptable accuracy and efficiency via limited datasets is still to be solved.
- The main purposes of existing recommendation systems mainly lie in phased guidance and learning resources, and have relatively little connection with the actual student learning process. How to develop a system based on factors which have strong relations with the learning process and provide recommendations which satisfies the basic demands for different students is still worthy of further development in order to meet the needs of extending systematic, integrated expert systems for recommendations.
- Although traditional offline classrooms are still the main content of higher education, online learning in higher education has a role in the development of traditional learning processes (Doering & Veletsianos, 2008; Wu et al., 2006; Yang, 2010). Due to practical needs and data accessibility, most data currently employed in the recommendation system is student online learning data. Current research on recommendation systems cannot address the main content of students' daily learning.

To compensate for these shortcomings, a personalized recommendation system for learning plan strategies, which focuses on students' daily courses, learning input and behaviour habits, should be established.

2.3. Data envelopment analysis with applications

The data envelopment analysis method (DEA) is suitable for multiple inputs and multiple outputs. DEA can solve the subjective determination of rights, especially when it is targeted at non-profit problems, such as education and learning. Many scholars study problems in the field of education based on the DEA method, specifically, the potency of analysing teaching efficiency with the help of DEA has been proven to be capable (Johnes et al., 2017). On the basis of previous algorithm related researches, DEA and its mutation methods, such as multistage DEA (Fuentes et al., 2016; Wolszczak-Derlacz, 2017), and fuzzy theory-related DEA (Aparicio et al., 2019; Nojavan et al., 2020), have been widely used in the current research field of education in various aspects. However, the research objects of efficiency in the field of education are mostly focused on macro individuals, such as schools, colleges or regions, and research on student individuals is lacking.

The traditional DEA method has the practical problem that the inefficient individual is too far from the frontier and cannot be reached in one step. The context-dependent DEA method can solve the problem of subjective weight determination in other models and the problem that the effective individual in the ordinary DEA method is too far from the front (Wei et al., 2012). Following researches have proven such features of context-dependent DEA to be beneficial in efficiency evaluation and promotion (Ulucan & Atici, 2010; Chung, 2010).

3. Materials and methods

To solve the problem of students' personalized learning strategy recommendations, the framework of the CHPI model is established, as shown in Fig. 1. The CHPI model consists of four main steps. First, the descriptive data of students are collected and pre-processed to satisfy the needs of the following procedures. Then, a cluster algorithm based on ontological features is performed to cluster the students into different types. Third, the improved context-dependent DEA method is used to determine the study efficiency of each student, which helps analyse the needs of low-efficiency students. Finally, we propose a recommended learning path for the students according to three weights for different concepts.

3.1. Data pre-processing

For education-related studies, data with different formats, measurements and magnitudes might be employed to describe particular

Table 1
Techniques applied in recommendation systems.

Techniques	Contributions	Advantages	Deficiencies	Related literature
Collaborative filtering algorithm	Resources and personal advices on learning	Simple concept; Easy implementation	Cold start, overfitting and data sparsity	Aleksandra et al. (2017) Khribi et al. (2008)
Matrix factorization	Filter and recommendations of valuable information for actual needs	More scalable, accurate, and flexible	Not ideal for single-type data and sparse data.	Wang & Ren (2009)Koren et al. (2009)Zhu et al. (2018)
KNN	Type-based student description and relevant recommendation	Overcoming the scalability problems; Faster and more accurate recommendations	Disregard for general diversity; Less accurate similarity enough for sparce data	Gao et al. (2017) Bag et al. (2019)
Neural network	Guidance and instructions according to personal behaviour	Alleviation of cold-start problems; Higher prediction accuracy.	Local minimum problem; Long training time	Adeniyi et al. (2014)Kiran et al. (2020) Andi et al. (2019)
Knowledge map	Learning objects relevant to intension and preference	Support for the formal representation, intelligent association and inference of semantic information of massive heterogeneous distributed data, avoidance of ambiguity in description	Vertical application; Difficulty in construction and evolution.	Tzone et al. (2007)
Ontology	Learning demand fulfilment and personal guidance	No cold start and data sparsity issues; Adaptively recommendation based on user characteristics	Time consuming; Less applicable for e-learning	Tseng et al. (2016) Sedleniece & Cakula (2013)Tseng et al. 2017

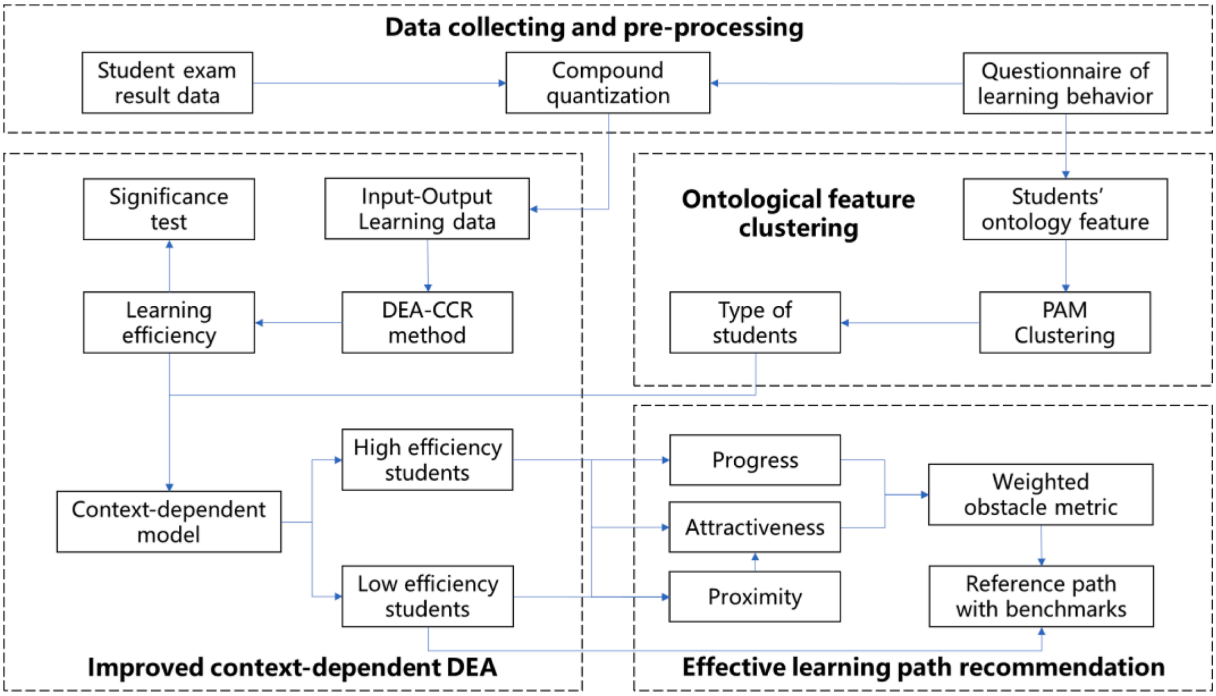


Fig. 1. Block diagram of CHPI model.

abstract concepts; thus, a pre-processing step is necessary before the research takes place. In this research, a composite quantification method is applied to process the raw data for further applications. The process is as follows:

(1) Valuation using the cumulative percentage method:

Each of the options is an ordinal variable sorted by the degree of the problem. Assume that the option for a problem is a_k, and assign a value y_k to each option a_k:

$$y_k = 100\sum_{i=1}^{k} x_i (i = 1, \cdots, n) \tag{1}$$

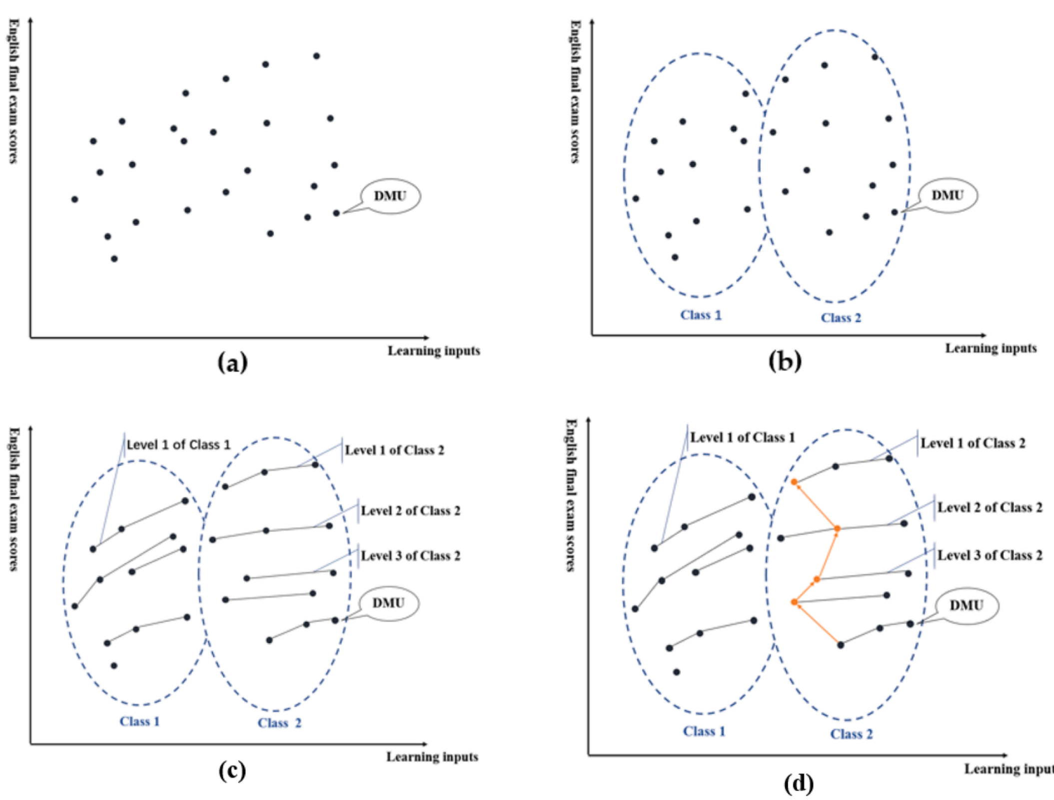


Fig. 2. Analysis modules of the CHPI model.(a) Student learning input–output data. (b) Clustered students. (c) Stratification within clusters. (d) Effective learning path generation.

where n is the number of options for the question, x_1 is the percentage of the total number of people who chose the lowest level option in the question, and x_n is the percentage of the total number of people who chose the highest-level option in the question.

(2) Calculation of the degree of dispersion of the various options for each question:

$$\sigma^2 = \frac{\sum_{i=1}^{n}(y_i - \overline{y})^2}{n} \tag{2}$$

(3) Reassignment to the problem that the degree of dispersion does not comply with current standards.

When the degree of dispersion of all the assignment option results of a problem is less than 10, the result cannot effectively distinguish the problem option, and the option needs to be reassigned manually.

After the above-mentioned pre-processing steps, the raw student learning procedure data have been processed into descriptive records for the input and output measures of study, as shown in Fig. 2 (a). The following three steps of the CHPI model aim to further analyse the data for actual usage through algorithms, which could be regarded as "analysis modules".

3.2. Ontological feature clustering

To fully consider the differences among students when recommending learning strategies, we apply cluster analysis to cluster students with similar ontological characteristics. Path selection in the same category solves the problem of the gap between the actual status of the inefficient student individual and the benchmark and the difficulty of references, which makes the suggestions provided more reasonable. The ontological characteristics could be obtained by the input indexes, reflecting the learning styles, preferences and latent demand of a particular student. The main purpose is to cluster all the students into several sets with similar characteristics, as shown in Fig. 2(b).

Considering the data structure of the students' ontological data, we apply the k-medoids method to cluster students according to the obtained number of categories. As the name suggests, the k-medoids method clusters instances around medoids chosen from the original instance set. Compared to the traditional k-means cluster method, which generates and revises cluster centres, the k-medoid shows better performance and robustness when processing data with noise and outliers, as well as generating a set of medoids that represents each cluster, helping to determine the characteristics of clusters from an individual perspective. The process of a frequently used k-medoid cluster algorithm, known as portioning around medoids (PAM), acts as Algorithm 1.

Algorithm 1. PAM cluster algorithm.
Input: S (the dataset consists of n p-dimensioned cases), k (the number of clusters)
Output: k clusters
Step 1: Select arbitrary k of the n cases as the medoids.
Step 2: Distribute n cases to k medoids according to their distance to the medoids.
Step 3: Update the medoid set by replacing a medoid with another non-medoid case.
Step 4: Calculate the distances of each non-medoid cases to the medoid of its cluster.
Step 5: Compare the sum of the distance before and after the change of the medoid set in step 3.
If the sum reduces, accept the change of the medoid set.
Step 6: If the set of medoids won't change, the algorithm stops;
Else go to Step 2.

As Algorithm 1, the optimization of the medoid set chooses the instances which have the minimal sum distances to other instances in the same cluster. Thus, a new definition of distance is needed. Inspired by related researches (Bektas & Schumann, 2019; Tuerhong & Kim, 2014), we employ Gower distance to create the latent space that the cluster algorithm requires. Gower distance is a type of metric that is effective in dealing with a mixture of categorical and continuous variables, essentially measuring the average of individual differences.

The $p+q$ particular characteristics of a case can be expressed by a $p+q$ dimension vector $x = (x_1, x_2\cdots, x_{p-1}, x_p, \cdots x_{p+q-1}, x_{p+q})^T = (z^T, c^T)$, with p categorical variables (which can be expressed as a p-dimensioned variable z^T) and q continuous variables (which can be expressed as a q-dimensioned variable c^T). The Gower distance between cases × and y can be defined as:

$$D_{xy} = \frac{\sum_{r=1}^{p} W_{xyz_r} D_{xyz_r}}{\sum_{r=1}^{p} W_{xyz_r}} + \frac{\sum_{r=1}^{q} W_{xyc_r} D_{xyc_r}}{\sum_{r=1}^{q} W_{xyc_r}} \tag{3}$$

where w_{xyz_r} and w_{xyc_r} are the weights of categorical variables z_r and continuous variables c_r. The calculation of the distance along categorical variables and continuous variables follows different distance metrics.

For categorical variables, the distance D_{xyz_r} can be defined in the form of the Dice coefficient, calculated as follows:

$$D_{xyz_r} = \begin{cases} 0, & z_r^x = z_r^y \\ 1, & otherwise \end{cases} \tag{4}$$

D_{xyc_r} is defined as the Manhattan distance between continuous variables c_r^x and c_r^y, calculated as follows:

$$D_{xyc_r} = \frac{c_r^x - c_r^y}{\max(c_r) - \min(c_r)} \tag{5}$$

3.3. Improved context-dependent DEA

3.3.1. Definition of learning efficiency

Many scholars have researched how to make learning more efficient. Bird and Bird (1945) analysed a large amount of experimental data to introduce how adults make learning efficient and the factors that affect efficient learning. Holley (2010) explored how to improve school learning efficiency based on the field of neurology. An accurate definition of learning efficiency has been obtained in many ways (Hooper & Hannafin, 1991; Kaklauskas et al., 2012), and most researchers have explained it as "the ratio of learners' input to output". Due to the individual characteristics of students, the learning habits of students, which are the allocation of input and output, are also different (Kuosmanen, et al., 2004). However, subjectively determining the weights of input–output indicators is difficult. The data envelopment analysis method can solve the subjective weight and multiple input–output problems. Taking this into consideration, we defined the learning efficiency according to the DEA method, and conducted subsequent analysis according to the learning efficiency of the students.

We propose that n students exist, each of whom has m input indicators and s output indicators. The student's learning efficiency maximizes the ratio of the student's learning output weighted sum to the input weighted sum:

$$\begin{aligned} & E_{j_0} = max \frac{\sum_{r=1}^{s} u_r y_{rj_0}}{\sum_{i=1}^{m} v_i x_{ij_0}} && j = 1, \cdots n; \\ & s.t. \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, u_r \geq 0 && r = 1, \cdots s; \\ & \quad v_i \geq 0 && i = 1, \cdots m; \end{aligned} \tag{6}$$

E_{j_0} represents the learning efficiency of the DMU_{j_0}, where $DMU_j(j = 1, \cdots n)$ represents the j-th student. x_{ij}, y_{rj} represents the number of inputs in the i-th input indicator and the number of outputs in the r-th output indicator, which is the input to the model. u_r and v_i represent the weights of the i-th input indicator and the r-th output indicator, both of which are variables. The final output includes the optimal solution u_r^* and v_i^*, which is the weight of each student's input and the weight of each student's output, respectively, that maximizes the learning efficiency value and the learning efficiency E_j. Generally, the learning efficiency value is less than or equal to 1. If the score is 1, the student's learning is considered effective; otherwise, the student's learning efficiency is considered inefficient. Being nonlinear programming, Eq. (6) is transformed into a linear model, and Archimedes infinitesimal is introduced to facilitate subsequent calculations. By maximizing the output as much as possible while keeping the input level constant, the output-oriented model is proposed as Eq. (7).

$$E_{j_0}^{output} = max\theta_{j_0} + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$s.t. \quad \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{i_0} \quad i = 1, \cdots m;$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = \theta_{j_0} y_{rj_0} \quad r = 1, \cdots s;$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \varepsilon > 0 \quad \forall j, i, r \tag{7}$$

where Archimedes' infinitesimal ε is a number that is greater than 0 and less than any positive real number. The slack variables s_i^- and s_r^+ represent the input change and output change, respectively, of individual students with low learning efficiency to achieve effectiveness. In addition, θ_{j_0} indicates the degree to which the output of DMU_{j_0} can increase when the input level x_{ij_0} remains unchanged; thus, Eq. (7) is an output-oriented model. The goal is to obtain a different optimal solution λ_j^* for each individual student j so that θ_j can reach the maximum value θ_j^*, where λ_j is the coefficient before each student. For student j_0, these points constitute a virtual reference point $(\sum_{j=1}^{n}\lambda_j^* x_{ij} \sum_{j=1}^{n}\lambda_j^* y_{rj})$, which is $(x_{j_0} - s_i^- y_{j_0} + s_r^+)$. When θ_j^* is equal to 1, the learning efficiency is effective, and when s_i^- and s_r^+ are equal to 0, it is strongly effective; otherwise, it is weakly effective.

3.3.2. Context-dependent DEA stratification

When the traditional DEA method selects the benchmark based on the shadow price, the distance between the decision unit and the effective frontier is too far to reach at one time. To solve the problem, the context-dependent DEA method is employed and improved to establish the improved context-dependent DEA module. The improved context-dependent DEA module of the CHPI model can effectively solve this problem and render the learning suggestions provided more reasonable and effective.

Let $S^1 = \{DMU_j, j = 1, \cdots n\}$ be the set of all student individuals. After the calculation of learning efficiency, the set of students with effective learning efficiency is denoted as E^1, and the set of students with low learning efficiency is represented as $S^2 = S^1 - E^1$. Following this rule, we obtain the stratification formula in the CHPI model as Eq. (8).

$$E_{j_0}^{output} = max\theta_{j_0} + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$s.t. \quad \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{i_0} \quad i = 1, \cdots m$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = \theta_{j_0} y_{rj_0} \quad r = 1, \cdots s$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \varepsilon > 0 \quad \forall j, i, r$$

$$j \in F\left(S_k^l\right) \tag{8}$$

where S_k^l represents the set of students from *Class k* after removing the *DMUs* on *Level 1* to *Level l-1*. When $l = 1$, E_k^1 represents the set of students in *Level 1* of *Class k*. When $l = 2$, E_k^2 represents the second effective student set in *Class k*, and E_k^l represents the set of students on *Level-l* of Class *k*. Algorithm 2 can divide all students in each category into several levels according to the effectiveness of learning.

Algorithm 2. Stratification algorithm.
Step 1: Set $l = 1$, $k = 1$, and S_1^1 is the set of all DMUs in Class k.
Step 2: Evaluate the learning efficiency of DMUs in S_1^1 to obtain the first level in Class 1 set E_1^l.

(*continued on next column*)

(*continued*)

Step 3: Exclude the efficient DMUs $S_k^{l+1} = S_k^l - E_k^l$. (If $S_k^{l+1} = \phi$, then $k = k + 1$).
Step 4: If $S_K^{l+1} = \phi$, the algorithm stops (K is the number of categories).
Else let $l = l + 1$, go to Step 2.

We can obtain the learning efficiency levels shown in Fig. 2(c) according to the algorithm. The main purpose of 2.3 is to divide all students into several levels with different degrees of learning effectiveness in each category, which is also significantly different from the traditional DEA method. Note that the efficiency evaluation is performed separately within different clusters to assess the efficiency of particular students relative to other students of the same cluster, that is, students with higher similarity to make recommendations more precisely.

3.4. Effective learning path recommendation

To select the most appropriate role models from the student set above the inefficient student individuals, we introduce the concepts of attractiveness, progress and proximity to describe the measure in selecting the promotion path.

A_j represents the attractiveness of DMU_j at *Level l* to all *DMU* at *Level l + 1*. The attractiveness measure in the context DEA method is defined as Eq. (9).

$$\Omega_{j_0}^* = max\theta_{j_0} + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$s.t. \quad \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{i_0} \quad i = 1, \cdots m;$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = \theta_{j_0} y_{rj_0} \quad r = 1, \cdots s;$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \varepsilon > 0 \forall j, i, r$$

$$j \in F\left(E^{l+1}\right), \quad j_0 \in F\left(E^l\right) \tag{9}$$

The progress represents the degree of improvement relative to a higher level. P_j represents the progress of DMU_{j_0} at *Level l* to all *DMU* at *Level l-1*. The progress measure in the context DEA method is defined as Eq. (10).

$$P_{j_0}^* = max\theta_{j_0} + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right)$$

$$s.t. \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = x_{i_0} i = 1, \cdots m$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} - s_r^+ = \theta_{j_0} y_{rj_0} \quad r = 1, \cdots s$$

$$\lambda_j, s_i^-, s_r^+ \geq 0, \varepsilon > 0 \quad \forall j, i, r$$

$$j \in F\left(E^{l-1}\right), j_0 \in F\left(E^l\right) \tag{10}$$

To transform the object from "DMU to layer" to "DMU to DMU", we define proximity to assist in forming an objective promotion path. Proximity represents the similarity between DMUs in adjacent layers. Taking input indexes as positive and output indexes as negative, it can be seen that the proximity between DMUs indicates the actual difficulty of improvement. $\omega_{j_0 j}^*$ represents the proximity between DMU_j and DMU_{j_0}, the last chosen reference individual from an upper layer (if it exists) as Eq. (11).

$$\omega_{j_0}^* = \sum_{i=1}^{m}\alpha_i \|x_{j0} - x_{i0}\|_1 - \sum_{r=1}^{s}\alpha_r \|y_{j0} - y_{i0}\|_1 \tag{11}$$

where α_i and α_r imply the weights of each input and output index, respectively, and $\|.\|_1$ denotes the L1-norm in R_{m+s} space.

Since an inefficient individual $DMU_{j_0}^{l+1}$ should be improved, where

$j_0^{l+1} \in F(E^l)$,we take $H_{j_0} = \frac{1}{\omega_j^* A_j} + P_j$ as the degree of obstruction to movement of DMU_j. If H_{j_0} is smaller, DMU_j is closer to the upper individuals and the supposed individual DMU_{j_0}.

Calculating obstructions and picking up the benchmark individuals at each layer, we can obtain an $m \times l$ matrix that contains the obstacles of each student drawn from higher levels, which are the candidates of a supposed reference path as Eq. (12).

$$\begin{pmatrix} H_1^1 & H_1^2 & \cdots & H_1^m \\ H_2^1 & H_2^2 & & H_1^m \\ \vdots & & \ddots & \vdots \\ H_l^1 & H_l^2 & \cdots & H_l^m \end{pmatrix} \tag{12}$$

where H_j^i is the obstruction of the i-th individual in the j-th layer, m is the maximum number of individuals in each layer, and l is the number of layers above the supposed individual DMU_{j_0}. H_j^i can be set as 0 if the number of layers is smaller than m, which is not included in the following calculation. Note that the obstruction matrix of one particular inefficient individual may differ from the matrix of one another.

To choose the most achievable reference path for inefficient individual DMU_{j_0}, the length of the path travelled by DMU_{j_0} to the highest efficiency level is recorded as the distance S_{j_0}. S_{j_0} is the sum of the degree of obstruction of the reference individuals selected in each layer on the reference path. When selecting the path, we choose the path with the smallest S_{j_0}, whose expression is presented as Eq. (13).

$$S_{j_0}^* = min\left(H_1^{j_1} + \cdots + H_l^{j_l}\right) \tag{13}$$

In practice, a combination of reference individuals who minimize the path distance is selected as a reference for recommending learning strategies to students. The $DMU_{j_l^l} \to DMU_{j_{l-1}^{l-1}} \to \cdots \to DMU_{j_2^2} \to DMU_{j_1^1}$ that corresponds to the output optimal value is the path to the highest efficiency level, shown in Fig. 2(d). When recommending strategies for students based on the optimal path, if the number of layers in the category is large, we can choose the first 2–3 reference individuals of inefficient individual DMU_{j_0} to analyse at the same time to rule out incidental factors. The resulting strategy is more comprehensive.

4. Empirical analysis

4.1. Learning data collecting and pre processing

To illustrate the methodology of the proposed CHPI model and test its validity, we employ the English subject as an example; other courses are also applicable. The data collected in this research are supported by the University of Science and Technology Beijing.

To quantify the learning input of particular students and perform further research on learning style analysis, a reasonable, effective data collecting method is necessary. Multiple measuring tools of student input have been developed to satisfy different needs of education (Fredricks et al., 2012), and the concept to measure and define the extent of student input, known as student engagement, has also been incorporated into the theory, together with different sets of indicators of student learning input (Heng, 2014; Oz & Boyaci, 2021). Traditionally, the student engagement indexes can be divided into three aspects: behavioural, emotional and cognitive (Fredricks et al., 2004). Considering the data availability and other factors, we employ student learning process indicators to reflect the effective input for students, with adoption of questionnaires as the data collecting method.

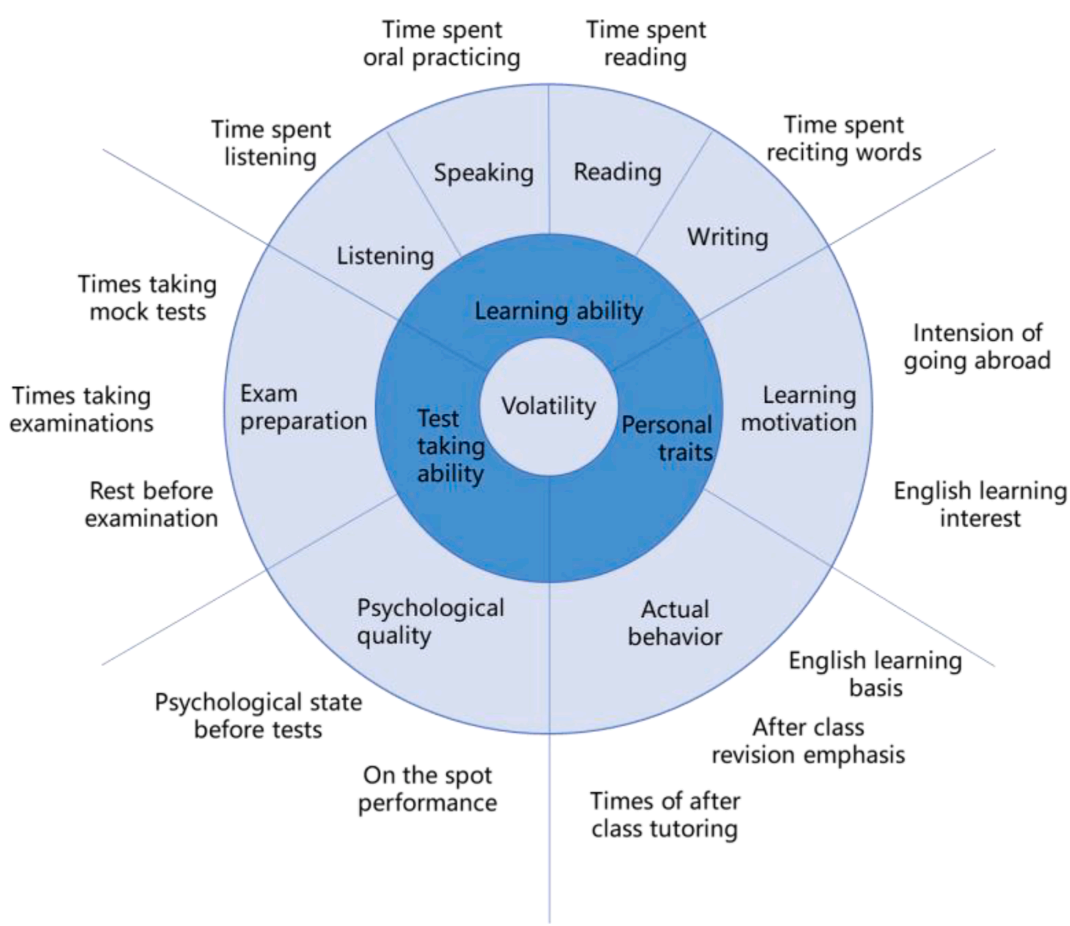


Fig. 3. Three-dimensional concept map of the learning record volatility.

Based on the principle of establishing the indicator system, we analyse the factors that influence students' academic performance and establish a three-dimensional concept map of the learning record volatility, which is shown in Fig. 3. The fluctuation of the learning record depends on three dimensions: task-taking ability, learning ability and personal traits. Learning ability mainly consists of four aspects: listening, speaking, reading, and writing, reflected as training time for each of the abilities, which have a great impact on student achievement. Task-taking ability includes pre-test preparation and psychological qualities, such as the time to take examinations, pre-test rest, on-the-spot performance status and other factors. Personal traits reflect the characteristics of different student individuals, including learning motivation and substantive performances such as English learning basis, after class revision emphasis, interest in English, among others.

We designed questionnaires with 14 questions that reflect students' investment in learning, such as the level of interest in English, whether they value after-school reviews or not, the amount of rest before the test, the time to recite words every day, and the intention to go abroad. A total of 600 copies of questionnaires were distributed to sophomores in 2017, of which 519 questionnaires were returned as valid questionnaires. In addition to the data obtained from the questionnaire, the final English exam scores of the students taking the questionnaires were included for further analysis.

To satisfy the input of the algorithm, we adopt the composite quantification method to quantify the raw data. The example is as follows:

(1) Quantification of the questionnaire results.

For example, the first question is "Do you have the habit of reviewing after class?". Its options represent "A. The review will be consolidated in a timely manner after the class", "B. The review will only begin before the exam" and "C. Essentially not", respectively. Options A, B, and C represent the importance of reviewing A > B > C. There were 222 students choosing Option A, which accounted for 42.69 % of the total participants; 42 students chose Option B, which accounted for 8.07 % of the total participants; and 255 students who chose Option C, which accounted for 49.04 % of the total participants. Therefore, Options C, B, and A are assigned values of 49.04, 57.12 and 100, respectively.

(2) Dispersion degree calculation and reassignment:

The questionnaire has 14 questions. Among them, 3 questions' discrete degrees are less than 10. The question options are A, B, and C. To effectively distinguish and reflect the order, the A, B, and C options are assigned values of 100, 70, and 30, respectively. The degree of dispersion at this time is 28.678, which can significantly distinguish the three options of the problem. To date, the raw data have been processed, which can be used in the following procedures.

4.2. Clustering students with different characteristics

All students can be clustered using their ontological characteristics, which are not easily changed in subsequent stages. The ontological characteristics have a significant influence on the learning style, preference, and arrangement in the daily study process. In the clustering, the quantified questionnaire result of the students is applied as the characteristics of the students' ontology, with the final examination score being a reference variable. The cluster results and the descriptive indexes are presented in Fig. 4 and Fig. 5.

According to related educational theory and ontological characteristics, the cluster of students can be explained as different types of learners with different learning bases, learning styles, and actual needs. Multiple concepts of different aspects of the learning process have been proposed to identify learners with different characteristics. We divide the students into five types of learners based on the cluster results. The types of students are shown in Table 2.

In the classification results, students in Cluster 5 can be described as

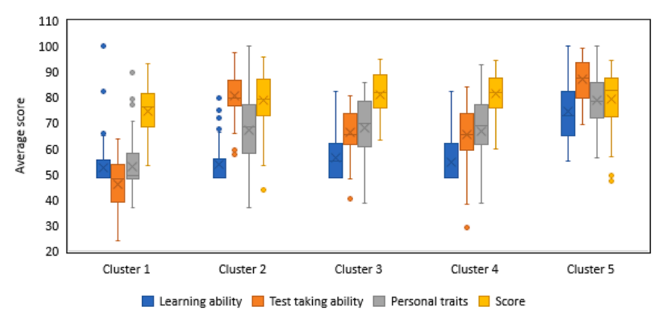


Fig. 5. Ontological characteristics from different clusters.

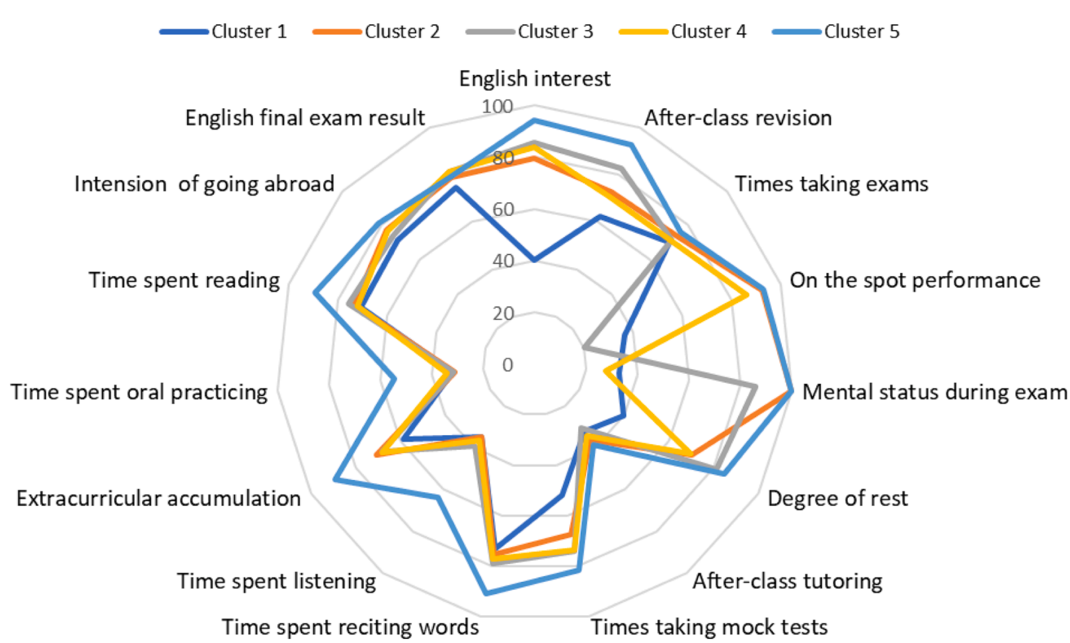


Fig. 4. Average score of characteristic indexes from different clusters.

Table 2
Types of learners according to cluster results.

	Personal traits	Learning ability	Test taking ability
Balanced learners	Initiative	Strong	Strong
Accumulation learners	Initiative	Weak	Weak
Potential learners	Passive	Strong	Strong
Passive learners	Passive	Weak	Weak

balanced learners, whose learning motivation is relatively active and who have strong learning and test-taking abilities. This type of student should pay attention to the broadening of the learning field and the expansion of recommended learning resources to give full play to their learning ability. Students in Cluster 3 and Class 4 can be described as accumulation learners, whose ability to take examinations, compared to learning ability and learning motivation, needs to be improved, so they should pay attention to test-related training and problem familiarity. Students in Cluster 2 can be described as potential learners; although they have a strong test-taking ability and learning ability, their lack of interest in the subject results in passive learning motivation, which limits their development. They require a more positive attitude on a large scale toward learning the subject. Students in Cluster 1 can be described as passive learners, with relatively low learning motivation, test-taking ability and learning ability, showing an urgent need for all-round learning process guidance, supervision and positive intervention.

4.3. Generating stratifications and learning path

The quantified student input–output data are used to measure the learning efficiency of each student. A regression analysis and significance test were performed with students' learning efficiency values and English final exam scores using SPSS. As shown in Fig. 6, learning efficiency is positively correlated with English final exam scores. Except for a few students who have high efficiency values but low scores, the overall English final exam scores of students increase significantly with the improvement in learning efficiency. Therefore, strategy recommendations from the perspective of improving learning efficiency can effectively improve the learning achievement of students.

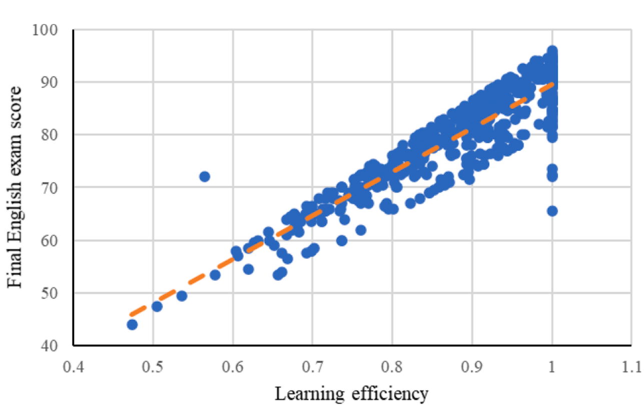


Fig. 6. Relationship between learning efficiency and final English exam score.

The improved context-dependent DEA module of the CHPI model is employed to analyse the input and output data of students based on the existing clustering results. Fig. 7 shows the stratification of students from the 5 different clusters.

Taking S480, an inefficient individual in the fifth layer of cluster 5, whose current learning efficiency is 0.6771, as an example. Based on the definition of attractiveness, progress, proximity, and obstruction in 2.3, we can calculate the obstructions of the individuals in the next layer, that is, layer 4. The specific results are presented in Table 3.

S502 on the fourth layer has the smallest obstruction among the DMUs and thus can be selected as the reference individual on the benchmarking path. The learning efficiency of S480 could be increased by 25.38 % in this step.

Continuing the procedure and constructing the rows of the matrix gradually, we can obtain the final matrix of obstruction for S480:

$$\begin{pmatrix} 2.9612 & 0.5431 & \dots & 0.3383 & 0.3228 & 0.5687 & \dots & 0.7387 & 0.4118 & \dots & 0.0715 \\ 0.6624 & 0.0934 & \dots & 1.7819 & 1.6035 & 1.6035 & \dots & 2.5473 & 0.0000 & \dots & 0.0000 \\ 0.1192 & 1.5537 & \dots & 0.1199 & 0.7608 & 0.0000 & \dots & 0.0000 & 0.0000 & \dots & 0.0000 \\ 0.4301 & 1.0120 & \dots & 5.1094 & 0.0000 & 0.0000 & \dots & 0.0000 & 0.0000 & \dots & 0.0000 \end{pmatrix}$$

By concluding the minimum obstructions of each layer, we can obtain a benchmarking path that improves S480′s current level to the highest level of efficiency. Taking this path, the student's learning efficiency can be improved by 43.97 %.

$S480 \rightarrow S502 \rightarrow S216 \rightarrow S50 \rightarrow S18$

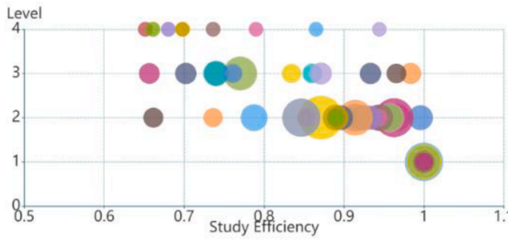
The stratification of the DMUs and the benchmarking path of S480 are shown in Fig. 8 visually.

For the traditional DEA methods that directly determine the reference individuals at higher levels, the actual feasibility may not be determined well. In that case, a lack of practical suggestions on study and possible confusion regarding the method of improvement may occur. For that case, the proposed model created a stepwise improvement benchmarking path that aims to make improvements gradually. Furthermore, the path helps to provide realistic suggestions for the promotion of learning efficiency, improving study and examination performance.

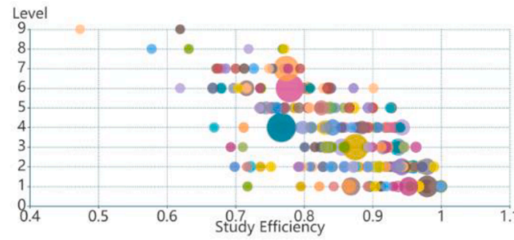
5. Conclusions

Taking learning efficiency as the starting point, we combine the PAM clustering method and context-dependent DEA method to propose a novel personalized learning recommendation system named CHPI. University English learners are an example for verification. The CHPI model includes four parts. Firstly, a new quantization method is performed to process the data. Secondly, we fully consider the differences among individuals, and then cluster the students according to their ontological features. Thirdly, we adapt the context-dependent DEA method, in which we stratify the students into different categories. Finally, we define the measure of obstacles and select the reference path. A path selection method is proposed by defining distance S_{j_0}. Selecting the reference path with the smallest S_{j_0} from all the reference paths, we can then recommend learning strategies through comparing the gap between individuals with inefficient learning processes and benchmarks.

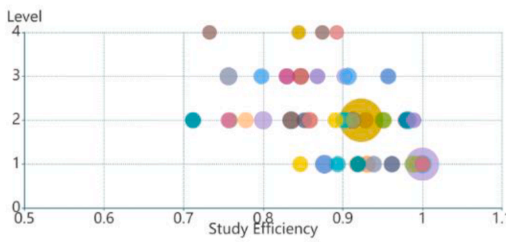
Based on college students' daily learning outcomes, a comprehensive analysis of the methods has been proposed to discuss the advantages and disadvantages of the current online learning recommendation system. The proposed CHPI model has short running time and low model complexity. To prove its efficiency, effective data for a total of 519 classmates were collected, and inefficient individual S480 was employed



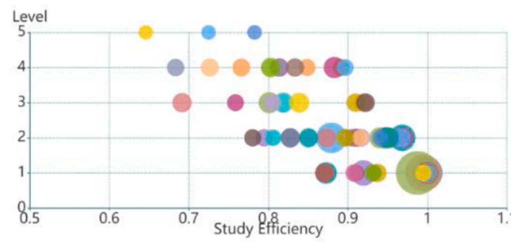
(**a**) Cluster 1



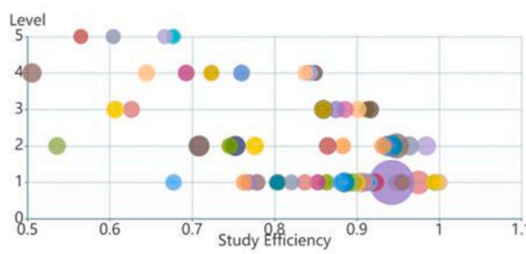
(**b**) Cluster 2



(**c**) Cluster 3



(**d**) Cluster 4



(**e**) Cluster 5

Fig. 7. Stratifications of students from different clusters.

Table 3
Obstruction evaluation for individuals in layer 4.

No.	Efficiency	Attractiveness	Progress	Proximity	Obstruction
247	0.8490	0.7409	0.0067	117.5769	0.4301
256	0.8429	0.6418	0.0313	235.9422	1.0120
258	0.8429	0.5907	0.0514	132.7110	0.6508
271	0.8377	0.6332	0.0775	113.9231	0.5575
393	0.7599	0.3762	0.1478	97.4418	0.8388
438	0.7232	0.5125	0.0806	340.3851	1.8524
465	0.6927	0.3665	0.1393	374.8466	2.8677
496	0.6446	0.3142	0.1780	195.0389	1.8338
518	0.5053	0.1398	0.1494	259.9620	5.1094

as an example. After the recommendation of the personalized strategy in this article, the first stage could increase the efficiency level by 25 %, and the maximum efficiency level could be increased by 44 %. This research can also be extended to the recommendation of learning strategies in other disciplines and forms of education. The context-dependent DEA method has been improved by defining measures, such as obstacles and distances, and participates in establishing the CHPI model in combination with cluster analysis methods. Considering the differences between students, the recommended learning strategies are more realistic by conducting stratification and reference path selection within categories.

Compared to existing learning recommendation systems, CHPI can quantitatively evaluate students' learning efficiency according to learning process data, and provide learning reference path recommendations and learning process improvement suggestions according to personalized characteristics, learning habits and particular needs. As a modularized, packaged framework, the simplicity and operability of CHPI makes it more efficient and practical dealing with learning recommendations, providing more explicit, specific evaluations and suggestions as outputs.

In view of the limitations and gaps in the process of empirical analysis, the CHPI model still has room for improvement. For example, although CHPI has few requirements for the quantity and format of input, the input data still have an impact on the effect of clusters and ulteriorly the efficiency and the applicability of the recommended learning path, which should be examined. Furthermore, the cycle of the learning process should be taken into consideration to examine the long-term effect of the algorithm, that is, whether taking the proposed reference path helps to improve the learning process in one semester or one year, and how the following path should be made according to the adjustments and changes during the period. In the future, we will

Fig. 8. The proposed benchmarking path.

explore the recommendation of learning strategies when no peers exist. In this way, individuals with inefficient learning processes can obtain learning recommendations without peer comparison. Because students with personalized needs often have many similarities, in the future, research will be conducted to make group recommendations based on ensuring accurate recommendations to provide a reference for a school's overall teaching plan.

CRediT authorship contribution statement

Lu-Tao Zhao: Conceptualization, Validation, Investigation, Writing – review & editing, Supervision, Funding acquisition. **Dai-Song Wang:** Methodology, Software, Formal analysis, Writing – original draft, Visualization. **Feng-Yun Liang:** Methodology, Resources, Writing – original draft. **Jian Chen:** Data curation, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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