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Application of AHP method in optimizing the allocation of practice teaching resources for preschool education majors in colleges and universities

Zhuzhu Ning[1,*]

[1] Advanced School of Humanities and Fine Arts, Xi'an International University, Xi'an, Shaanxi, 710077, China

SUMMARY: *The paper constructs a multi-objective planning model which will help in optimizing the distribution of practical teaching resources among the preschool education majors. The best allocation plan is evaluated depending on various planning scenarios by applying an enhanced AHP method. The research uses ten universities in City A as the samples and one university is chosen to conduct a deep case study. The optimized model of allocation of teaching resources is solved using the improved method of constructing the judgment matrices to determine the weight of the indicators at each level. Data of the other nine universities are used to test the validity of the model and the evaluation findings are compared with real survey data to prove the strength of the suggested multi-objective planning model and evaluation system. The rationality of the evaluation process is verified by means of grey correlation analysis and independent sample t-test. The maximum overall benefits of the resource allocation plan that aims at maximizing the efficiency of test scores in S1 schools is obtained. Allocation values of the resources are 0.846, 0.812 and 0.724, respectively (Network resources, Teacher resources, Multimedia resources), Library and Information resources, Traditional teaching resources and Implicit resources (0.702, 0.751 and 0.741).*

KEYWORDS: *preschool education program; multi-objective planning model; improved AHP algorithm; optimal resource allocation evaluation*

1 Introduction

Theoretical teaching is also an important factor to improve the hands-on skills of students and this in turn enhances the competitiveness of college students [1]. The preschool education constitutes the initial stage of the whole educational framework, whereas universities and colleges are aimed at cultivating applied talents in preschool education, who have both high-level practical skills and innovative mindset [2]. This should be done according to the objective of nurturing these applied talents, creating an organized practical teaching system that would meet the objectives of professional training, focusing on the advancement of practical skills of students and eventually improving the quality of talent development on the whole [3]. Nevertheless, along with the increase in the number of colleges and universities, the rate of allocation and use of practice teaching resources has not accelerated, and this has led to a condition that impedes the enhancement of quality of talent cultivation and impedes the development of preschool education programs [4, 5]

To address the challenges in the allocation of teaching resources within colleges and

*2016122159@jou.edu.cn
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universities, previous studies [6] have pointed out several issues, including limited funding, excessive reliance on competitive distribution models, an increased private financial burden, and insufficient investment in basic education. These factors contribute to widening educational inequality and raise concerns about the adequacy of resources allocated to fundamental teaching needs, as well as the impact on the public welfare aspect of education. In addition, literature [7] highlights that a major issue in the current allocation of resources in higher education is the stark disparity between urban and rural areas, as well as among different regions and institutions. This imbalance restricts students' ability to access quality educational resources equitably. Meanwhile, inefficient resource utilization, coupled with waste and underutilization, further hampers improvements in the overall educational standards. Literature [8] points out that with the decentralization of university governance, faculties and departments need to be responsible for their own finances, but it is not clear how the university allocates resources according to external expectations, therefore, through the survey of middle-level administrators, it reveals the connection between resource allocation practices and government functions, and points out that part of the allocation elements are more susceptible to the influence of government regulation and funding opportunities. Literature [9] demonstrated that universities are faced with the problem of outstanding contradiction between supply and demand, and in addition to increasing inputs, the key lies in enhancing effectiveness by optimizing resource allocation, arguing that there are challenges such as uneven efficiency and imbalance between supply and demand in the current resource allocation. According to literature [10], in the context of big data, the efficient distribution of innovative educational resources within higher education institutions faces several challenges. These include the reliance on traditional teaching methods, information overload, and cultural shocks that adversely impact students' physical and mental well-being. Furthermore, the existing teaching approaches struggle to adequately address students' evolving learning needs.

In order to solve the mentioned problems, it is important to optimize the distribution of teaching resources. The emergence of artificial intelligence (AI) has made its implementation the key to improving resource distribution efficiency. In this case, literature [11] explores the possibilities of applying AI to maximize the use of teaching resources. By using surveys and random forest analysis, the research concludes that AI contributes greatly to improving the teaching level and addresses the specific requirements of students. Nonetheless, it also points out some shortcomings, including bias in the data samples and small generalization of models, which gives further room to research on the topic. Literature [12] aims to explore the application of machine learning in resource allocation and management of colleges and universities, and for the growth of educational data and management complexity, it adopts a variety of models, such as time series analysis, decision trees and random forests, to optimize enrollment prediction, faculty deployment and teaching resource management, and verifies its effectiveness in prediction accuracy and resource optimization through empirical analysis, and develops a real-time decision support system, which shows that machine learning can significantly improve the efficiency and effectiveness of resource allocation in universities. Literature [13] as the quantity of teaching resources in colleges and universities increases, optimizing their allocation has gained significant attention. The study suggests an enhanced adaptive genetic algorithm, applied to the training of the BP network, integrating additional momentum and an adaptive learning rate strategy. Furthermore, AI networks are deployed within wireless networks to facilitate data collection and processing, effectively improving both the efficiency of resource allocation and the overall quality of teaching. The Literature [14] underscores the direct impact of a university's development concept on its scale, quality, and efficiency. It proposes an upgraded fuzzy clustering algorithm, combining particle swarm optimization with the FCM (Fuzzy C-Means) clustering method, to optimize resource allocation using intelligent algorithms. Experimental results indicate that this new approach outperforms traditional methods in clustering real-world data.

Although artificial intelligence (AI) has advantages in resource allocation in teaching, it is also prone to constraints, including bias of data samples and inability to properly balance multi-dimensional goals of optimization. As a solution to these problems, the Analytic Hierarchy Process (AHP), which is a multi-criteria decision-making system based on both qualitative and quantitative assessment, can be used to maximize the use of teaching resources. The AHP uses a hierarchical approach to arrange objectives, criteria, and alternatives and creates a judgment matrix using pair-wise comparisons. It finally comes up with the relative weights of every option and this is why it can be useful in many areas like allocating resources, choosing a program, and assessing policies [15, 16]. In this regard, literature [17] analyzes the application of participatory hierarchical analysis in the determination of selection criteria and resource allocation of agricultural projects, and through the practice in the parish of Goma, Congo, the method effectively facilitates the adjustment of preferences and the achievement of consensus, and is applicable to the training of the project team and the allocation of resources to match the international agricultural guidelines. Literature [18] highlights that marine internet relies on large-scale heterogeneous dynamic wireless networks and faces challenges due to resource uncertainty in network selection. The study explores a network selection scheme based on the Analytic Hierarchy Process (AHP), with simulation results demonstrating its superior performance compared to simple weighting and multiplicative exponential weighting methods. Similarly, literature [19] applied fuzzy hierarchical analysis to evaluate key indicators of health promotion policies in Taiwan's aging society. Through a literature review and expert interviews, four assessment dimensions and 16 indicators were identified. The study concluded that the “healthy living” dimension was the most important and highlighted six key indicators, such as increasing personal health awareness and promoting home healthcare. These findings provided a valuable basis for evaluating related policies..

The study provides a multi-objective planning model that considers test scores, awareness improvement, mastery of learning processes, and the intensity of lifelong learning concepts in accordance with the features of various resources. Enhancing the AHP algorithm, the construction of the judgment matrix is enhanced. The research will be on ten universities in city A applying the multi-objective planning model to obtain optimized resource allocation schemes. An enhanced AHP system structure model is created and a judgment matrix is generated. The real data of every assessment parameter is normalized and an overall benefit assessment of each plan is computed. The connection between the indexes of the evaluations and resource allocation is explored and the significance of each index in resource allocation is quantified. These results are then contrasted with information obtained through real-world surveys and assessments to confirm the validity of the results obtained by the method.

2 Optimization of Teaching Resource Allocation and AHP Evaluation for Preschool Education Majors

Since the introduction of the new era of educational reforms, the issue of the quality of talent development in preschool education programs at universities has attracted an increasing attention of various stakeholders. Practical teaching is not only one of the key aspects of this development but also serves as the main link between theory and practical experience. The distribution of teaching resources is what determines the effectiveness of training talent. The application of Analytic Hierarchy Process (AHP) as a method of decision-making, which incorporates both qualitative and quantitative considerations, to optimize practice teaching resource allocation of preschool education majors will be used to show how the various resource components and training goals are interrelated.

2.1 Establishment of Optimization Model of Practical Teaching Resource Allocation for Preschool Education Majors

2.1.1 Overview of Classification of Practical Teaching Resources for Preschool Education Programs

The preschool education majors are exposed to many practical teaching resources, including online material, teacher materials, multimedia applications, reference books, traditional teaching aids, and other unrevealed sources within some range. Such resources, particularly case-based materials, make an essential contribution to promoting student engagement and developing their passion to learn.

2.1.2 Establishment of the Optimization Model of Practical Teaching Resource Allocation for Preschool Education Majors

Due to the variety of purposes of practical teaching in preschool education programs at universities, the spending of resources should be flexible to accommodate different types. Nevertheless, there are inevitable conflicts between such educational goals and the resources that can be used to achieve them. It is necessary to rethink and redistribute the resources in order to create an effective teaching model. This paper will therefore start by presenting a multi-objective planning model that has been designed based on various objectives of teaching and subsequently defining the objective function of the model to be followed during the reallocation process.

Teaching objectives are usually divided into: test scores, awareness improvement, mastery of learning methods and lifelong learning concept cultivation, this paper focuses on test scores function f_1, awareness improvement status function f_2, learning methods mastery status function f_3, and lifelong learning concept solid degree function f_4 for the optimization of the allocation of the six resource types, and then the integration of the four kinds of teaching objectives to explore the current best political teaching resource allocation.

Assuming that each of the five resource elements in each resource category has an optimal allocation of learning time in a manner that is optimal for each objective function, for the purpose of the establishment of the multi-objective planning model, this paper explains the model variables as follows.

Due to too many time parameters, the actual operation of resource allocation has a greater impact, and all types of teaching resources have a role in promoting the teaching objectives, this paper summarizes and analyzes the various types of resources, are presented in five items, but these these contents and can not all be presented in terms of learning time and learning effects, such as teacher resources in the teachers' preparation and the distribution of teachers' academic qualifications, etc. in the model does not There is no quantitative nature in the model. Therefore, it is necessary to integrate the time variables in the multi-objective planning model, and therefore set to represent the total time of students' practical learning in a semester; $t_{1j}\left(j=1,2,\cdots,5\right)$ denotes the time spent on the A resource; denotes the time spent on the j th resource out of the five resource contents of the A resource; $t_i\left(i=2,3,\cdots,6\right)$ denotes the time consumed on the first class of resources among the B resources $\sim F$ resources, where 2, 3, 4, 5, 6 correspond to the resource classes B, C, D, E, and F respectively; t_{ij} said in the first I resource in the first item j resource content consumption time, need to abandon the $t_{ij}(i=2,4,5,6; j=1,\cdots,5)$ corresponding resources learning time also becomes only a general t_2,t_4,t_5,t_6, you also need to give up time variable t_{34} and t_{35}, Therefore, in terms of the proportion of learning time for the six types of resources, there are only five types of content in online resources and the learning time for courseware, video and audio in multimedia resources. $G(N_i)$ denotes the effect of learning the i th resource per unit of time, where N_i denotes the degree of superiority of the i th class of resources; $g(n_{ij})$ denotes the effectiveness of student learning on the j th resource content in the i th resource per unit of time, assuming that $g(n_{ij})$ varies with n_{ij} as a quadratic function with quadratic coefficients less than 0 and passing through the origin, i.e., the amount of resources is not as large as it should be, and there is an optimal metric; a_{1j} denotes the weight of the learning effect on the i th$ resource against the test score; $a_{ij}(i=1,\cdots,4; j=1,\cdots,6)$ denotes the weights of the learning effects on the j -type resources for the i -objective, where $i=1,2,3,4$ corresponds to the test scores, the awareness-raising function, the mastery of the learning methods, and the firmness of the lifelong learning concepts, respectively; $\beta_i\left(i=1,2,3,4\right)$ denotes the current best four target weights based on the expert interviews and $\sum_{i=1}^{4}\beta_i=1$.

The objective function of the multi-objective planning model is shown in equation (1)

$$\max\ f_1, f_2, f_3, f_4, \sum_{i=1}^{4}\beta_i f_i \tag{1}$$

The expression of each function in equation (1) is shown in equation (2)

$$f_i=\sum_{j=1}^{6}\left[a_{ij}G(N_j)\cdot t_j\right] \tag{2}$$

The constraints are shown in equation (3)

$$s.t\begin{cases}\sum_{i=1}^{6}t_i\le T;\sum_{j=1}^{5}t_{1j}\le t_1;\sum_{j=1}^{3}t_{3j}\le t_3\\ N_j\ge 0;n_{1j}\ge 0\left(j=1,\cdots,5\right)\\ G\left(N_i\right)=aN_i^2+bN_i,\left(a<0,b>0\right)\\ \sum_{i=1}^{4}\beta_i=1;\sum_{j=1}^{5}\alpha_{1j}=1\end{cases} \tag{3}$$

2.2 Optimization Evaluation of Teaching Resource Allocation Based on Improved AHP Algorithm

2.2.1 AHP algorithm

Due to the variety of purposes of practical teaching in preschool education programs at universities, the spending of resources should be flexible to accommodate different types. Nevertheless, there are inevitable conflicts between such educational goals and the resources that can be used to achieve them. It is necessary to rethink and redistribute the resources in order to create an effective teaching model. This paper will therefore start by presenting a multi-objective planning model that has been designed based on various objectives of teaching and subsequently defining the objective function of the model to be followed during the reallocation process.

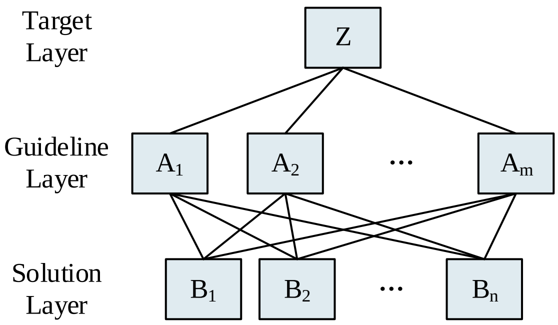

Figure 1: Structure of analytic hierarchy process

Problem solving according to the AHP method requires a four-step judgmental assessment.

(1) Establishment of hierarchical organization

The primary objective of this problem is to reach goal level Z. To achieve this, begin from the criterion level A, and in order to solve criterion level A, you must first address the problem at the solution level B, solving it progressively in a hierarchical manner.

(2) Expert comparison scoring to construct a comparative judgment matrix

The consistent matrix approach is the judgment matrix method applied in hierarchical analysis, where instead of comparing all factors at once, comparisons are done pair-wise. It is achieved through the use of a relative scale that reduces the challenge of comparing and analyzing factors that can vary widely, thus enhancing the accuracy of the analysis. As an illustration, if we consider criterion layer A_1, we aim to allocate specific weights to the program layers $B_1, B_2, \cdots, B_n$ in accordance with predetermined rules. In this step, the experts should assess what of the two program layers, B_1 or B_2, has more weight concerning the criterion layer EEE and give it a suitable number to indicate its importance.

(3) Calculate the weights

After the matrix has been computed, as depicted in Equation (4), the subsequent process will be the identification of the eigenvector that corresponds with the maximum eigenvalue of the matrix, which indicates the relative weight of the factors involved.

$$A = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{4}$$

Normalize each column of the judgment matrix A as shown in equation (5):

$$b_{ij} = \frac{a_{ij}}{\sum_{k=1}^{n} a_{kj}}, \left(i, j = 1, 2, \cdots, n\right) \tag{5}$$

Each column of the normalized judgment matrix is summed up by rows as shown in Equation (6):

$$\bar{W}_i = \sum_{j=1}^{n} b_{ij}, \left(i, j = 1, 2, \cdots, n\right) \tag{6}$$

Normalize vector $\bar{W}$ as shown in equation (7):

$$\bar{W}_i = \frac{\bar{W}_i}{\sum_{k=1}^{n} \bar{W}_k}, \left(i = 1, 2, \cdots, n\right) \tag{7}$$

Then Eq. (8) is the desired eigenvector:

$$W = \left[W_1\, W_2\, \cdots W_n\right]^T \tag{8}$$

The maximum eigenvalue of the judgment matrix can also be calculated as shown in equation (9):

$$\lambda_{\max} = \sum_{i=1}^{n} \frac{\left(AW\right)_i}{nW_i}, \left(i = 1, 2, \cdots, n\right) \tag{9}$$

(4) Consistency test

Consistency here means that the judgments made in the evaluation process should remain logically coherent. For instance, if B_1 is considered strongly more important than B_3, and B_2 is regarded as only slightly more important than B_3, then B_1 should naturally be more important than B_2. This reflects the logical coherence of the judgment process. Otherwise, contradictions will appear in the evaluation results. For this reason, a consistency test is required, namely, the calculation of the consistency index CI, as shown in formula (10):

$$CI = \frac{\lambda - n}{n - 1} \tag{10}$$

The lower the CI value is, the higher the consistency it has, which means that the judgment process is also reliable. The random consistency index (RI) is brought in to determine the scale of the CI. The RI is alternatively known as the random index and it depends upon a standard that is defined through random trials. In the case of determining the composition of the judgment matrix, the appropriate random consistency index can be determined using the table.

When the consistency ratio $CR < 0.1$ shows that the level of inconsistency in the judgment matrix is within the acceptable limits, it is considered that it has good consistency. When this happens, normalized eigenvectors could be taken as weight vectors. Nevertheless, in case the consistency ratio is not standard, the reconstruction and modification of the pairwise comparison matrix are necessary.

The main strength of the AHP algorithm compared to other modeling techniques is that it is based on subjective assessment to determine the ranking of the available options. It has low data requirements and enables quick decision-making. On a broad level, AHP provides a quantitative analysis of complex decision making by utilizing the preference data of decision makers who were gathered via pairwise comparison to offer analytical and decision support services. It is an effective way of integrating qualitative knowledge and quantitative knowledge to obtain a systematic and scientifically inspired approach to decision making.

2.2.2 Improved AHP algorithm

The conventional AHP algorithm described in section 2.2.1 comprises the following: (1) creating a hierarchical structure, (2) developing the judgment matrix, (3) conducting the hierarchical ranking and consistency testing, and (4) performing the overall hierarchical ranking to establish the weights of the factors. The procedure shows that constructing the judgment matrix and performing such consistency test play an important role since they have a direct impact on the outcomes of decision-making concerning the subject which should be assessed. After consideration, there are three major factors influencing decision making: first, creation of the judgment matrix, second, selection of scale system, and third, the consistency testing process. These problems can be solved by suggesting modifications to the AHP algorithm, especially the part regarding the construction of the judgment matrix, so as to increase the precision and validity of the decisions made.

(1)Changes that are inspired by the Delphi approach

The Delphi method is famous with its specific characteristics: experts are anonymous, every expert gives independent evaluations of the evaluation target, and there is a full use of the knowledge and experience of the participants. The decision results are obtained after several rounds of aggregating and providing feedbacks until the experts agree on the decision.The approach is easy to apply and eliminates any bias that could be influenced by personal opinions of experts. It also makes sure that there is no influence of authorities when it comes to group discussions which will result in more objective and accurate outcomes of decisions made. The procedures of the Delphi method are as follows:

(1) Choice of evaluation experts: Depending on the goals and objectives of decision-making, a team of experts will be selected. The size of the expert group must correspond to the complexity and level of difficulty of the decision-making problem. Nevertheless, a group cannot be too big because it can make the decision-making process more complicated.

(2) Supplying the requirements of decision-making to experts: The appropriate decision problem requirements are delivered to the chosen experts. They are subsequently requested to provide feedback on the required information and requirements and provided with any pertinent background information to help them evaluate it.

(3) The experts give their opinions anonymously on the decision-making issues based on the background information provided and their own empirical knowledge, and may attach certain reasons according to the situation.

(4) The statistician will summarize the experts' opinions and feedback the statistical results to each expert, who will modify his/her own opinion by comparing others' opinions.

(5) The expert's opinion will be summarized and organized again, and then feedback will be collected, and so on until all the experts' opinions tend to be unified, and the final decision-making result will be obtained.

According to the characteristics and advantages of the Delphi method, this paper introduces it into the hierarchical analysis method and improves the construction of judgment matrix. The specific steps are as follows:

(1) Determine the problem to be decided. Fully prepare relevant information so that experts can understand the decision-making problem faster and more comprehensively.

2) Select the evaluation experts. Put forward the objectives and requirements of the decision-making problem, and consult the experts on what other information is needed and add it as soon as possible.

3) Give a preliminary judgment matrix. Experts based on the information provided and their own expertise, to give a preliminary judgment matrix, if necessary, with the reasons.

4) Revise the judgment matrix. The statistician collects and summarizes the judgment matrices of the experts and feeds back the statistical results to the experts, who modify their own judgment matrices by comparing the opinions of others.

5) Get the final judgment matrix. Collect and summarize the judgment matrix of the experts again, and continuously feedback until the experts' opinions converge.

(2) Modification based on weighted average judgment matrix

Although the Delphi method can be used in building a judgment matrix, the views of individual experts might agree but not necessarily be coherent. As the hierarchical analysis method needs a specific judgment matrix, the natural differences in how the experts think should be taken care of. Furthermore, since experts have various degrees of experience and knowledge about the project, it is important to give a grade of authority based on the level of experience and familiarity with the project to every expert. The sum of the weights of all the experts will be equal to 1. To solve this problem, the paper suggests that the weighted average of all the judgment matrices will be calculated using the weights of the experts, which will ultimately provide a single definitive final judgment matrix. The weighted average judgment matrix is therefore given by:

Let $\{P_1, P_2, P_3, \cdots, P_k\}$ be the n judgment matrices provided by the n experts, where, $P_k = \left(p_{ij}^{(k)}\right), (k = 1, 2, 3 \cdots, n)$, $p_{ij}^{(k)}$ denote the elements in the k th judgment matrix, meanwhile, the weight of the k th expert is a_k, where, $(a_1 + a_2 + a_3 + \cdots + a_k = 1)$, thus the weighted average judgment matrix of these n judgment matrices is shown in Equation (11):

$$\bar{P} = \left(\overline{p_{ij}}\right) = \left[\sum_{k=1}^{n} a_k \cdot p_{ij}^{(k)}\right] \tag{11}$$

The weighted average of several judgment matrices results in a weighted average judgment matrix, and its properties are consistent with the properties of a weighted average. Like an arithmetic mean, a weighted average is different in that all data points do not have the same importance: some data points are more authoritative and influential than others. It is consequently important to allocate sensible proportions when computing the raw data. This method has a lower sensitivity to random variations, providing a more accurate, precise, and unbiased description of the average.

3 Empirical Analysis of Optimization of Practice Teaching Resource Allocation for Pre-school Education Majors in Colleges and Universities

The data in this paper mainly comes from research information and official statistics. In order to ensure the scientificity and representativeness of the study, ten colleges and universities offering preschool education majors in City A are selected as the overall study population, and the strategy of stratified sampling and typical sampling is used to determine the sample. In the stratified sampling stage, the institutions were divided according to their levels and nature of operation to ensure a balanced sample structure. In the typical sampling stage, one institution from each stratum is selected as a typical case for in-depth analysis, and the remaining nine constitute the sample set for comparison and verification. In this paper, the case institution S1 University is first selected to conduct a comprehensive and in-depth analysis of its current situation of practical teaching resource allocation.

3.1 Teaching resource allocation optimization model solving

Based on the multi-objective planning model and variable definitions constructed in the previous section, combined with the current situation of practical teaching resource allocation for preschool education majors in S1 University in 2024, this paper solves the optimal allocation scenarios with test scores, awareness improvement, learning method mastery and lifelong learning concept cultivation as a single objective, respectively. By solving this nonlinear planning model, the resource allocation effects under the four scenarios are obtained, and the specific data are shown in Table 1, which are normalized by dimensionless normalization. In Scenario A, the allocation ratios of network resources and teacher resources are significantly improved, reaching 0.846 and 0.812, respectively, and these two types of resources have the highest marginal benefits in improving students' test-taking ability and knowledge mastery in the short term, which is in line with the law of growth in the initial period of resource investment. In contrast, Program B focuses on the investment of implicit resources, and its allocation value is raised to 0.765. Program C's library information resources and multimedia resources allocation values are 0.745 and 0.783 respectively, and the acquisition of learning methods such as information retrieval and cooperative inquiry is highly dependent on information carriers and interactive media. Scheme D, on the other hand, puts traditional teaching resources in the first place, with an allocation value of 0.778.

Table 1: Resource allocation status and optimization schemes

	Status	Plan A	Plan B	Plan C	Plan D
Network resources	0.742	0.846	0.801	0.782	0.769
Teacher resources	0.685	0.812	0.794	0.758	0.731
Multimedia resources	0.631	0.724	0.753	0.783	0.746
Books and information resources	0.593	0.702	0.668	0.745	0.719
Traditional teaching resources	0.647	0.751	0.727	0.693	0.778
Hidden resources	0.618	0.741	0.765	0.728	0.754

3.2 Evaluation of the combined benefits of the programs

3.2.1 Modeling the structure of the hierarchical analysis system

The initial stage in applying hierarchical analysis approach to assess total advantages of each program is defining the structural structure of hierarchical analysis system. The model that is suggested in this paper is given in Table 2. There are four levels: the highest level denotes the maximum comprehensive benefit (A) of the preschool education resource allocation program towards practical teaching, which is used as the target layer. The second level comprises four subsystems test scores (B1), awareness enhancement (B2), mastery of learning methods (B3), and cultivation of lifelong learning concepts (B4) to form the constraint layer. The indicator layer, third layer, is made up of particular evaluation indices (Ci). The last level consists of the program layer, and these are the different programs to be evaluated.

Table 2: Structural model of AHP system

<table>
<tr><th>Objective layer</th><th>Constraint layer</th><th>Indicator layer</th><th>Scheme layer</th></tr>
<tr><td rowspan="14">Comprehensive benefit</td><td rowspan="4">Examination scores</td><td>Theoretical scores</td><td rowspan="4">Plan A</td></tr>
<tr><td>Practical scores</td></tr>
<tr><td>Homework scores</td></tr>
<tr><td>Quiz scores</td></tr>
<tr><td rowspan="3">Awareness</td><td>Professional identity</td><td rowspan="3">Plan B</td></tr>
<tr><td>Sense of responsibility</td></tr>
<tr><td>Social service participation rate</td></tr>
<tr><td rowspan="4">Learning methods</td><td>Information retrieval ability</td><td rowspan="4">Plan C</td></tr>
<tr><td>Cooperative learning ability</td></tr>
<tr><td>Independent learning ability</td></tr>
<tr><td>Reflection summary habit</td></tr>
<tr><td rowspan="3">Lifelong learning concept training</td><td>The willingness of continuous learning</td><td rowspan="3">Plan D</td></tr>
<tr><td>The amount of extracurricular reading</td></tr>
<tr><td>The participation rate of continuing education</td></tr>
</table>

3.2.2 Constructing judgment matrices

In order to find out the weights of the indicators, the calculations of the weights at each level are made and then consistency is checked. Judgment matrices of four evaluation indicators were formed concerning four subsystems. Industry experts with experience were assigned to put values to all elements in these matrices according to the Saity scaling principle. Following the weighted averaging process, the obtained judgment matrices are given in Tables 3 to 6. Consistency indicators (CI) of four matrices were determined as 0.0033, 0.0045, 0.007, and 0.0045, whereas the consistency ratio indicators (CR) were 0.0037, 0.0078, 0.0078, and 0.0078. These values satisfy all necessary consistency requirements.

Table 3: B1-Ci judgment matrix and operation results

B1	C1	C2	C3	C4
C1	1	2	3	2
C2	1/2	1	2	1
C3	1/3	1/2	1	1/2
C4	1/2	1	2	1

Table 4: B2-Ci judgment matrix and operation results

B2	C5	C6	C7
C5	1	2	3
C6	1/2	1	2
C7	1/3	1/2	1

Table 5: B3-Ci judgment matrix and operation results

B3	C8	C9	C10	C11
C8	1	3	2	2
C9	1/3	1	1/2	1
C10	1/2	2	1	1
C11	1/2	1	1	1

Table 6: B4-Ci judgment matrix and operation results

B4	C12	C13	C14
C12	1	2	3
C13	1/2	1	2
C14	1/3	1/2	1

3.2.3 General hierarchical ranking and weighting analysis of evaluation indicators

The total ranking of indicator levels was calculated from top to bottom, and the results of the total ranking of indicator level weights are shown in Table 7. Among them, test scores were given the highest weight value of 0.4668, and in the current evaluation system, students' academic performance is still the core explicit indicator to measure the effectiveness of resource allocation. The status of learning method mastery is the next most important, with a weight of 0.2776, and the cultivation of students with scientific inquiry and self-learning ability is equally important in practical teaching. The weight of awareness improvement is 0.1603, while the weight of lifelong learning concept is only 0.0953. However, it does not mean that lifelong learning concept is not important, but in the limited cycle of resource investment, its benefits are lagging behind, so it is slightly lower than the other three in the short-term prioritization of resource allocation.

Table 7: Total ranking results of index hierarchy weights

	B1	B2	B3	B4	Total weight ranking
	0.4668	0.1603	0.2776	0.0953	
C1	0.4231	0	0	0	0.1975
C2	0.2274	0	0	0	0.1062
C3	0.1222	0	0	0	0.0570
C4	0.2274	0	0	0	0.1062
C5	0	0.5396	0	0	0.0865
C6	0	0.2970	0	0	0.0476
C7	0	0.1634	0	0	0.0262
C8	0	0	0.4288	0	0.1190
C9	0	0	0.1472	0	0.0409
C10	0	0	0.2304	0	0.0640
C11	0	0	0.1937	0	0.0538
C12	0	0	0	0.5396	0.0514
C13	0	0	0	0.2970	0.0283
C14	0	0	0	0.1634	0.0156

3.2.4 Results of evaluation of programs

Using the method of this paper for program selection decision-making, the evaluation index value of each program is shown in Table 8, and the data are normalized by dimensionless normalization. According to the results of the total hierarchical ranking and weighting analysis of the evaluation indexes, the comprehensive benefit evaluation values of the four programs are calculated to be 0.777, 0.754, 0.762 and 0.748, respectively.From the perspective of the comprehensive benefit evaluation value, Program A is the highest in terms of the overall resource allocation benefit, and it is suitable for pursuing the enhancement of the level of students' academic performance and skills assessment in the short term.

Table 8: Evaluation index values of each scheme

	Plan A	Plan B	Plan C	Plan D
C1	0.854	0.802	0.781	0.768
C2	0.823	0.795	0.759	0.732
C3	0.735	0.681	0.747	0.698
C4	0.713	0.647	0.682	0.645
C5	0.812	0.829	0.776	0.741
C6	0.779	0.803	0.725	0.688
C7	0.761	0.825	0.772	0.736
C8	0.742	0.685	0.788	0.753
C9	0.758	0.712	0.773	0.737
C10	0.784	0.729	0.792	0.756
C11	0.731	0.674	0.749	0.713
C12	0.762	0.717	0.734	0.791
C13	0.738	0.694	0.712	0.776
C14	0.715	0.669	0.687	0.742

3.3 Reliability verification of evaluation results

3.3.1 Gray correlation analysis of integrated benefits and and impact factors

Ten universities in city A were picked as the sample points and the outcomes of evaluating the gray correlation degree between the total benefits and assessment indicators of every university resource allocation plan are shown in Table 9. The correlation findings are fairly similar to the global weight ranking determined by the enhanced hierarchical analysis process used in this paper. It is indicative of sound internal coherence and structural validity in the evaluation system created in this case.

Table 9: Results of grey correlation degree

	Grey correlation degree
C1	0.792
C2	0.538
C3	0.342
C4	0.539
C5	0.461
C6	0.314
C7	0.205
C8	0.516
C9	0.277
C10	0.369
C11	0.334
C12	0.318
C13	0.226
C14	0.173

3.3.2 Reliability verification of calculation results

In order to confirm a scientific reason why the enhanced AHP analysis should be applied to measure the overall advantages of practical allocation of teaching resources of preschool education majors in higher learning institutions, the study compares the values of the computed total benefits of ten universities in City A in 2024 with the real survey and assessment data. Comparison also covers the discounted total benefits of teaching resource allocation as presented in this paper. An independent sample T-test is used on SPSS software to test the reliability of the results obtained through both data sets to determine whether there are any significant differences between the two approaches.

The results of the data conversions and the independent sample T-test are displayed in Tables 10 and 11, respectively. The Levene's test produced an F-value of 0.803 with a corresponding probability value of 0.398, which is higher than the significance level of 0.05. This suggests no significant difference between the actual survey results and the improved AHP analysis results. Furthermore, the variance analysis showed a probability statistic of 0.998, well above the significance threshold of 0.05, confirming that the mean difference between the two sets of data is not statistically significant. Additionally, the 95% confidence interval for the sample mean difference spans zero, further indicating no significant difference between the two methods' results. Among the ten universities in City A, S1 had the best overall teaching resource allocation effectiveness in 2024, while S4 had the lowest.

Table 10: Results of data conversion of the two groups

School	The proposed	Actual investigation and evaluation of data results
S1	0.2197	0.2235
S2	0.1994	0.2032
S3	0.2153	0.2191
S4	0.1837	0.1825
S5	0.1926	0.1914
S6	0.2047	0.2035
S7	0.2118	0.2106
S8	0.2047	0.2085
S9	0.1935	0.1973
S10	0.1962	0.2001

Table 11: Independent sample t-test results

	Levene's test		t test						
								95% CI for MD	
	F	Sig	t	df	Sig.	MD	SE	Lower bound	Upper bound
Suppose the variances are equal	0.803	0.398	0.000	14	0.998	0.0000	0.1083	-0.236	0.2366
						0.0000	27155	693726	30184
Suppose the variances are not equal			0.000	13.917	0.998	0.0000	0.1083	-0.238	0.2381
						0.0000	27155	128846	61647

4 Conclusion

The present research work proposes a multi-objective optimization model that is used to allocate the practice teaching resources in preschool education programs offered by colleges and universities in an effort to analyze the overall benefits of the resource allocation using the improved AHP algorithm.

Four optimized schemes of resource allocation were determined by solving the multi-objective planning model, and the weightings of the four teaching objectives are given as follows: test scores (0.4668), increased awareness (0.1603), learning techniques mastery (0.2776) and lifelong learning concepts development (0.0953). The total benefit assessment values of the four scenarios were determined to be 0.777, 0.754, 0.762 and 0.748 respectively by the use of improved AHP algorithm. The validity of the comprehensive benefit assessment in accordance to the improved AHP approach was validated by the outcome of gray correlation analysis and independent samples t-test.

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About the Author

Zhuzhu Ning received her M.S. degree in Education from Shaanxi Normal University in Xi'an, China.Her research interest is mainly in the area of university specialty construction, curriculum and teaching; Basic principles of preschool education.She has published several research papers in scholarly journals in the above research areas and has participated in several conferences.

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