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PAPER

Harnessing Educational Big Data Analytics for Decision-Making in Enhancing School Teaching Quality

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ABSTRACT

The application of educational big data analytics holds significant importance in enhancing decision-making processes for school teaching quality. This study explores the effective utilization of educational big data analytics technologies to support the improvement of teaching quality in schools. Initially, the challenges and needs faced by current school teaching quality decision-making were analyzed, highlighting the critical role of educational big data analytics in this context. Subsequently, the limitations and gaps in existing study were identified through a review of related studies, underscoring the study value of this study. Based on this foundation, this study progresses through an examination of the decision-making factors that influence school teaching quality, problem description and model assumptions, construction of decision models, and model solutions using genetic algorithms. By analyzing key factors and constraints in the decision-making process for school teaching quality and integrating optimization algorithms, a viable decision support model was proposed and empirically analyzed. This study aims to provide a scientific basis for school administrators and decision-makers, thereby promoting continuous improvement in school teaching quality.

KEYWORDS

educational big data analytics, school teaching quality, decision support, model construction, genetic algorithms

1 INTRODUCTION

Enhancing school teaching quality has consistently been a focal issue of concern for both school administrators and educational policymakers [1–3]. With the rapid advancement of information technology and the widespread application of educational big data, an increasing number of schools have begun to utilize big data analytics to improve their teaching management and decision-making processes, aiming for continuous improvement in teaching quality [4–6]. However, in practical applications, many schools face challenges in using educational big data analytics to support decisions on teaching quality, necessitating systematic study and exploration.

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Previous studies have demonstrated the significant role of educational big data analytics in enhancing school teaching quality. By conducting in-depth mining and analysis of data related to student learning behaviors, teaching effectiveness, and the utilization of teaching resources, schools can identify potential teaching issues, optimize teaching processes, and provide personalized teaching support and services [7–13]. Thus, exploring the effective utilization of educational big data analytics technology has become a hot study topic in the field of education.

However, despite some achievements in existing study, there are still several challenges and deficiencies in practice. Firstly, most existing studies focus on single data sources or metrics, lacking a systematic and comprehensive analysis; secondly, some study methodologies lack specificity and practicality, making them difficult to directly apply in real-life decision-making scenarios [14–16]. Additionally, there remains a study gap in integrating educational big data analytics with actual decision-making processes.

Therefore, this study aims to fill these gaps by delving into how educational big data analytics can support decision-making processes for enhancing school teaching quality. Specifically, three main areas were explored in this study. Firstly, after analyzing the key factors affecting decisions on school teaching quality and describing specific problem scenarios within school teaching quality decisions, related model assumptions were presented. Secondly, a model framework suitable for school teaching quality decisions was constructed by considering various constraints and influencing factors in actual application scenarios. Finally, effective model-solving methods were proposed based on optimization algorithms such as genetic algorithms, providing decision support and guidance for schools to enhance teaching quality. This study aims to offer scientific decision-making bases for school administrators and policymakers, thereby promoting continuous improvement in school teaching quality. Therefore, this study holds significant theoretical and practical value.

2 PROBLEM DESCRIPTION AND MODEL ASSUMPTIONS

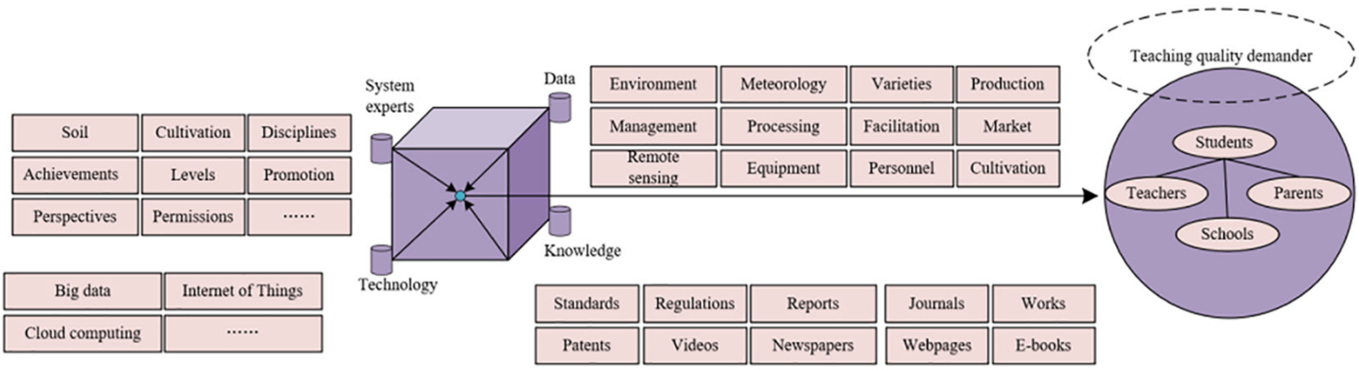

Fig. 1. Online learning resource sharing technology platform

The teaching environment and resources encompass both hardware facilities and software resources. Hardware facilities, which include classroom settings, laboratory equipment, and library resources, directly influence the convenience and effectiveness of teaching. Software resources, such as educational software and online learning platforms, can expand students' learning pathways and resources. Through educational big data analytics, these influencing factors can be more precisely identified and quantified, thereby providing a scientific basis and guidance for schools to formulate and adjust decisions aimed at enhancing teaching quality. Figure 1 illustrates the architecture of the online learning resource sharing technology platform.

In order to better depict the satisfaction of both suppliers and demanders when making decisions to enhance school teaching quality, a definition of satisfaction was first presented.

In the context of enhancing school teaching quality, demand-side stakeholders may include students, parents, teachers, and school administrators, denoted as set $X = \{X_1, X_2, \ldots, X_l\}$, where X_u represents the u-th sub-demand. Supply-side stakeholders may include providers of teaching environments and resources, educational technology companies, and teaching methodology training institutions, represented as set $Y = \{Y_1, Y_2, \ldots, Y_v\}$, where Y_k denotes the k-th teaching support supply.

Definition 1: When making decisions to enhance school teaching quality, supply-demand matching is defined by a one-to-one mapping ($\omega: X \cup Y \rightarrow X \cup Y$), indicating that demand and teaching support supply can correspond through matching operations. For achieving ideal levels of school teaching quality, $\omega(X_u)$ represents the teaching support supply matched to the demander X_u, and $\omega(Y_k)$ indicates the demander that the teaching support supply Y_k is matched to or the teaching support supply itself.

Definition 2: In satisfaction assessment, β_{uk} represents the satisfaction of demander X_u with the teaching support supply Y_k, and α_{uk} represents the satisfaction of the teaching support supply Y_k with the demander X_u. α_{uko} represents the satisfaction evaluation of demander X_u with the teaching support supply Y_k on the o-th indicator, and α_{ukw} represents the satisfaction evaluation of the teaching support supply Y_k with the demander X_u on the w-th indicator.

For ease of solution, the variable A_{uk} (0–1) was introduced. When $\omega(X_u) \in Y_k$, then $A_{uk} = 1$; when $\omega(X_u) \notin Y_k$, then $A_{uk} = 0$. That is, when X_u and Y_k are matched, then $A_{uk} = 1$; when X_u is not matched with Y_k, then $a_{uk} = 0$, as illustrated in Equation (1).

$$A_{uk} = \begin{cases} 1, \omega(X_u \in Y_k) \\ 0, \omega(X_u \notin Y_k) \end{cases} \tag{1}$$

Different evaluation methods can better adapt to various satisfaction assessment needs. Multi-granularity linguistic information is suitable for qualitative assessment, expressing satisfaction through descriptive language, which is closer to subjective feelings and specific requirements. However, interval number information, on the other hand, is suitable for quantitative assessment, precisely indicating the level of satisfaction through a range of values, thereby offering greater quantifiability. Both multi-granularity linguistic information and interval number information were employed in this study to evaluate satisfaction with improvements in school teaching quality.

I) Multi-granularity linguistic information

The multi-granularity linguistic information collected for the enhancement of school teaching quality specifically includes:

a) Very dissatisfied, which indicates extreme dissatisfaction with a certain aspect of teaching quality, possibly due to severe issues or unmet needs. For example, students might feel very dissatisfied with the quality of teaching resources for a particular course.

b) Dissatisfied, which indicates dissatisfaction with a certain aspect of teaching quality, where there are some problems or it is not ideal. For instance, parents might be somewhat dissatisfied with the course setup on online learning platforms.
c) Neutral, which reflects a neutral attitude towards a certain aspect of teaching quality, neither particularly satisfied nor dissatisfied. For example, teachers might consider the adequacy of recommended resources on a platform to be average.
d) Satisfied, which indicates general satisfaction with a certain aspect of teaching quality, essentially meeting needs. For example, students might feel satisfied with the learning resources provided by the school.
e) Very satisfied, which represents very high satisfaction with a certain aspect of teaching quality, meeting or exceeding expectations. For instance, school administrators might be very satisfied with the results of a particular teaching quality assessment.

These linguistic phrases were quantitatively described through a five-granularity language evaluation set T, with each evaluation phrase representing a degree of satisfaction or dissatisfaction, namely, T = {T_0 = NO(very dissatisfied), T_1 = O(dissatisfied), T_2 = L(neutral), T_3 = H(satisfied), and T_4 = NH(very satisfied)}. When collecting evaluations from the demanders about the suppliers, satisfaction levels were described using phrases from the language evaluation set T based on different indicators Z_o, which were then transformed into a corresponding triangular fuzzy number matrix $(O_{uko})_{v*l}$, denoted as $\tilde{\psi} = (\psi_u^m, \psi_u^l, \psi_u^i)(0 <= \psi_u^m <= \psi_u^l <= \psi_u^i <= 1)$.

$$\tilde{\psi} = (\psi_u^m, \psi_u^l, \psi_u^i) = \left(MAX\left\{\frac{u-1}{S}, 0\right\}, \frac{u}{S}, MIN\left\{\frac{u+1}{S}, 1\right\}\right), u = 0,1,2,\ldots S \tag{2}$$

The distance between any two elements $\tilde{x} = (x^m, x^l, x^i)$ and $\tilde{y} = (y^m, y^l, y^i)$ is represented by $M'_{\tilde{x}\tilde{y}}$, with the calculation formula given as follows:

$$M'_{\tilde{x}\tilde{y}} = \sqrt{\frac{1}{3}[(x^m - y^m)^2 + (x^l - y^l)^2 + (x^u - y^u)^2]} \tag{3}$$

II) Interval number information

In the process of evaluating improvements in school teaching quality, the collection of interval number information allows for a more precise expression of the needs and expectations of both the supply and demand sides. When evaluating teaching quality, both the demand and supply sides often provide a range of satisfaction rather than a specific value, denoted as $\tilde{\delta}_u = [\delta_u^m, \delta_u^i]$, where δ_u^m is the lower limit of the interval and δ_u^i is the upper limit. For example, parents may indicate that their satisfaction with the school's provision of learning resources lies between 70% and 90%. For calculation and comparison, these interval numbers need to be standardized. This usually involves identifying the maximum value of each interval's upper limit and using a standardization formula to map the interval numbers to a standardized range, enabling comparison and calculation between different intervals.

To further analyze the gap and similarity between the supply and demand sides, the distance between any two interval numbers should be calculated. This can be achieved by defining a distance function to measure the degree of difference between two interval numbers. Additionally, the collection of interval number information can also reflect the uncertainty on both sides regarding teaching quality. A wider interval may suggest greater uncertainty about the specific values of satisfaction, while a narrower interval may indicate more precise expectations. Specifically, let the demander X's language evaluation matrix for the supplier Y under the evaluation indicators Z_o be $(O''_{uko})_{v*l}$, and let $\delta^i = MAX\{\delta^i_u\}$, where δ^i is the maximum value of all interval upper limits. Then the standardized interval number can be calculated using the following formula:

$$O'''_{uko} = \frac{O''_{uko}}{\delta^i} \tag{4}$$

The distance between any two interval numbers $\tilde{x} = (x^m, x^i)$ and $\tilde{y} = (y^m, y^i)$ is denoted by $M''_{\tilde{x}\tilde{y}}$, and the calculation formula is provided below:

$$M''_{\tilde{x}\tilde{y}} = \sqrt{\frac{1}{2}[(x^m - y^m)^2 + (x^i - y^i)^2]} \tag{5}$$

III) Evaluation information organization

In the process of evaluating improvements in school teaching quality, after utilizing multi-granularity linguistic information and interval number information, the collected evaluation data should be organized and processed to facilitate subsequent satisfaction calculations and decision analysis. For linguistic evaluation information, the ideal point is usually set at (1, 1, 1), representing a state of complete satisfaction. Using this ideal point method, the distance between the evaluation data and the ideal point can be calculated. The greater the distance, the lower the user's satisfaction. Considering the varying importance of different evaluation indicators, the evaluation data need to be weighted to reflect the impact of each indicator on overall satisfaction. For ease of calculation, a range transformation was applied to process the distance, resulting in the final satisfaction evaluation matrix.

Specifically, the formula for calculating the distance between the evaluation information and the ideal point $(n'^{m+}, n'^{l+}, n'^{i+})$ is as follows:

$$M(O'_{uko}, n'^{+}) = \sqrt{\frac{1}{3}\left[(O'^{m}_{uko} - n'^{+m})^2 + (O'^{m}_{uko} - n'^{l})^2 + (O'^{m}_{uko} - n'^{+i})^2\right]} \tag{6}$$

After considering the weights of each evaluation indicator, the formula for the matrix $(\sigma'^{+}_{uk})_{v*l}$ is as follows:

$$\sigma'^{+}_{uk} = \sum_{o=1}^{g}\left[\mu^X_O M(O'_{uko}, n'^{+})\right] \tag{7}$$

The range transformation processing formula used is as follows:

$$\beta_{uk1} = 1 - \sigma'^{+}_{uk} \tag{8}$$

$$\beta'_{uk1} = \frac{\beta_{uk1} - MIN\,\beta_{uk1}}{MAX\,\beta_{uk1} - MIN\,\beta_{uk1}} \tag{9}$$

Specifically, the distance between the evaluation information and the ideal point (n^{m+}, n^{i+}) can be calculated through the following formula:

$$M(O''_{uko}, n''^{+}) = \sqrt{\frac{1}{2}\left[(O''_{uko} - n''^{+m})^2 + (O''^{i}_{uko} - n''^{+i})^2\right]} \tag{10}$$

Combining the weights of each indicator, the matrix $(\sigma''^{+}_{uk})_{v*l}$ can be calculated as follows:

$$\sigma''^{+}_{uk} = \sum_{o=1}^{g}\left[\mu^{X}_{O} M(O''_{uko}, n''^{+})\right] \tag{11}$$

After applying range transformation to σ''^{+}_{uk}, the satisfaction levels of the demander towards the supplier under interval number evaluation information, β_{uk2} and β'_{uk2}, can be calculated using the formulas:

$$\beta_{uk2} = 1 - \sigma''^{+}_{uk} \tag{12}$$

$$\beta'_{uk2} = \frac{\beta_{uk2} - MIN\,\beta_{uk2}}{MAX\,\beta_{uk2} - MIN\,\beta_{uk2}} \tag{13}$$

3 CONSTRUCTION OF A DECISION MODEL FOR ENHANCING SCHOOL TEACHING QUALITY

I) Indicator selection:

Figure 2 illustrates the decision-making process for enhancing school teaching quality. In constructing a decision model to improve school teaching quality, appropriate evaluation indicators should be selected to comprehensively assess various aspects of teaching quality. Combining existing study and actual needs, the following indicators were selected:

a) Evaluation indicators considered by the demander:
- Teaching costs: The expenses required for the teaching services provided by the school, including tuition fees, textbook costs, etc.
- Duration of teaching: The time students spend receiving teaching services at school, including class schedule arrangements and the duration of teaching activities.
- Degree of teaching needs met: the extent to which students' needs for the school's teaching services are actually met, including coverage of course content and teaching quality.
- Effectiveness of teaching feedback: Students' satisfaction with the school's modifications to teaching support methods following feedback.

b) Evaluation indicators considered by the supplier:
- Costs of teaching services: The costs associated with providing teaching services, including platform operation and teaching resource procurement costs.
- Ease of meeting teaching needs: The difficulty of satisfying students' teaching needs, including the flexibility of course settings and personalized path recommendations.
- Time required for teaching services: The time required for the provision of teaching services, including the availability of teaching resources.

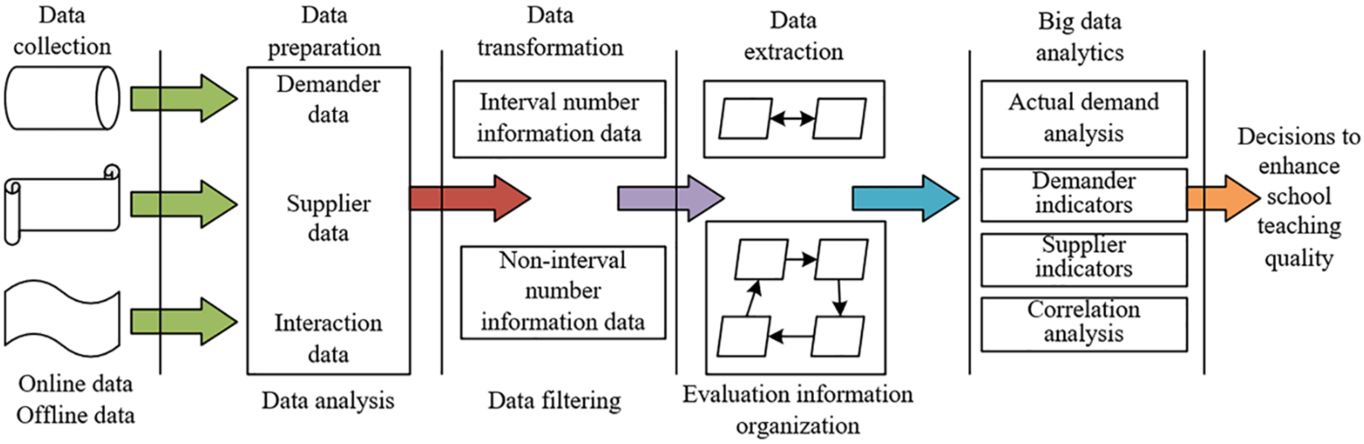

Fig. 2. Decision-making process for enhancing school teaching quality

When determining the weights of each indicator, the analytic hierarchy process (AHP) was utilized to consider expert opinions and the interrelationships between indicators comprehensively. Initially, a hierarchical structure was established, dividing the ultimate goal into the satisfaction levels of the demand and supply sides. Then the weights of each evaluation indicator were considered. Expert scoring was used to obtain pairwise comparison judgment matrices, from which the largest Eigen root and Eigen vectors were calculated to ultimately determine the weights of the indicators. Specifically, assuming that the number of satisfaction indicators for the demander and the supplier is represented by h and g, respectively, the weight of the demander X for the supplier Y under indicator o is denoted by μ_o^X:

$$\sum_{o=1}^{h} \mu_O^X = 1, u = 1, \ldots, 2, h \tag{14}$$

The weight of the supplier for the demander under indicator w is represented by μ_w^X, satisfying the formula:

$$\sum_{w=1}^{g} \mu_w^Y = 1, u = 1, \ldots, 2, g \tag{15}$$

II) Objective function construction

In the construction of a decision model for enhancing school teaching quality, a similar objective function construction method can be used to comprehensively consider the satisfaction of both the demander and the supplier. The satisfaction of the demander X towards the supplier Y can be expressed as the weighted sum of various evaluation indicators, where C_X is the satisfaction of the demander X under the u-th evaluation indicator towards the supplier Y, and μ_X is the weight of the u-th evaluation indicator for the demander X. Similarly, the satisfaction of the supplier Y towards the demander X can be expressed as the weighted sum of various evaluation indicators, where C_Y is the satisfaction of the supplier Y under the k-th evaluation indicator towards the demander X, and μ_Y is the weight of the k-th evaluation indicator for the supplier Y. It is stipulated that $\sum_{u=1}^{l} A_{uk} \leq 1$ and $\sum_{k=1}^{v} A_{uk} \leq 1$, resulting in:

$$C_X = \sum_{u=1}^{l}\sum_{k=1}^{v}\beta_{uk}A_{uk} \tag{16}$$

$$C_Y = \sum_{u=1}^{l}\sum_{k=1}^{v}\alpha_{uk}A_{uk} \tag{17}$$

The objective function is formulated as:

$$\begin{aligned} MAX\ C &= \mu_X \times \left(\sum_{f=1}^{l}\mu_f^X \times C_X\right) + \mu_Y \times \left(\sum_{f=1}^{l}\mu_f^Y \times C_Y\right) \\ &= \mu_X \times \left(\sum_{f=1}^{l}\mu_f^X \sum_{u=1}^{l}\sum_{k=1}^{v}\beta_{uk}A_{uk}\right) + \mu_Y \times \left(\sum_{f=1}^{l}\mu_f^Y \sum_{u=1}^{l}\sum_{k=1}^{v}\alpha_{uk}^S A_{uk}\right) \\ & t.s. \sum_{u=1}^{l} A_{uk} \leq 1 (u \in U) \\ & \sum_{k=1}^{v} A_{uk} \leq 1 (k \in K) \\ & \mu_X + \mu_Y = 1 (0 < \mu_X < 1, 0 < \mu_Y < 1) \\ & u \in U, k \in K, A_{uk} = 0\ or\ 1 \end{aligned} \tag{18}$$

4 MODEL SOLUTION BASED ON GENETIC ALGORITHMS

For the decision model aimed at enhancing school teaching quality, a solving approach based on genetic algorithms was employed. However, adjustments and customizations are necessary to adapt to the characteristics of the educational field. The detailed steps are as follows:

Step 1: Encoding and initial population setup

Given the multidimensionality of school teaching quality, suitable encoding methods, such as binary encoding or floating-point encoding, were selected to represent candidate solutions. In terms of the initial population setup, an appropriate number of individuals and the length of each individual were determined based on actual conditions.

Step 2: Fitness function

The objective function to be solved was transformed into a fitness function, which should comprehensively evaluate the quality of each individual. Given the multi-objective nature of enhancing teaching quality, multiple evaluation indicators were incorporated into the fitness function to assess the merits of each solution.

$$MAXC = \mu_X \times \left(\sum_{f=1}^{l}\mu_f^X \times C_X\right) + \mu_Y \times \left(\sum_{f=1}^{l}\mu_f^Y \times C_Y\right) \tag{19}$$

Step 3: Selection and mutation

The selection process involves choosing superior individuals based on the results of the fitness function and retaining them for the next generation. The evaluation outcomes of the fitness function were used in the mutation operations to determine the mutation probability and method, ensuring the diversity and exploratory nature of new individuals.

Step 4: Iterative optimization

The optimal solution in the solution space was sought through continuous iteration and optimization of populations and individuals using genetic algorithms.

During the iteration process, appropriate termination conditions were set to ensure the algorithm finds a superior solution within a limited timeframe.

Step 5: Solution experimentation

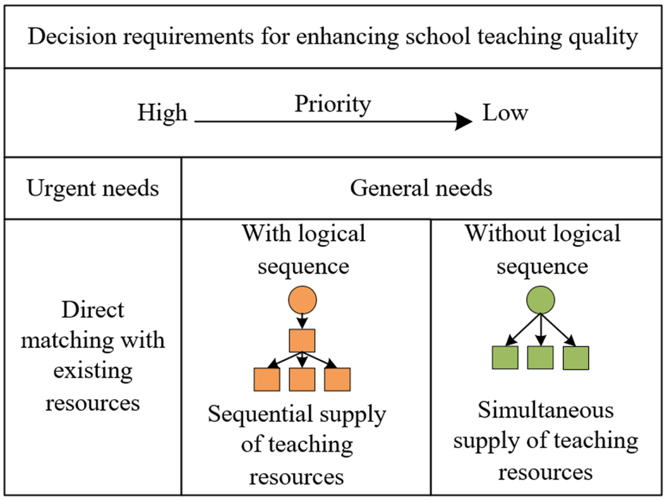

Fig. 3. Optimal decision combination

The model was implemented using MATLAB or another programming language, and genetic algorithm libraries were invoked according to actual conditions. Before conducting experiments, parameter settings and algorithm tuning were performed based on the specific characteristics of the problem to enhance the efficiency and accuracy of the solution.

After obtaining the solution results, the decision strategies need to be combined in a certain order of priority, aligning with the demander's specific needs, to form a specialized and systematic decision plan. Figure 3 illustrates a schematic of the optimal decision combination method.

5 EXPERIMENTAL RESULTS AND ANALYSIS

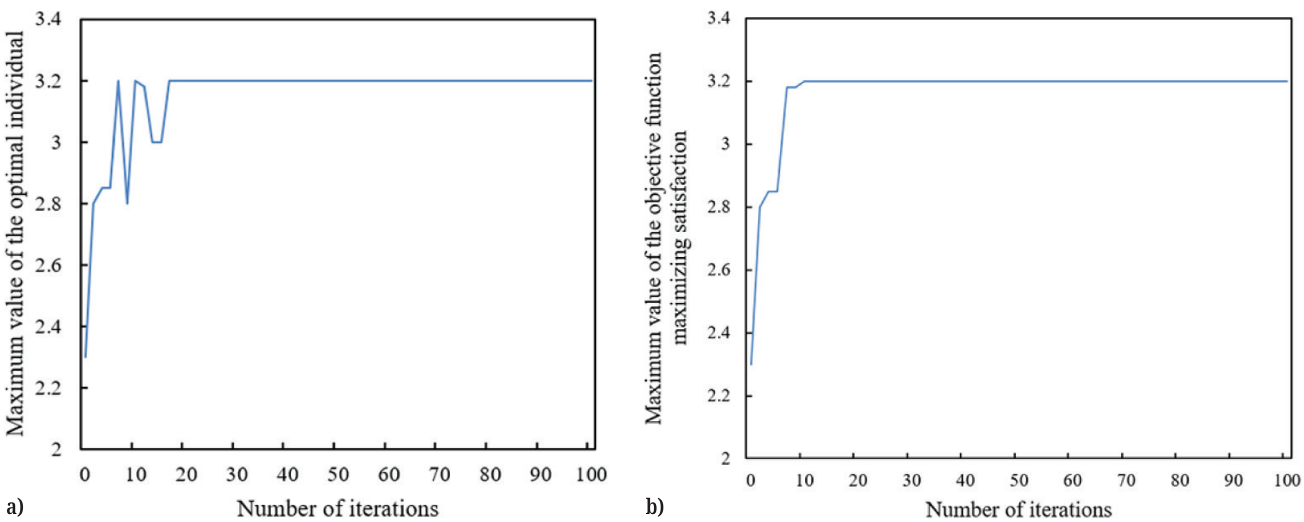

Fig. 4. Trends in the optimal individual and objective function values after 100 iterations

In this study, MATLAB 2016b software was employed to solve the decision model constructed for enhancing school teaching quality. The experimental results revealed that the optimal solution of the optimization model was $A1–3 = l$, $A2–8 = 1$, $A3–10 = l$, $A4–12 = 1$, and $A5–15 = 1$, with all other solutions being zero, and the objective function *max C* reached 3.269. Figure 4 illustrates the continuous optimization and eventual convergence of the objective function *max C* as the number of iterations increased. Specifically, the results of the model operation indicated that the decision variables for school teaching quality were $\omega(X_1) \in Y_3$, $\omega(X_2) \in Y_8$, $\omega(X_3) \in Y_{10}$, $\omega(X_4) \in Y_{12}$, and $\omega(X_5) \in Y_{15}$. These results demonstrate that specific decision points played a key role in the process of enhancing school teaching quality.

Analysis of the experimental results leads to the following conclusions: firstly, the allocation of decision variables suggests that resource allocation at specific locations (Y_3, Y_8, Y_{10}, Y_{12}, and Y_{15}) is the optimal choice for enhancing school teaching quality, indicating the high importance of these nodes in the decision-making process. Secondly, the gradual optimization and final convergence of the objective function *max C* reflect the effectiveness and stability of the genetic algorithm in solving the model. As the number of iterations increased, the objective function gradually reached its optimal value, indicating that the model effectively found the best decision path under a series of complex constraints. This provides school administrators with clear guidance on optimizing resource allocation to effectively enhance teaching quality.

Table 1. Satisfaction evaluation statistics for flipped classroom decision support

Sample No.	Total Satisfaction Value	Flipped Classroom Satisfaction Value and Resource Matching Percentage (%)					
		Very Satisfied		Satisfied		Neutral	
		Satisfaction Value	Percentage	Satisfaction Value	Percentage	Satisfaction Value	Percentage
1	17.26	2.51	15.25	6.23	35.62	6.02	33.26
2	38.25	1.07	2.89	8.45	22.31	13.26	38.25
3	16.23	0.03	0.15	0.52	3.12	2.87	15.32
4	22.58	4.25	17.26	5.62	22.54	4.26	21.24
5	17.59	0.19	0.98	1.89	11.24	4.25	22.69
6	22.36	0.05	0.23	1.23	5.69	4.89	21.58
7	47.5	0.18	0.34	3.56	6.58	8.25	16.59
8	8.69	1.23	14.23	2.56	32.48	2.25	25.32
Total	190.46	9.51	51.33	30.06	139.8	46.05	194.5

Sample No.	Total Satisfaction Value	Flipped Classroom Satisfaction Value and Resource Matching Percentage (%)			
		Dissatisfied		Very Dissatisfied	
		Satisfaction Value	Percentage	Satisfaction Value	Percentage
1	17.26	1.02	5.89	1.25	8.56
2	38.25	8.23	21.47	6.23	15.64
3	16.23	8.35	45.26	6.58	33.68
4	22.58	6.54	25.36	2.54	12.58
5	17.59	8.24	42.87	3.89	22.36
6	22.36	7.12	32.15	8.15	37.15
7	47.5	15.23	33.26	18.23	41.25
8	8.69	1.59	15.89	0.98	12.65
Total	190.46	56.32	222.5	47.85	183.7

Combining specialized teaching models and decision support for teaching environments and resources proved effective in enhancing school teaching quality. Satisfaction evaluation experiments for three typical teaching models and their associated decision support methods were further conducted in this study. According to the statistical data from Table 1, the overall satisfaction value for flipped classroom decision support is 190.46. In the detailed satisfaction categories, the total satisfaction value for "very satisfied" is 9.51, accounting for 5% of the total; "satisfied" accounts for 15.8% with a total value of 30.06; "neutral" represents 24.2% with 46.05; "dissatisfied" comprises 29.6% with 56.32; and "very dissatisfied" makes up 25.1% with 47.85. In terms of the resource matching percentage, high satisfaction samples 1, 2, and 7 have "very satisfied" and "satisfied" resource matching percentages of 35.62%, 22.31%, and 6.58%, respectively, whereas samples 3, 5, and 6 exhibit a higher proportion of "very dissatisfied," at 33.68%, 22.36%, and 37.15%, respectively. These figures reflect varying levels of satisfaction and resource matching in flipped classroom decision support among different samples, showing significant variation in satisfaction levels.

From this analysis, several conclusions can be drawn: Firstly, although the total value for "satisfied" and above is relatively low, representing only 20.8%, some samples still display high proportions of "satisfied" and "very satisfied," indicating that flipped classroom decision support can effectively enhance satisfaction with teaching quality decisions in specific contexts. Secondly, a higher proportion of "dissatisfied" and "very dissatisfied" samples indicates that resource matching in current flipped classroom decision support needs further optimization, particularly evident in samples 3, 5, and 6.

Table 2. Satisfaction evaluation statistics for project-based learning decision support

Sample No.	Total Satisfaction Value	Project-Based Learning Satisfaction Value and Resource Matching Percentage (%)					
		Very Satisfied		Satisfied		Neutral	
		Satisfaction Value	Percentage	Satisfaction Value	Percentage	Satisfaction Value	Percentage
1	17.26	6.32	36.25	6.56	36.25	2.04	12.35
2	38.25	5.62	13.25	10.25	26.58	10.23	26.35
3	16.23	0.12	0.82	0.68	3.26	1.36	7.58
4	22.58	4.25	16.58	5.26	22.31	6.23	25.34
5	17.59	0.42	2.35	1.65	9.54	4.15	22.31
6	22.36	0.52	2.57	2.14	9.36	4.89	23.21
7	47.5	1.23	2.43	6.89	14.23	10.25	22.14
8	8.69	1.58	18.23	3.25	42.58	2.31	25.69
Total	190.46	20.06	92.48	36.68	164.11	41.46	164.97

(Continued)

Table 2. Satisfaction evaluation statistics for project-based learning decision support *(Continued)*

Sample No.	Total Satisfaction Value	Project-Based Learning Satisfaction Value and Resource Matching Percentage (%)			
		Dissatisfied		Very Dissatisfied	
		Satisfaction Value	Percentage	Satisfaction Value	Percentage
1	17.26	1.23	6.57	1.32	6.89
2	38.25	7.24	17.56	5.12	14.56
3	16.23	5.68	32.15	9.63	55.24
4	22.58	4.56	17.56	3.65	14.23
5	17.59	7.98	41.21	4.28	23.58
6	22.36	7.84	35.69	6.32	26.35
7	47.5	15.23	31.25	13.56	28.31
8	8.69	0.68	8.23	0.32	4.01
Total	190.46	50.44	190.22	44.2	173.17

A statistical analysis of the satisfaction evaluation for project-based learning decision support was conducted based on the data in Table 2. The overall satisfaction value for the sample is 190.46. In the detailed satisfaction categories, "very satisfied" accounts for the least, with a value of 20.06, representing 10.5% of the total; "satisfied" amounts to 36.68, representing 19.3%; "neutral" has a value of 41.46, making up 21.8%; "dissatisfied" scores 50.44, accounting for 26.5%; and "very dissatisfied" totals 44.2, representing 23.2%. Specifically, samples 1 and 2 have lower "very satisfied" and "satisfied" resource matching percentages, while sample 7 exhibits higher percentages of "satisfied" and "very satisfied," at 14.23% and 2.43%, respectively. In the "dissatisfied" and "very dissatisfied" categories, samples 3 and 5 have notably higher proportions, at 32.15% and 41.21%, as well as 55.24% and 23.58%, respectively. These data reveal different levels of satisfaction and resource matching in project-based learning decision support across various samples, showing significant variance in satisfaction levels.

From the analysis of the data in Table 2, the following conclusions can be drawn: First, although the total value of "satisfied" and above constitutes only 29.8% of the overall satisfaction, some samples still display high proportions of "satisfied" and "very satisfied," particularly sample 7. This indicates that project-based learning decision support can effectively enhance satisfaction with teaching quality decisions in specific contexts. However, a higher proportion of "dissatisfied" and "very dissatisfied" samples, especially samples 3 and 5, suggests that there is substantial room for improvement in resource matching within the current project-based learning decision support.

A statistical analysis of satisfaction evaluation for blended learning decision support was conducted based on the data in Table 3. The overall satisfaction value for the samples is 192.67. In the satisfaction categories, "very satisfied" comprises the smallest proportion, with a value of 14.78, representing 7.67% of the total; "satisfied" accounts for 74.94 or 38.9%; "neutral" totals 158.6 or 82.36%; "dissatisfied" is 187.6 or 97.4%; and "very dissatisfied" is 147.1 or 76.4%. In specific samples, sample 1 exhibits higher percentages of "satisfied" and "very satisfied," at 5.87% and 5.36%, respectively; sample 2 displays percentages of "satisfied" and "very dissatisfied" at 9.87% and 12.35%, respectively. Additionally, sample 7 shows "satisfied" and "very dissatisfied" percentages of 12.68% and 15.32%, respectively. These data indicate significant variances in satisfaction levels and resource matching in blended learning decision support among different samples, reflecting variations in satisfaction in specific applications.

From the analysis of the data in Table 3, the following conclusions can be drawn: First, although the total proportion of "satisfied" and above is 46.57%, some samples exhibit high satisfaction ratios, particularly sample numbers 1 and 7, indicating that blended learning decision support can significantly enhance satisfaction with teaching quality decisions in certain contexts. However, the high proportions of "dissatisfied" and "very dissatisfied," especially in samples 3 and 6, suggest that the resource matching and implementation effects of current blended learning decision support require improvement. These results validate the necessity of this study, illustrating that by analyzing key factors affecting school teaching quality and constructing optimized models, deficiencies in the current decision support systems can be identified and improved, providing more accurate and effective decision support to enhance overall school teaching quality.

Table 3. Satisfaction evaluation statistics for blended learning decision support

Sample No.	Total Satisfaction Value	Blended Learning Satisfaction Value and Resource Matching Percentage (%)					
		Very Satisfied		Satisfied		Neutral	
		Satisfaction Value	Percentage	Satisfaction Value	Percentage	Satisfaction Value	Percentage
1	16.25	5.36	31.25	5.87	32.25	3.65	20.16
2	38.23	1.34	3.21	6.56	16.98	10.47	26.68
3	17.52	0.45	2.34	2.38	12.36	4.56	22.36
4	23.65	2.25	9.68	6.98	26.89	6.35	25.69
5	18.56	1.68	8.97	3.54	18.98	4.25	21.34
6	22.34	0.79	3.56	2.45	12.36	4.68	22.36
7	47.89	1.85	3.57	6.89	13.65	12.68	24.58
8	8.23	1.06	12.36	2.23	24.59	1.89	24.59
Total	192.67	14.78	74.94	36.9	158.6	48.53	187.6

Sample No.	Total Satisfaction Value	Blended Learning Satisfaction Value and Resource Matching Percentage (%)			
		Dissatisfied		Very Dissatisfied	
		Satisfaction Value	Percentage	Satisfaction Value	Percentage
1	16.25	0.91	5.12	1.65	10.25
2	38.23	12.35	17.26	9.87	23.25
3	17.52	8.36	44.23	2.65	15.68
4	23.65	5.69	26.35	2.98	12.31
5	18.56	6.12	31.24	3.24	16.58
6	22.34	6.34	28.62	7.58	32.24
7	47.89	15.32	33.12	12.36	25.25
8	8.23	2.24	24.58	1.02	12.35
Total	192.67	57.33	210.2	41.35	147.1

6 CONCLUSION

An in-depth analysis of the key factors influencing school teaching quality decisions was conducted, and a model framework suitable for school teaching quality decisions was constructed in conjunction with specific problem scenarios in this study. Further, optimization algorithms such as genetic algorithms were applied to solve the model, providing effective decision support and guidance for enhancing school teaching quality. The specific experimental content includes analyzing the satisfaction evaluation information of demander X towards supplier Y across different sub-needs, assessing the satisfaction indicators of supplier Y towards demander X in the process of enhancing school teaching quality, analyzing the trends in the optimal individual and objective function through 100 iterations, and statistically analyzing the satisfaction evaluations of three decision support modes, i.e., flipped classroom, project-based learning, and blended learning. The results indicate significant differences in satisfaction and resource matching among different teaching modes, revealing the strengths and weaknesses of each mode in practical applications.

As for future study directions, the sample size could be expanded to enhance the representativeness and diversity of the data, thereby strengthening the universality of the study conclusions. The model could be dynamically adjusted and optimized in conjunction with actual application scenarios to enhance its applicability and effectiveness across different teaching models. In addition, more advanced optimization algorithms, such as deep learning and reinforcement learning, could be incorporated to further enhance the intelligence level and decision-making efficiency of the decision support system. Through continuous optimization and improvement, future study will provide more scientific and effective decision support for the continuous enhancement of school teaching quality.

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