Learning Behavioral Characteristics and Teaching Intervention Strategies of Midwifery Students in Higher Vocational Colleges Using K-means Clustering Algorithm

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ABSTRACT To address the difficulty of integrating multi-source heterogeneous learning behavior data and the broadness of conventional teaching intervention strategies, this paper proposes a data-driven analysis framework based on K-means clustering for higher vocational midwifery education. The study collects multidimensional behavioral data from online learning logs, smart classroom interaction records, and practical training assessments, and constructs a 12-dimensional feature system covering cognitive input, behavioral activity, practical competence, and comprehensive performance. Zscore standardization is used to eliminate dimensional differences, and the optimal cluster number K=3 is determined by combining the elbow rule and silhouette coefficient. Students are classified into actively balanced, theoretically weak, and practically lagging groups. Experimental results show that targeted interventions based on clustering profiles significantly improve core competency indicators in theoretical and practical dimensions. Hotelling's T^2 tests and external evaluation indicators confirm the statistical significance and educational interpretability of the clustering structure. The framework can also support engineering training environments using smart classrooms, wireless sensing, and electromagnetic-compatible data acquisition systems for precise learning diagnosis and intervention.

INDEX TERMS k-means clustering, learning behavior, teaching intervention, smart classroom, wireless sensing

I. INTRODUCTION

WITH the deepening of digital transformation in education, higher vocational education in engineering and materials science is rapidly evolving from experience-driven paradigms to data-driven smart manufacturing instruction. As a typical highly skilled and practical medical-related major, midwifery's talent training quality is directly related to maternal and infant safety and the capacity of primary healthcare services. However, in current teaching practice, although teachers can obtain a large amount of student learning behavior data through channels such as smart teaching platforms and training management systems, this data often presents characteristics of being multi-sourced, heterogeneous, and high-dimensional, making it difficult to effectively integrate and interpret [1-2]. Meanwhile, teaching intervention strategies still generally adopt a uniform, experience-based "one-size-fits-all" approach, lacking precise responses to individual differences. This results in high-quality educational resources failing to efficiently match the truly needy student groups, creating a structural contradiction of "rich data but poor insights, frequent interventions but limited effects." While existing learning analytics research has made some progress in general courses, it still has significant limitations in highly specialized vocational education scenarios, especially in professions like midwifery that emphasize the integrated training of "theory-skills-competencies" [3-4]. On the one hand, most studies focus only on single-dimensional learning indicators, failing to fully integrate multimodal behavioral data such as classroom interaction, virtual simulation operations, and clinical training performance, making it difficult to comprehensively depict the true learning status of midwifery students. On the other hand, even when some studies attempt to introduce clustering algorithms for student grouping, the results often remain at the descriptive profile level, lacking a logical connection mechanism with subsequent teaching actions, making it difficult to transform the analytical results into executable and assessable teaching intervention plans [5-6]. To address the aforementioned issues, this paper focuses on midwifery majors in higher vocational colleges and proposes a data-driven teaching intervention framework that integrates the K-means clustering algorithm. Based on real teaching scenarios, this framework systematically collects and integrates online learning logs, smart classroom interaction records, and practical training assessment data to construct a multi-dimensional feature system covering cognition, behavior, and skills. On this basis, by scientifically determining the optimal number of clusters, it achieves refined segmentation of the student population. More importantly, it constructs a "clustering profile—intervention strategy" mapping rule library, directly transforming the behavioral pattern labels output by the algorithm into specific teaching measures that align with the training objectives of the midwifery major, such as personalized resource delivery, group collaborative task design, and simulated operation reinforcement training. This provides a practical teaching path for midwifery majors while offering a methodological reference for data-driven reforms in engineering and other highly practical vocational fields focused on advanced fiber processing technology.

II. RELATED WORK

In recent years, Educational Data Mining (EDM) technology has shown great potential in student behavior modeling and academic early warning. Among them, unsupervised learning methods are widely used in learner classification research because they can discover potential group structures without prior labels [7-8]. K-means clustering, as the most classic partitioning clustering algorithm, has become the mainstream tool for identifying student behavior patterns in educational scenarios due to its advantages such as high computational efficiency, clear principles, and strong interpretability of results. Studies generally construct feature spaces by defining indicators such as learning input, resource usage frequency, and test performance, and use K-means to divide students into several homogeneous subgroups, thereby providing a basis for differentiated teaching [9-10]. To further improve cluster stability, researchers often combine internal evaluation indicators such as the elbow rule and silhouette coefficient to determine the optimal number of clusters, avoiding biases caused by subjective settings [11-12].

In the field of higher vocational education, research on student learning behavior has gradually shifted from macro-level attitude surveys to micro-level process tracking. Related work indicates that higher vocational students generally suffer from insufficient learning motivation, weak self-learning ability, and a disconnect between theory and practice, exhibiting significant unevenness in their learning engagement [13-14]. Based on this, some studies have attempted to identify typical groups such as "low-participation," "subject-specific," and "passive follower" through clustering methods and explore their causes. However, these studies largely rely on static data such as questionnaires or final exam scores, lacking fine-grained capture of dynamic behavior throughout the learning process, especially neglecting behavioral representations of core vocational education aspects such as practical training and hands-on practice, resulting in weak correlation between the identified group characteristics and professional competence development [15-16].

At the level of teaching intervention, the data-driven precision teaching concept has gained widespread acceptance. Learning analytics should form a closed loop of "collection analysis diagnosis intervention evaluation" [17-18]. However, most current research is limited to the diagnostic stage and has not established an effective conversion mechanism from data insights to teaching actions. Especially in courses with strong professionalism and high skill requirements, how to transform abstract clustering results into concrete, feasible, and professionally logical intervention measures remains a key challenge that has not yet been systematically addressed [19-20]. The existing intervention strategies are mostly general recommendations, lacking deep coupling with professional core competency indicators, making it difficult to support teachers in carrying out targeted teaching adjustments [21-22].

In summary, although K-means clustering has been widely applied in educational analysis, there is still a lack of an end-to-end research framework that integrates multi-source heterogeneous behavior data, achieves refined group recognition, and can directly generate professional oriented intervention strategies in highly specialized scenarios such as vocational midwifery. This article is dedicated to bridging the gap between data analysis and educational practice, and promoting the transformation of learning analytics technology from visible to actionable.

III. MATERIALS AND METHODS

A. DATA COLLECTION AND PREPROCESSING

The data collection follows the principle of "multi-source, whole process, high fidelity", aiming to comprehensively reflect the training characteristics of the "theory skills literacy" trinity in the midwifery profession. The data sources include three categories: (1) Online learning platform log data comes from the smart teaching platform deployed by the school, recording students' behavior trajectories in core courses such as Obstetrics and Gynecology Nursing and Midwifery Technology, such as video viewing time, chapter test submission times and scores, resource download frequency, etc. (2) The interactive data of smart classroom teaching is automatically captured through the classroom response system and teaching management platform, including classroom question response rate, in class test accuracy, group discussion participation, etc. (3) The training assessment data is provided by the on campus simulated delivery room training center, covering structured evaluation indicators such as standardized operation process execution scoring, simulated delivery scenario response ability, and sterile operation standardization.

Based on the above raw data, this article constructs a feature vector space containing 12 dimensions to quantify students' learning behavior, as shown in Table 1.

Due to significant differences in the dimensions and value ranges of each feature, directly inputting it into the clustering model can result in distortion in distance calculation. Therefore, Z-score normalization is used to preprocess all features, ensuring that each dimension has equal weight in the clustering process. The standardized formula is:

$$Z_{ij} = \frac{X_{ij} - \mu_j}{\sigma_j} \tag{1}$$

X_{ij} represents the original value of the i-th student on the j-th feature, where μ_j and σ_j are the mean and standard deviation of the feature in the entire sample, respectively. After this processing, all features follow a standard normal distribution with a mean of 0 and a standard deviation of 1.

B. CONSTRUCTION OF K-MEANS CLUSTERING MODEL

The core goal of K-means clustering is to divide n samples into K mutually exclusive clusters $C = \{C_1, C_2, \ldots, C_K\}$, minimizing the Sum of Squared Errors (SSE) within each cluster. The optimization objective function can be formalized as $\min_C \sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - \mu_k\|^2$, where x_i is the standardized eigenvector of the i-th student, μ_k is the centroid of the k-th cluster, and $\|\cdot\|$ represents the Euclidean distance [23-24]. To address the well-known sensitivity of the standard K-means algorithm to initial centroid selection, this study adopted the K-means++ algorithm for initial centroid initialization, which selects initial centroids with large mutual distances to avoid local optimal solutions. Meanwhile, the model was independently run 20 times with different random seeds, and the clustering result with the minimum intra-cluster sum of squared errors was selected as the final result.

The determination of the optimal number of clusters K is crucial for model construction [25-26]. A single indicator is susceptible to subjective influence, so this article uses the elbow rule and contour coefficient to jointly determine. The elbow rule calculates SSE at different K values:

$$SSE(K) = \sum_{k=1}^{K} \sum_{x_i \in C_k} \|x_i - \mu_k\|^2 \tag{2}$$

Draw the K-SSE curve and select the "inflection point" as the candidate K [27-28]. The silhouette coefficient evaluates the clustering quality from the perspectives of cohesion and separation. The silhouette coefficient of a single sample i is:

$$s(i) = \frac{b(i) - a(i)}{\max\{a(i), b(i)\}} \tag{3}$$

$a(i)$ is the average distance between sample i and other samples in the same cluster, and $b(i)$ is the minimum average distance between sample i and all samples in the nearest neighboring cluster. The overall contour coefficient is:

$$\bar{s} = \frac{1}{n} \sum_{i=1}^{n} s(i) \tag{4}$$

This article selects the K value that maximizes $\bar{s}$ and causes a clear inflection point in the SSE curve. The effectiveness evaluation of clustering adopts two external indicators: Calinski-Harabasz (CH) index and Davies-Bouldin (DB) index [29-30]. The CH index measures the ratio of inter cluster dispersion to intra cluster compactness:

$$CH = \frac{Tr(B_K)/(K-1)}{Tr(W_K)/(n-K)} \tag{5}$$

B_K is the inter group dispersion matrix, W_K is the intra group dispersion matrix, and $Tr(\cdot)$ is the matrix trace. The larger the CH value, the better the clustering effect. The DB index calculates the average similarity between each cluster and its most similar cluster:

$$DB = \frac{1}{K} \sum_{i=1}^{K} \max_{j \neq i} \left(\frac{R_i + R_j}{d(\mu_i, \mu_j)} \right) \tag{6}$$

R_i is the average dispersion of cluster i. The smaller the DB value, the better the clustering effect. In addition, to quantify the significance of inter cluster differences, Hotelling's T^2 test was introduced:

$$T^2 = \frac{n_1 n_2}{n_1 + n_2} (\bar{x}_1 - \bar{x}_2)^T S_p^{-1} (\bar{x}_1 - \bar{x}_2) \tag{7}$$

$\bar{x}_1$ and $\bar{x}_2$ are the centroids of the two clusters, and S_p^{-1} is the merged covariance matrix. If the T^2 statistic corresponds to $p < 0.01$, it is considered that there is a significant difference between the two clusters in the multidimensional feature space [31-32].

C. CONSTRUCTION OF INTERVENTION STRATEGY MAPPING RULE LIBRARY

The value of clustering results lies in guiding teaching actions. To this end, this study constructed a structured "clustering portrait intervention strategy" mapping rule library, achieving a closed-loop transformation from data insights to educational practice [33-34]. This process is divided into three steps:

Step 1: Semantic interpretation of centroid features. Analyze the centroid vector $\mu_k = [\mu_{k1}, \mu_{k2}, \ldots, \mu_{k12}]^T$ of each cluster and identify the dimensions that are significantly higher or lower than the global mean. It can be labeled as 'weak in theory but strong in practice'. Z-score normalization was applied to all 12-dimensional features to eliminate dimensional differences and ensure equal weight in the K-means clustering process, which guaranteed the objectivity of sample distance calculation and cluster division without subjective feature weighting. The subsequent definition of

TABLE 1. 12 dimensional feature vector space

Feature No.	Feature Category	Feature Name	Calculation method/explanation
X1	Cognitive Engagement	Average Video Completion Rate	Total effective video watching duration / Total course video duration
X2	Cognitive Engagement	Average Score of Chapter Quizzes	Arithmetic mean of all chapter quiz scores
X3	Cognitive Engagement	Classroom Interaction Accuracy Rate	Number of correct classroom answers / Total number of answers
X4	Behavioral Activity	Weekly Average Login Frequency	Total login times during the semester / Number of teaching weeks
X5	Behavioral Activity	Community Participation	Number of forum posts + Number of replies
X6	Behavioral Activity	Homework Submission Timeliness Rate	Number of on-time homework submissions / Total number of homework assignments
X7	Practical Competence	Average Score of Practical Training Operations	Arithmetic mean of practical training project scores
X8	Practical Competence	Completeness Score of Simulated Delivery Operation	Completeness score assessed by teachers based on standardized checklists
X9	Practical Competence	Responsiveness (Agility)	1 / Emergency handling response time
X10	Comprehensive Performance	Standardized Score of Midterm Theoretical Exam	Raw score processed by Z-score standardization
X11	Comprehensive Performance	Mean of Teachers' Process-oriented Evaluation	Mean of teachers' comprehensive scores on learning attitude, collaboration, and other dimensions
X12	Comprehensive Performance	Peer Evaluation Z-score	Raw peer evaluation scores processed by Z-score standardization

the feature significance index was a post-clustering semantic interpretation step for labeling group characteristics, rather than a reweighting of features in clustering. To quantify significance, define the feature significance index:

$$\delta_{kj} = \frac{|\mu_{kj}|}{\sigma_{\mu j}} \tag{8}$$

$\sigma_{\mu j}$ is the standard deviation of the centroid values of all clusters in the j-th dimension. When $\delta_{kj} > 1.5$, it is considered that this feature plays a decisive role in group labeling.

Step 2: Expert collaboration strategy generation: a focus group meeting with three midwifery teachers with over 10 years of teaching experience and two educational technology experts can be organized. The meeting focused on discussing "how to improve the weaknesses of this group" and "how to strengthen its advantages". For the "theoretically weak" group, experts suggest: "pushing obstetric pathology mechanism animation micro courses" and "organizing" case theory "paired learning groups"; For the "practice lag type", it is recommended to "increase the duration of high fidelity simulated childbirth operations to 2 hours per week" and "implement a one-on-one skill mentorship system between experienced and new staff". The baseline duration of high-fidelity simulated childbirth operation training for all three student groups was uniformly set at 1 hour per week in this study. The expert-recommended increase to 2 hours per week for the practice lagging group was a targeted adjustment based on their core competency weakness in practical operation, rather than a blind increase in practice volume. For the balanced & active group and theory weak group, their baseline training duration was maintained unchanged during the intervention period, which ensured that the improvement in practical competency of the practice lagging group could be attributed to the precision of the clustering-based targeted intervention strategy, rather than the simple change in practice time.

Step 3: Formalize and store rules: it can transform expert consensus into structured production rules, expressed using the "IF-THEN" logic. The general form is:

$$\text{IF}\left(\left(\bigwedge_{j\in H} X_j > \theta_j^+\right) \wedge \left(\bigwedge_{j\in L} X_j < \theta_j^-\right)\right)\text{THEN } I_k \tag{9}$$

H is a high score feature collection, L is a low score feature collection, θ_j^+, θ_j^- are thresholds, and I_k is a set of intervention measures for the k-th group. This mapping rule library not only ensures the professionalism and operability of intervention measures, but also establishes a traceable and iterative optimization mechanism [35-36].

D. EXPERIMENTAL DESIGN AND QUANTITATIVE INDICATORS

This study adopted a pre-test experimental design to verify the effectiveness of the data-driven teaching intervention framework. The experimental subjects were 120 midwifery students divided by K-means clustering, corresponding to three groups: "positive balance type", "theoretical weakness type", and "practice lag type". This study was approved by the Ethics Committee of Laiwu Vocational and Technical College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. The classification results are shown in Figure 1.

From Figure 1, it can be seen that the "positive balance type" group (blue circular dots, 42 people) is concentrated in the upper right area of the coordinate system; Theoretical weak groups (purple square dots, 38 people) gather in the middle area of the coordinate system, while practical lagging groups (green triangle dots, 40 people) are distributed in the lower right middle area of the coordinate system.

At the same time, 36 students from the same major in the previous academic year were selected as the control group. The two groups maintained consistency in curriculum system, teacher configuration, and assessment standards. The control group only received traditional standardized teaching and did not receive targeted interventions based

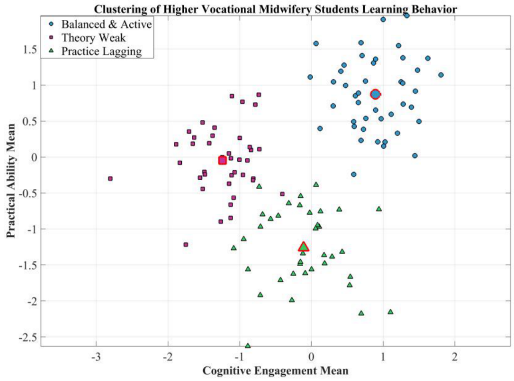

FIGURE 1. Classification results of three types of students

on clustering portraits. To ensure the rigor of the experiment, homogeneity tests were conducted on the baseline characteristics of each group before intervention, including the average scores of the college entrance examination, the average scores of professional basic courses in the first semester, and the scores of the learning motivation scale. The results of one-way ANOVA showed no significant differences between the groups, ensuring good comparability between the groups. To mitigate potential confounding variables introduced by selecting students from the previous academic year as the control group, rigorous homogeneity tests were conducted on the baseline characteristics of both the intervention and control groups, covering college entrance examination average scores, first-semester professional basic course scores, and learning motivation scale results. One-way ANOVA confirmed no significant intergroup differences ($p>0.05$). Meanwhile, the same curriculum system, teacher configuration, and assessment standards were strictly maintained for both groups, minimizing the impact of non-intervention factors and ensuring the reliability of the experimental results despite the between-academic-year control group design.

The quantitative indicator system is constructed around the training objectives of "theory-skills-literacy" in the midwifery profession, taking into account the evaluation of clustering quality and the verification of intervention effects. The internal evaluation of clustering uses SSE, silhouette coefficient, CH index, and DB index to measure the effectiveness of clustering from dimensions such as intra cluster compactness, sample clustering rationality, inter cluster dispersion and intra cluster compactness balance, and inter cluster similarity; The external intervention effect indicators include the average score improvement rate of the final theoretical exam, the achievement rate of practical training skills, and the growth rate of online learning activity. At the same time, additional indicators such as the pass rate of professional core courses, the improvement value of simulated childbirth operation integrity, and the derived indicators of classroom interaction participation rate are supplemented. The subjective evaluation indicators are evaluated by two professional teachers with more than 8 years of teaching experience in a double-blind manner, and the consistency of the scores is tested by the correlation coefficient within the group to ensure the objectivity and reliability of the data.

IV. RESULTS AND DISCUSSION

A. QUANTITATIVE ANALYSIS OF CLUSTERING AND GROUPING FEATURES

To accurately characterize the behavioral differences among three groups of students, a quantitative comparison table was constructed based on clustering centroid data of 12 dimensional feature vectors. A systematic analysis was conducted from four dimensions: cognitive investment, behavioral activity, practical ability, and comprehensive performance. The results are shown in Table 2.

Table 2 shows that the centroid values of the positive balanced group in all feature dimensions are significantly higher than the global mean, with outstanding scores in weekly login frequency, average video completion rate, and timely homework submission rate, reflecting the comprehensive advantages of sufficient cognitive investment, active behavioral participation, and solid practical skills. The core weakness of the theoretically weak group is concentrated in the dimension of cognitive investment. The centroid values of the average scores in chapter tests and the standardized scores in mid-term theoretical exams are significantly lower than those of other groups, while the characteristics related to practical ability are close to the global average, showing a non-equilibrium feature of strong practical ability and weak theoretical ability. The practice lagging group shows obvious disadvantages in the dimension of practical ability, with the lowest scores in the completeness of simulated childbirth operations and the average score in practical training operations among the three groups. The characteristic values of cognitive investment and behavioral activity dimensions are at a moderate level, forming a behavior pattern that is theoretically acceptable but lacks practical experience. The ranking results of feature saliency further validated the core difference dimensions of various groups, providing a quantitative basis for the precise design of subsequent

TABLE 2. Behavioral differences among three types of student groups

Feature No.	Feature Category	Feature Name	Balanced & Active	Theory Weak	Practice Lagging
X1	Cognitive Engagement	Average Video Completion Rate	1.28	0.35	0.82
X2	Cognitive Engagement	Average Score of Chapter Quizzes	1.15	-1.32	0.21
X3	Cognitive Engagement	Classroom Interaction Accuracy Rate	1.07	-0.45	0.53
X4	Behavioral Activity	Weekly Average Login Frequency	1.31	0.47	0.79
X5	Behavioral Activity	Community Participation	1.02	0.33	0.51
X6	Behavioral Activity	Homework Submission Timeliness Rate	1.24	0.58	0.87
X7	Practical Competence	Average Score of Practical Training Operations	1.19	0.92	-1.27
X8	Practical Competence	Completeness Score of Simulated Delivery Operation	1.23	0.85	-1.35
X9	Practical Competence	Responsiveness (Agility)	1.05	0.78	-0.93
X10	Comprehensive Performance	Standardized Score of Midterm Theoretical Exam	1.21	-1.18	0.36
X11	Comprehensive Performance	Mean of Teachers' Process-oriented Evaluation	1.17	0.29	0.64
X12	Comprehensive Performance	Peer Evaluation Z-score	1.03	0.21	0.57

intervention strategies.

B. CLUSTER VALIDITY VERIFICATION ANALYSIS

The reliability of clustering results directly determines the targeting of subsequent intervention strategies, and a single evaluation indicator is difficult to fully reflect the quality of clustering. Therefore, from the three dimensions of intra cluster compactness, inter cluster separation, and statistical significance, combined with elbow rule, contour coefficient, CH index, DB index, and Hotelling's T^2 test, a multi-index validation system is constructed to comprehensively evaluate the K-means clustering results. Among them, Figure 2 accurately locates the optimal number of clusters through the synergistic changes of intra cluster compactness (SSE) and inter cluster separation (contour coefficient).

From Figure 2, it can be seen that as the number of clusters K increases, the sum of squared errors (SSE) within the clusters generally decreases, indicating that increasing the number of clusters helps to improve the compactness of samples within the clusters. However, when K increases from 2 to 3, the decrease in SSE is most significant, and then the rate of decrease slows down significantly. The curve shows a typical "elbow" feature at K=3, indicating that further subdivision of the cluster structure has limited marginal improvement in compactness. At the same time, the average silhouette coefficient reaches the second highest value at K=3, indicating that the sample achieves a better balance between intra cluster consistency and inter cluster discriminability under this cluster number condition; When K further increases, the contour coefficient decreases significantly, indicating that excessive clustering may weaken the inter class separation effect. Combining the two indicators, it can be concluded that K=3 is a more reasonable and robust clustering scheme for the current dataset, as it can maintain clear inter cluster boundaries while ensuring stable intra cluster structure. To further verify the rationality of K=3, from the perspectives of comprehensive evaluation of clustering quality and statistical significance, the significance of inter cluster differences was quantified through the ratio of inter cluster dispersion to intra cluster compactness and the Hotelling's T^2 test. The results are shown in Figure 3.

Figure 3a shows the joint evaluation results of clustering quality, quantified by CH index and Adjusted Rand Index (ARI). ARI is used to measure the consistency between clustering results and real population labels, with a range of -1 to 1. The closer the value is to 1, the higher the fit between the clustering and the actual population structure. The results showed that when the number of clusters K=3, the CH index reached a peak of 296.4, indicating the maximum inter cluster differences and the optimal intra cluster density; Meanwhile, the ARI reached 0.823, indicating that the clustering scheme is highly consistent with the actual student population structure. Figure 3b shows the p-value heatmap of the Hotelling's T^2 test between clusters at K=3. The p-values of pairwise comparisons of the three groups - positive equilibrium type, theoretical weak type, and practical lagging type - are all less than 0.01, fully indicating that there are significant differences among the three groups in the 12 dimensional feature space. Overall, K=3 is the optimal number of clusters, which can balance intra cluster tightness, inter cluster separation, and consistency of the true population structure.

C. DIFFERENTIAL VALIDATION ANALYSIS OF TEACHING INTERVENTION EFFECTS

To comprehensively evaluate the practical application value of the data-driven intervention framework, a comparative analysis was conducted on the differential performance between the intervention group and the control group in terms of enhancing core competencies. The changes in core competency indicators before and after intervention are shown in Figure 4.

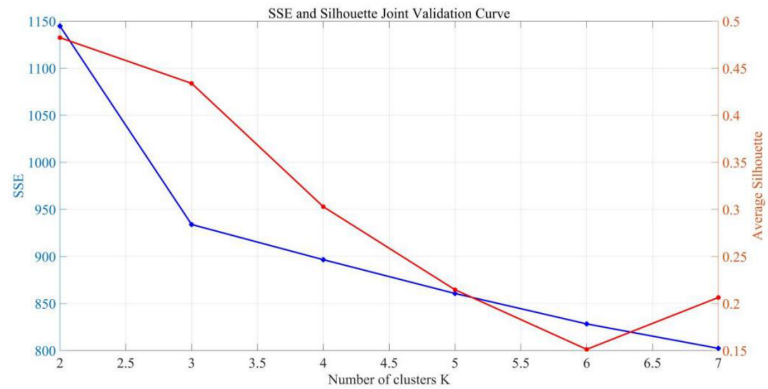

FIGURE 2. Collaborative variation of SSE and contour coefficient

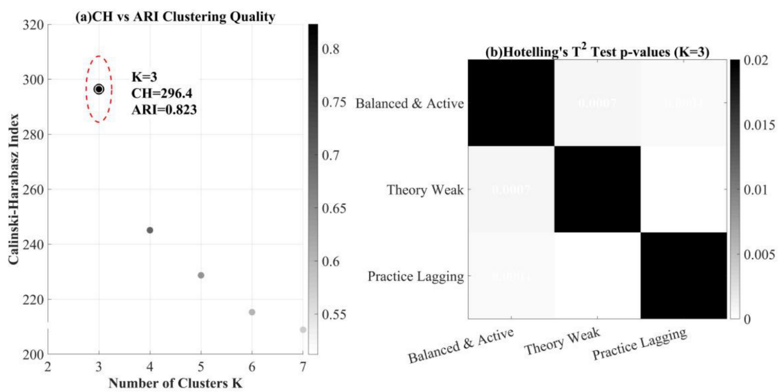

FIGURE 3. Scatter matrix of clustering quality index and significant differences between clusters

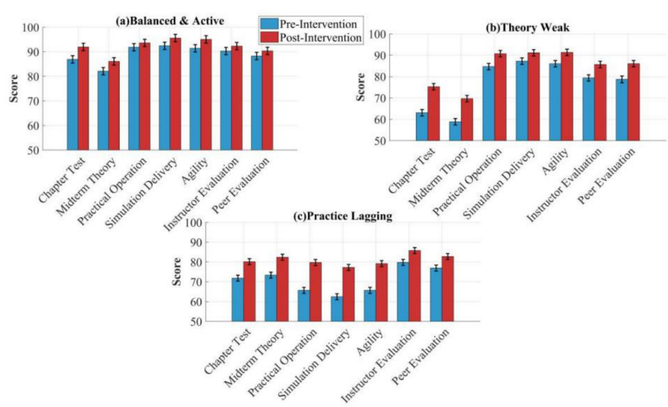

FIGURE 4. Differential performance between intervention group and control group

The five dimensions of weekly average login frequency, community participation, homework submission timeliness rate, mean of teachers' process-oriented evaluation, and peer evaluation Z-score were excluded from the intervention effect analysis. The first three are learning behavior process indicators, only used for clustering to characterize students' behavioral features rather than reflecting the core competency outputs of midwifery. The latter two are multi-dimensional comprehensive evaluation indicators, whose results can be embodied by core competency indicators and would cause result overlap if included. Additionally, these five indicators were not the targets of targeted interventions in this study, and their changes occurred naturally with the improvement of core competencies, thus they were not analyzed as independent indicators for intervention impacts. Figures 4a, 4b and 4c compare the scores of three typical student groups - positive balanced, theoretically weak, and practice lagging - before and after intervention on seven core competency indicators, presenting the pre- and post intervention scores with error bars of assumed standard deviation, facilitating observation of individual differences within the group. It can be seen that the positive balanced group maintains a high level in all indicators, and after intervention, there is a slight improvement, indicating that their basic abilities are relatively stable; The theoretically weak group showed a significant improvement in theoretical indicators, and after intervention, they all approached the equilibrium level significantly. At the same time, practical indicators also improved to some extent; The practice lagging group showed significant improvement in skill indicators such as practical operation and simulated childbirth, and the overall performance after intervention was close to the group average level. Figure 4 emphasizes the differences and pertinence of intervention responses among different groups, providing quantifiable and visual evidence support for the effectiveness of teaching interventions. Overall, it can be seen that the intervention program has a significant effect on improving students' comprehensive theoretical and practical abilities, and has differentiated promotion effects on different characteristic groups.

V. CONCLUSION

This article constructs and validates a data-driven teaching intervention framework integrating K-means clustering, which resolves the core contradiction between fragmented learning behavior data and extensive teaching strategies in engineering and midwifery vocational programs focused on medical fiber application. By synthesizing multi-source data, the framework optimizes the precision of instructional interventions for advanced material processing and clinical midwifery skills. Based on 12 standardized features of 120 students in the dimensions of cognition, behavior, and practice, the optimal cluster number K=3 was determined by combining the elbow rule and contour coefficient. Three typical groups, namely "positive equilibrium type", "theoretical weakness type", and "practice lag type", were successfully identified, and their clustering structures were fully validated. On this basis, a mapping rule library of "clustering portrait intervention strategy" was established, and targeted teaching interventions were implemented. The experimental results show that students with weak theoretical knowledge have significantly improved their theoretical scores, while those with lagging practical skills have significantly improved their skill indicators. This validates the practical value of the framework in improving the accuracy of midwifery and engineering talent cultivation, providing reusable methodological support for data-empowered teaching reform in advanced fiber manufacturing and other high-precision vocational fields.

AUTHOR CONTRIBUTIONS

Conceptualization – Yan Sun, Na Han, Cui Liu, Yanqiang Bi, Lingchun Meng and Guohua Gao; methodology – Yan Sun, Na Han, Cui Liu, Yanqiang Bi, Lingchun Meng and Guohua Gao; investigation – Yan Sun, Na Han, Cui Liu, Yanqiang Bi, Lingchun Meng and Guohua Gao; writing-original draft preparation – Yan Sun, Na Han, Cui Liu, Yanqiang Bi, Lingchun Meng and Guohua Gao. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Laiwu Vocational and Technical College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

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