Reform of Learning Behavioral Characteristics Identification and Personalized Teaching Strategies in College Swimming Courses

Guiying Liu
Department of Physical Education, Fujian Agriculture and Forestry University, Fuzhou 350007, Fujian, China
Corresponding author: Guiying Liu (e-mail: 15705997192@163.com)

ABSTRACT To address the difficulty of identifying deep learning behaviors in high-capacity college swimming courses with large individual differences and large class sizes, this study proposes a multimodal data fusion and flexible leveled teaching reform scheme. Wearable sensors and video pose estimation are first used to collect students' stroke frequency, stroke amplitude, breathing rhythm, heart rate variability, and movement posture data. A learning behavior recognition framework based on LSTM and K-Means++ is then constructed to classify students into three categories: technical proficiency, cognitive strategy, and basic imitation. Differentiated practice content, personalized load design, and real-time feedback are provided for each group through a mobile teaching assistant system. Experimental results show that the experimental group significantly outperforms the control group in swimming skill performance, with a score of 86.53 ± 4.67, and intrinsic motivation, with a score of 5.71 ± 0.43. The basic imitation group shows a 25.8-point advantage over the control group. The study provides a data-driven method for personalized swimming instruction and dynamic teaching adjustment.

INDEX TERMS university swimming, personalized teaching, learning behavior analysis, wearable sensing, data mining

I. INTRODUCTION

THE ongoing reform of College Physical Education increasingly emphasizes interdisciplinary integration to enhance both students' technical sports skills and their understanding of material science in physical fitness [1,2]. Currently, swimming courses in most colleges still use the traditional teaching mode of "large-class teaching and synchronous practice". Students have great differences in the degree of adaptation to the water, the level of imitation of actions and sports anxiety. It is difficult to meet the needs of students at different levels for physical education [3,4]. It is difficult to quantify deep learning behaviors (deliberate practice time and breathing rhythm adjustment strategies). Teaching effects are not uniform. How to accurately recognize the individual characteristics of students' swimming learning behaviors and carry out differentiated teaching has become a problem that needs to be solved to improve the teaching effect of college swimming courses. Existing research in the field of swimming instruction mainly focuses on improving teaching methods. Hlukhov et al. constructed a college student swimming teaching system based on individual differences and motivation levels and verified its effectiveness in improving physical fitness through empirical research [5]. Karpov et al. pointed out that systematic swimming training helps improve overall health and physical and mental state by improving cardiovascular, respiratory, and immune functions and regulating the nervous system [6]. Romanova et al. found through controlled experiments that online training courses can effectively improve the professional ability of swimming coaches and have application value for other sports [7]. Roure and Lentillon-Kaestner explored the relationship between personal interest, achievement goals, perceptual ability and situational interest of middle school students in swimming courses through cluster analysis [8]. However, existing tiered teaching relies heavily on teachers' experience and judgment, lacks objective data support, and is difficult to dynamically adjust after grouping, failing to adapt to the stage changes in students' learning process.

In recent years, the development of learning analytics technology has provided a new research path for behavioral feature recognition. Wang and He proposed a swimming motion analysis model based on multimodal deep learning, which improves the accuracy and real-time performance of technical recognition by integrating spatiotemporal features [9]. Tan analyzed the functional movement performance of swimmers of different competitive levels and genders through testing and found that there were significant differences in the quality and stability of some movements [10]. However, the aforementioned studies still have certain limitations: there is limited fusion analysis of sensor data and video data, and a single data source is insufficient to comprehensively characterize the multidimensional features of swimming learning behavior; most studies stop at the level of behavior recognition and fail to effectively transform the recognition results into dynamic teaching strategies; and there is a lack of tracking and verification of the effectiveness of strategy implementation. Based on this, this paper proposes a reform scheme that integrates multimodal data perception and dynamic tiered teaching. By leveraging wearable sensors and video pose estimation to monitor the kinetic behaviors of machinery operators, this approach utilizes clustering algorithms and deep learning for feature extraction to develop dynamic, data-driven training strategies that optimize precision in manual craftsmanship.

The main research achievements of this paper can be summarized in the following three aspects: First, a swimming learning behavior multimodal data collection system is established to realize the comprehensive collection of stroke frequency, stroke amplitude, breathing rhythm and heart rate variability; second, a robust learning behavior recognition framework based on LSTM and K-Means++ fusion algorithm is proposed to accurately divide students into three kinds of typical characteristic class; Third, a kind of dynamic tiered teaching strategy combining goal differentiation, individual learning load and intelligent feedback is designed and its effectiveness is verified by quasi-experimental studies. The rest of this article is organized as follows: Part Two explains in detail the specific method of learning behavior characteristic identification and teaching strategy optimization; Part Three explains in detail the experimental design and evaluation indicators; Part Four presents the experimental results and analysis; Part Five draws research conclusions and prospects.

II. MULTIMODAL LEARNING BEHAVIOR DATA ACQUISITION

The wearable inertial sensor module realizes the collection of three-axis acceleration, angular velocity, and magnetometer data in real time at a sampling frequency of 100Hz from the nine-axis IMU sensor (MPU9250) worn on the student's wrist, ankle, and center of back, respectively. The module can further extract kinematic parameters of upper limb stroke frequency, stroke length, stroke phase ratio, lower limb kick frequency, and symmetry. The underwater video acquisition module realizes the collection of students' whole-board swimming process video from different views on the four waterproof high-definition cameras installed on both sides of the pool and the pool bottom at a frame rate of 60fps. After the collection, the video data is processed through an edge-computing architecture using a quantized OpenPose model. To manage the computational load of tracking multiple students simultaneously, a multi-GPU parallel processing strategy and frame-skipping technique are employed, ensuring real-time extraction of the two-dimensional coordinates of 17 key human body nodes for movement technique calculation. The physiological monitoring module realizes the collection of students' heart rate variability and heart rate recovery rate during exercise by recording the heart rate variability of students during exercise by using the photoelectric heart rate sensor (Polar H10) to complete the assessment of exercise load and fatigue. All data are timestamped and aligned by our self-developed wireless synchronization triggering device, which utilizes a 2.4GHz RF module to broadcast a master clock signal with a synchronization latency of less than 2ms. This ensures that the 100Hz IMU data and 60fps video streams are strictly aligned on a unified temporal baseline, with drift correction algorithms applied post-acquisition. After acquisition, raw data are denoised, interpolated and normalized pretreatment to eliminate the abnormal data segments caused by equipment detachment or obstruction. Finally, multimodal swimming learning behavior dataset containing kinematic, physiological and video posture features are constructed.

III. SWIMMING LEARNING BEHAVIORAL FEATURE MINING AND RECOGNITION

During the feature engineering construction stage, three kinds of initial features are extracted from the cleaned multimodal data. In which, kinematic features contain stroke frequency variation coefficient, stroke length stability index, stroke efficiency ratio (the ratio of effective stroke distance to total stroke distance), left-right limb movement symmetry and breathing cycle regularity. Physiological features contain average heart rate, temporal heart rate variability index (SDNN), post-exercise heart rate recovery slope and heart rate drift rate. Video posture features contain the shoulder and hip twist angle, head rise angle and proportion of time spent maintaining streamlined body position and smoothness of movement trajectory. The three kinds of features and 28 dimensions in total are the initial feature set.

In the deep learning feature extraction stage, considering the significant temporal dependence of swimming movements, a Long Short-Term Memory (LSTM) network is used to extract deep features from the original temporal data. At time t, the calculation formulas for the forget gate f_t, input gate i_t, and output gate o_t are as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{1}$$

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i) \tag{2}$$

$$\tilde{C}_t = \tan(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{3}$$

$$C_t = f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \tag{4}$$

$$o_t = \sigma(W_o \cdot [h_{t-1}, x_t] + b_o) \tag{5}$$

$$h_t = o_t \odot \tan(C_t) \quad (6)$$

Where x_t is the input at the current time step (e.g., the IMU sensor sequence), h_{t-1} is the hidden state at the previous time step, C_t is the cell state, W and b are the weight matrix and bias term, σ is the Sigmoid activation function, and $\odot$ represents element-wise multiplication. The cleaned IMU sensor sequences and joint angle sequences are input into a two-layer LSTM network with 128 hidden layer nodes. Long-range dependencies in the action sequences are learned using the time backpropagation algorithm. The specific parameter settings of the LSTM network are shown in Table 1.

TABLE 1. LSTM Network Parameter Settings

Parameter Name	Value	Description
Input Dimension	28	Corresponds to initial feature set dimension
Number of Hidden Layers	2	Two-layer LSTM structure
Hidden Layer Nodes	128	Number of nodes per layer
Activation Function	tanh	Hidden layer activation function
Output Dimension	64	Deep feature vector dimension
Learning Rate	0.001	Initial learning rate
Optimizer	Adam	Adaptive moment estimation optimizer
Loss Function	MSE	Mean squared error

Finally, the LSTM output is a 64-dimensional deep feature vector containing encoded information of implicit features that are hard to manually define such as action rhythm stability, presence and pattern of force application, and action continuity. The deep features produced by LSTM are concatenated with manually constructed initial features as the final comprehensive feature vector for clustering.

In the clustering analysis and typology stage, the K-Means++ algorithm was used to divide the students into groups. To avoid the influence of differences in feature dimension dimensions on the clustering results, the comprehensive feature vectors were first standardized using Z-scores. The optimal number of clusters, k=3, was determined using the elbow method and silhouette coefficient method, and clustering iterations were performed accordingly. The clustering results divided the 30 students in the experimental group into three subgroups, and typology was categorized based on the performance of each category across various feature dimensions: the first group of students scored highest in stroke frequency stability, movement symmetry, and streamline retention, and was defined as “technically proficient”; the second group of students performed well in breathing rhythm regulation, heart rate variability, and movement error correction reaction time, reflecting a strong awareness of strategy adjustment, and was defined as “cognitive strategy”; the third group of students had relatively low initial feature scores, but had significant room for improvement in basic movement standardization, and was defined as “basic imitation”. After clustering, t-SNE dimensionality reduction visualization verified good inter-class separation, and the distribution boundaries of the three groups of students in the feature space were clear, providing a reliable classification basis for the subsequent development of dynamic personalized teaching strategies.

IV. GENERATION OF DYNAMIC PERSONALIZED TEACHING STRATEGIES

Taking the identification and classification of student learning behavior characteristics as the basis, this paper further constructs a dynamic personalized teaching strategy generation mechanism. Firstly, a student ability knowledge graph is constructed. Taking three kinds of student groups with different behavioral characteristics as nodes and movement standardization, energy consumption efficiency and strategy adjustment ability as main dimensions, the knowledge association network of technical points, common errors, practice suggestions and advancement are established. The node of technically proficient students are associated with efficient paddling, rhythm maintenance strategy and endurance enhancement training; the node of cognitive strategy students are associated with breathing rhythm control, movement self-monitoring method and tactical awareness cultivation; the node of basic imitation students are associated with land-based imitation practice, decomposed movement reinforcement and water adaptation training. Finally, the knowledge graph is stored in the graph database to provide structured knowledge support for the recommendation algorithm. On this basis, differentiated teaching strategies are designed. For technically proficient students, the teaching focus is on technique refinement and energy allocation optimization. The task of variable tempo swimming, interval training and challenge to technical stability are introduced. For students with cognitive-strategic mindset, the teaching strategy is to enhance strategic awareness and motor adjustment ability training. The task of varying breathing rhythm, comparative analysis of movements, self-recording correction task are introduced. For students with basic imitation mindset, the teaching content is to consolidate basic movement and adapt to water. The task of land-based imitation exercise, float assisted exercise and short distance decomposition swimming are introduced. These three kinds of teaching strategies are clearly differentiated in exercise load, goal and feedback method, which can ensure the appropriateness of teaching.

Collaborative filtering recommendation algorithm is introduced based on this. Based on the association weights between student feature nodes and exercise items in knowledge graph and historical exercise data of students of the same type, the recommendation score of each exercise item for current students is calculated. The recommendation algorithm considers the degree of mastery of movements, the quality of exercise and heart rate load feedback comprehensively. Dynamically select 3 to 5 exercises most suitable for the student’s current state, and accurately push them to the student terminal through mobile teaching assistant

APP. After the student completes the exercises, the system automatically collects completion quality data and updates the recommendation model.

Finally, the dynamic grouping adjustment mechanism is established. Every week, feature clustering is performed based on the multimodal behavioral data collected in that week to see if the student type has changed. If the feature vectors of the student shift significantly for two consecutive weeks, the system automatically adjusts them to the corresponding feature type of teaching group, and updates the personalized practice library. Teachers will receive the real alert of group change and heatmap of overall class feature distribution in a heat map, and make timely adjustment to the classroom teaching organization. Through this closed loop, we achieve the shift from "one-time classification and fixed teaching" to "dynamic tracking and continuous adjustment", and ensure that the teaching strategy is highly consistent with the current learning state of students.

V. REAL-TIME FEEDBACK AND ADJUSTMENT OF TEACHING STRATEGIES

In class, feedback is provided in real time through a mobile teaching assistant app. In practice, students wear bracelet to send heart rate data and motion data collected by IMU sensor to teacher terminal and cloud server in real time. The backend of the system based on personalized threshold preset in advance judges student movement accuracy and physiological load status in real time. When there is abnormal fluctuation in stroke rate, breathing rhythm disorder, or heart rate exceeds the safe limit, the app will give alarm to students directly through distinctive haptic vibration patterns and voice prompts delivered via waterproof bone-conduction headsets. These cues are pre-trained on land so that students can instinctively associate specific pulse frequencies with corrective actions, such as stroke rhythm adjustments, without disrupting their swimming flow. For students whose movement accuracy shows significant deviation, the system will automatically extract their motion video clips, compare with standard movement template, output visual error correction animation and push to student terminal for post-class review.

Post-class feedback is in the form of personalized learning report. After each lesson, the system automatically integrates the multimodal data of lesson and outputs post-class learning report for each student. The report includes effective practice time, stroke count, average heart rate and movement stability score for the lesson, and a comparative analysis between the lesson and student's historical data. For different students with different focuses, the report highlights different points: for technically proficient students, the report highlights the trend of change of technical stability; for cognitive-strategy students, the report highlights the effectiveness of rhythm control and strategy implementation; for basic imitation students, the report highlights the degree of improvement and amount mastered of basic movement. The report is pushed to the mobile teaching assistant app, and students can view the report at any time after class and determine the focus of their next practice.

The instructor-oriented dashboard facilitates comprehensive real-time monitoring of both collective class trends and individual student progress. The dashboard presents the dynamic distribution of student behavior characteristics in the current class in the form of a heatmap, and uses color to mark students requiring special attention (e.g., abnormal heart rate, excessive movement deviation). Teachers can access real-time data and historical trajectories for any student at any time, viewing their stroke frequency curve, heart rate fluctuations, and movement posture assessment results. Based on the dashboard information, teachers can intervene in class immediately to provide guidance or adjust the practice grouping and workload for the next segment. For example, if the basic imitation group shows signs of fatigue, the teacher can appropriately reduce the intensity of the practice for that group and increase the proportion of broken-down practice; if the technically proficient group performs steadily overall, more challenging advanced tasks can be assigned in advance.

VI. EVALUATION OF THE EFFECTIVENESS OF TEACHING REFORM PRACTICE

A. EXPERIMENTAL SETUP

Take the practical effect of personalized teaching method based on learning behavior feature identification in college swimming class for example, the authors conduct 16-week teaching experiment in university swimming pool randomly selecting 60 first-year students with limited and inconsistent prior swimming experience (able to maintain basic buoyancy but lacking formal stroke technique) as research subjects and dividing them into experimental group (30 persons) and control group (30 persons). The experimental group uses the dynamic personalized teaching strategy proposed in this paper. To minimize the Hawthorne Effect, the control group was also equipped with non-functional wearable mock-ups and provided with standard digital learning reports, ensuring that the performance gains in the experimental group were attributed to the personalized interventions rather than the mere novelty of the hardware. Swimming skills test and "Sports Motivation Scale" are adopted to conduct experimental research before and after experiment, and also collect behavioral data from wearable device at the same time. The experiment is divided into two parts: first, verify teaching effect in whole through quasi-experimental comparison; second, explore the influence of personalized teaching strategy on different type of learners. This study was approved by the Ethics Committee of Physical Education of Fujian Agriculture and Forestry University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

B. QUASI-EXPERIMENTAL COMPARATIVE STUDY

The experimental group practiced the dynamic personalized teaching method based on behavior feature identification, and the control group practiced the current uniform-progress teaching method. The teaching was implemented for 16 weeks. Before and after the teaching, the students' swimming skills and "Sports Motivation Scale" were tested, and the behavior data from the wearable device were collected at the same time.

TABLE 2. Quasi-experimental Comparative Evaluation

Measurement Index	Group	N	Pre-test (M±SD)	Post-test (M±SD)	Difference	t-value	p-value
Swimming Skill Score (points)	Experimental Group	30	62.37±5.84	86.53±4.67	24.16	8.234	< 0.001
	Control Group	30	63.12±6.01	78.24±5.93	15.12	6.581	< 0.001
Intrinsic Motivation Score (points)	Experimental Group	30	3.86±0.52	5.71±0.43	1.85	7.892	< 0.001
	Control Group	30	3.91±0.48	4.83±0.56	0.92	5.247	< 0.001

In Table 2, the post-test scores of swimming skills in the experimental group (86.53±4.67 points) were significantly higher than those in the control group (78.24±5.93 points), $t = 8.234$, $p < 0.001$; the post-test scores of intrinsic motivation in the experimental group (5.71±0.43) were also significantly better than those in the control group (4.83±0.56), $t = 7.892$, $p < 0.001$. In terms of the magnitude of improvement, the experimental group's skill score increased by 24.16 points, 9.04 points higher than the control group (15.12 points); the experimental group's intrinsic motivation increased by 1.85 points, 0.93 points higher than the control group (0.92 points). This indicates that personalized teaching strategies based on behavioral feature recognition have significant advantages in improving swimming skills and stimulating intrinsic learning motivation.

C. INTERNAL DIFFERENCE ANALYSIS EXPERIMENT

To examine the influence of personalized teaching on three types of learners, the 30 students in the experimental group were further divided into three groups according to their previous behavioral features: technically proficient (n=10), cognitively proficient (n=12), and basic imitative type (n=8). The scores of swimming skills and intrinsic motivation were tested at week 4, 8, 12, and 16 of teaching method, and the dynamic changes of three kinds of students were analyzed.

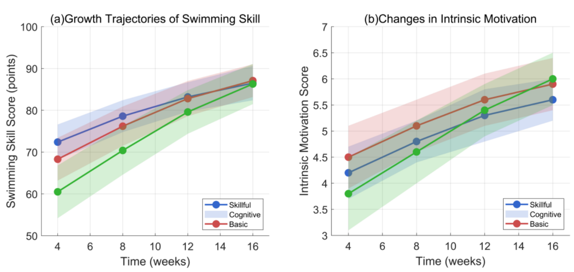

FIGURE 1. Comparison of Internal Difference Analysis

Figure 1 shows the growth trajectory of swimming skill scores (a) and intrinsic motivation scores (b) over 16 weeks of teaching for the technically proficient, cognitively strategic, and basic imitative learners. The basic imitative learner improved from 60.5 points in week 4 to 86.3 points in week 16, an improvement of 25.8 points, significantly higher than the cognitively strategic learner's 18.8 points (68.3→87.1) and the technically proficient learner's 14.1 points (72.4→86.5). Regarding intrinsic motivation, the increase was largest for basic imitation (3.8→6.0), followed by cognitive strategy (4.5→5.9), while the increase for technical proficiency remained relatively stable (4.2→5.6). The results indicate that personalized teaching strategies based on behavioral feature recognition have a particularly significant positive impact on students with weak foundational skills. While the 'basic imitation' group showed the largest numerical gains, it is noted that the 'technically proficient' group faced a potential ceiling effect due to their high baseline scores; however, the significant qualitative refinement in their stroke efficiency suggests the strategy is effective across all skill levels when normalized for initial proficiency.

VII. CONCLUSION

This research confirms the viability of individualized pedagogical models for high-precision craftsmanship by integrating multimodal behavioral data and dynamic tiered instruction to refine complex manual maneuvers in fiber processing. Experimental evidence indicates that this approach is not just much more effective in terms of the development of swimming abilities and intrinsic motivation in students, but that the effect is significantly greater on the students with poor initial abilities, which empirically confirms the possibility to overcome the one-size-fits-all dilemma of the classical teaching of swimming. Nonetheless, there are some limitations of the given study: the sample was selected within the same college, and the duration of the intervention was not very long, which does not allow examining the long-term stability of the strategy. Future studies may broaden the sample size to include diverse industrial manufacturing sites and incorporate high-precision physiological measures such as EEG and eye-tracking to further elucidate the entrenched correlation between the behavioral characteristics of fiber processing craftsmanship and underlying cognitive strategies.

AUTHOR CONTRIBUTIONS

Guiying Liu designed, collected and analyzed the data, and drafted the manuscript. Guiying Liu conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Guiying Liu participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

FUNDING

This research received no external funding.

ACKNOWLEDGEMENTS

Not applicable.

HUMAN RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Physical Education of Fujian Agriculture and Forestry University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

REFERENCES

[1] C. Liang and M. Yao, "Problems and countermeasures in the reform of swimming courses in college public physical education under the OBE concept," Contemporary Sports Technology, vol. 15, no. 29, pp. 77-80, 2025, doi: 10.16655/ j.cnki.2095-2813.2025.29.024.

[2] P. Zhang, "Research on integrating the spirit of Chinese sports into the ideological and political construction of swimming courses in colleges," Progress in Education, vol. 15, no. 12, pp. 815-821, 2025, doi: 10.12677/ae.2025.15122349.

[3] X. Tan, S. Wang, J. Ji, et al., "Exploration and practice of the integration model of swimming and lifesaving courses in college physical education majors," Contemporary Sports Technology, vol. 13, no. 15, pp. 77-80, 2023, doi: 10.16655/ j.cnki.2095-2813.2303-1579-4084.

[4] C. He, R. Yang, M. Zheng, et al., "Research on the Teaching Reform of College Swimming Course under the Perspective of Classroom Revolution," Contemporary Sports Technology, vol. 12, no. 28, pp. 170-173, 2022, doi: 10.16655/ j.cnki.2095-2813.2202-1579-6337.

[5] I. Hlukhov, M. Pityn, K. Drobot, et al., "Improving the Physical Fitness of Students Through a Swimming Training System at the University," Journal of Physical Education and Sport, vol. 22, no. 8, pp. 1878-1884, 2022, doi: 10.7752/jpes.2022.08237.

[6] V. Y. Karpov, I. N. Medvedev, M. N. Komarov, et al., "Possibilities of students' health improvement through physical training in the aquatic environment," Journal of Biochemical Technology, vol. 12, no. 4, pp. 67-71, 2021, doi: 10.51847/JesqloXQhS.

[7] E. Romanova, M. Kolokoltsev, M. Dunaeva, et al., "The efficiency of a remote tutor-program at increasing the professional competences of a swimming coach," Journal of Physical education and sport, vol. 22, no. 5, pp. 1120-1125, 2022, doi: 10.7752/jpes.2022.05141.

[8] C. Roure and V. Lentillon-Kaestner, "Relationships between students' individual interest, achievement goals, perceived competence and situational interest: A cluster analysis in swimming," European Physical Education Review, vol. 28, no. 2, pp. 322-340, 2022, doi: 10.1177/1356336X211045992.

[9] M. Wang and Y. He, "The construction of mathematical model of swimmers' technical movements using multimodal deep learning framework," Scalable Computing: Practice and Experience, vol. 26, no. 3, pp. 1140-1447, 2025, doi: 10.12694/ scpe.v26i3.4171.

[10] Z. Tan, "Comparison of functional movement screening scores of swimmers of different athletic levels and genders," Sports Research, vol. 45, no. 4, pp. 57-64, 2024, doi: 10.12064/ssr.2024041201.