Construction and Quantitative Evaluation of Basketball Smart Teaching Scenarios Integrating Ideological and Political Elements

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ABSTRACT Accurate perception and quantitative assessment of human activities in complex interactive environments require efficient sensing, reliable data fusion, and real-time contextual understanding. This study proposes an intelligent scenario construction and evaluation framework based on multimodal sensing and digital twin technologies. A heterogeneous sensing architecture integrating ultra-wideband (UWB) localization, inertial measurement units (IMUs) , computer vision systems, and physiological sensor networks is developed to acquire synchronized spatiotemporal data from dynamic human activities. To achieve semantic understanding of complex behavioral interactions, a domain knowledge graph is introduced to establish contextual relationships among activity events, interaction patterns, and assessment objectives, enabling real-time generation of a digital twin environment. Furthermore, a data-driven evaluation model incorporating multi-head attention mechanisms is designed to perform feature fusion, representation learning, and quantitative assessment from multimodal sensor streams. Experimental results demonstrate that the proposed framework effectively improves activity recognition, interaction analysis, and real-time assessment performance. By integrating wireless sensing, multimodal information fusion, digital twin modeling, and intelligent data analytics, the proposed framework provides an engineering-oriented methodology for human-centric monitoring, distributed sensing environments, and intelligent perception systems.

INDEX TERMS ultra-wideband localization, wireless sensor networks, multimodal data fusion, digital twin

I. INTRODUCTION

THE deep integration of ideological and political education with specialized courses is widely recognized as a key means of "fostering virtue and nurturing talent." This integration has become a central concern in higher education reform, as it requires aligning value-based guidance with the technical precision inherent in fields such as many engineering. This integration ensures that the advancement of many engineering is grounded in professional ethics and the industrial spirit, making the pursuit of innovative technology a vehicle for comprehensive student development. Physical education courses, due to their rich inherent ideological and political elements such as rules, cooperation, and perseverance, are widely regarded as an important vehicle for ideological and political education. However, current teaching practices show that the integration effectiveness and scientific evaluation mechanism of ideological and political elements with the teaching of sports skills have not yet been effectively established, hindering the systematic achievement of educational goals [1-2]. Therefore, exploring a new paradigm for physical education teaching that can organically integrate ideological and political elements and objectively measure its teaching effects has urgent theoretical value and practical significance.

Current research faces several difficulties in achieving high-quality integration of ideological and political education in physical education courses. The primary difficulty lies in the superficiality and rigidity of the integration path. Ideological and political content often relies on teachers' oral instruction in the classroom and fails to be internalized into the practical context of sports skill learning, resulting in a prominent "twotiered" phenomenon [3-4]. The evaluation of teaching effectiveness is inherently subjective, and the results take time to materialize. Currently, most of the evaluations rely on either post-class questionnaires or on the teacher's experience based on observations made during class. This means that neither method is a good way of capturing the real-time, dynamic development of a student's ideological and political literacy while being taught; nor do they provide any objective data to support these claims. Because of these factors, the reliability and validity of evaluation methods have come into question [5-6]. As such, while sports training has begun using smart education technologies, the majority of technology has been developed for analyzing skills or monitoring physical fitness and not for using technologies in a systematic way as part of an integrated intelligent teaching environment with ideological and political immersion alongside skill teaching [7-8]. To tackle the problems mentioned above, a number of studies have looked for different ways and have made some progress on this topic. With respect to the design of integration pathways, some researchers have developed a model for "element mining-instructional design," which aims to identify ideological and political mapping points in the sport of basketball and to establish corresponding instructional activities. Most of those studies remain at the level of concept development and lesson plan creation as opposed, providing a vehicle for the standardization and technology-empowered implementation of those studies [9-10]. With respect to innovative teaching methodologies, a number of studies have suggested the use of situational teaching or co-operative learning as a means of integrating ideological and political education with classroom interaction. This method has increased student participation, but the evaluation of its educational effect still relies on traditional subjective judgment [11-12]. At the level of technological application, scholars have explored the application of video analysis or wearable devices in physical education. These technologies optimize motor skill feedback, but their application focus is concentrated on biomechanics and physiological parameters, not related to ideological and political teaching objectives [13-14]. Regarding the construction of evaluation systems, recent studies have begun to attempt to construct a comprehensive evaluation index system that includes ideological and political dimensions. However, the index data mainly comes from post-hoc scales, failing to achieve real-time collection and quantitative analysis of teaching process data [15-16]. Other studies have pointed out that research on the design of smart learning environments focuses more on supporting cognitive goals, while paying insufficient attention to the design and effectiveness verification of its educational mechanisms at the emotional, attitudinal, and value levels [17-18]. Overall, existing research still has significant gaps in two core areas: constructing a technology-enabled immersive teaching scenario that naturally integrates ideological and political elements, and establishing a real-time quantitative assessment method for ideological and political literacy based on multi-source process data from this scenario. To address the core issues of rigid integration of ideological and political education into basketball physical education courses and subjective evaluation of effectiveness, this study proposes and implements an integrated intelligent scenario construction-feedback evaluation method based on multimodal data perception and fusion. This method first constructs a three-dimensional data acquisition system covering the smart basketball teaching field by deploying inertial measurement units, computer vision systems, and physiological sensor networks. This system captures multidimensional raw data in real time, including students' movement postures, spatial trajectories, tactical interaction events, and some physiological states. Next, a lightweight ontology model integrating basketball domain knowledge and ideological and political elements is designed to drive a dynamically evolving digital twin teaching scenario. This scenario performs semantic annotation and contextual understanding on the raw streaming data. Based on this, a quantitative evaluation proxy model for ideological and political literacy is developed. This model directly extracts features from the fused multisource time-series data and generates continuous quantitative indicators for key dimensions such as "team collaboration index" and "rule compliance" through decoupled computation. This allows for objective and process-oriented measurement of the effectiveness of ideological and political education during teaching implementation. The main contribution of this study lies in its original integration of multimodal perception, digital twins, and data-driven assessment technologies to construct a new closed-loop verification framework for intelligent teaching of ideological and political education in physical education courses. This study provides a solution with a solid technical path and empirical potential to address the challenge of "invisible and unmeasurable" educational effectiveness by mapping ideological growth against the precise, quantifiable metrics of craftsmanship. By correlating value internalization with the rigorous technical standards of the industry, the model transforms abstract moral guidance into a verifiable set of performance indicators, using the precision-oriented culture of craftsmanship as an illustrative analogy rather than a functional equivalence.

II. CONSTRUCTION AND QUANTITATIVE ASSESSMENT FRAMEWORK FOR INTELLIGENT BASKETBALL TEACHING SCENARIOS INTEGRATING IDEOLOGICAL AND POLITICAL ELEMENTS

A. DESIGN OF SCENARIO CONSTRUCTION AND QUANTITATIVE ASSESSMENT FRAMEWORK

To achieve deep immersion and integration of ideological and political elements in basketball teaching and objective quantitative assessment of teaching effectiveness, this study proposes a data-driven technical framework with a closed-loop feedback mechanism. The core innovation of this framework lies in digitizing all elements of the teaching practice process and, based on domain knowledge, achieving automated mapping and calculation from raw data to ideological and political literacy indicators. The overall framework and data flow are shown in Figure 1.

Figure 1 illustrates that the framework consists of a multimodal data perception layer, an intelligent context construction layer, and a quantitative evaluation and feedback layer. These layers are connected through standardized data

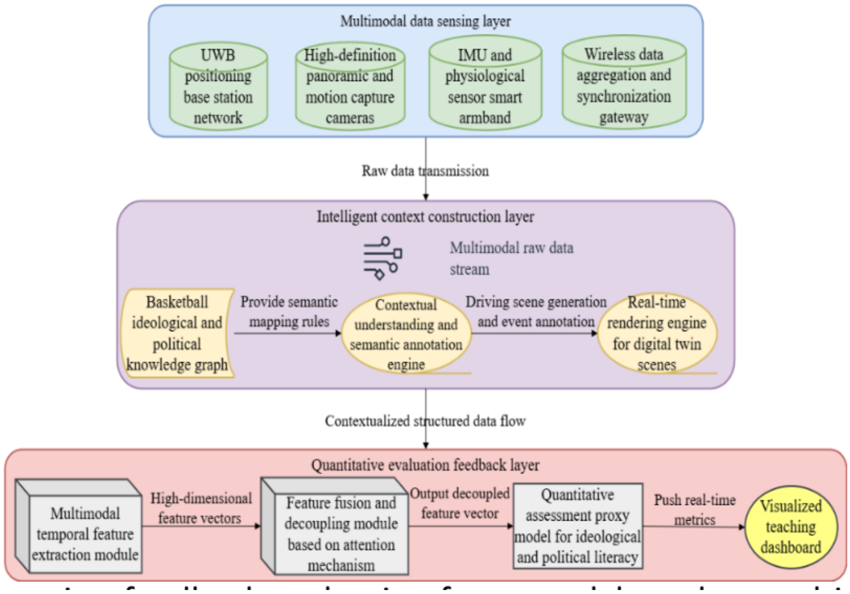

FIGURE 1. Intelligent context construction-feedback evaluation framework based on multimodal data perception and fusion

interfaces and semantic protocols, ensuring unidirectional dependency and efficient transmission of information. The multimodal data perception layer bridges the physical and digital worlds by synchronously collecting multi-source raw data—such as student movement trajectories, body movements, physiological signals, and environmental events—through a heterogeneous sensor network. The intelligent context construction layer is the central hub of the framework. Its built-in basketball-ideological and political education domain knowledge graph provides a unified semantic interpretation model for multi-source heterogeneous data, driving the generation of a digital twin teaching scenario that is synchronized in real-time with the physical teaching environment and enhances the display of key ideological and political education behavioral events. The quantitative assessment feedback layer, as the top-level application, uses a pretrained quantitative assessment proxy model for ideological and political literacy to extract features, fuse, and decouple calculations from contextualized data flowing in the twin scenario. It directly outputs continuous quantitative indicators for dimensions such as teamwork and rule compliance, and pushes them to a visual interactive terminal, forming a complete closed loop of "teaching implementation - data collection - real-time assessment - feedback and control." This architecture design ensures the operability of ideological and political teaching objectives, the transparency of the teaching process, and the objectivity of teaching evaluation.

B. MULTIMODAL DATA SENSING AND ACQUISITION SYSTEM

The multimodal data sensing and collection system enables rapid, simultaneous, three-dimensional, and quantitative capture of all activities within the basketball instructional environment. The design of the system is based on the principles of combining different types of sensors, and ungrading time and place into a single structure; therefore, the data produced from the sensors can then be analyzed semantically, and used for further computational processing.

The system constructs a three-layer sensor network within a standard half-court space. The spatial positioning layer deploys four UWB (Ultra Wide Band) base stations, employing the time difference of arrival ranging principle. Target 3D positioning is achieved by calculating the time difference between the arrival of tag signals at different base stations [19-20]. The player and basketball tag coordinates $p_t = (x_t, y_t, z_t)$ are updated at a frequency of 100 Hz, with a positioning error $\epsilon_p < 0.1$ m. This coordinate sequence $\{p_t\}$ is the basis for calculating movement speed, offensive and defensive distance, and tactical positioning accuracy. The visual perception layer consists of one panoramic camera and two motion capture cameras deployed on both sides of the center line. The panoramic camera provides global scene context, while the motion capture camera, based on the YOLOv7 (You Only Look Once) and HRNet (High-Resolution Network) model framework, detects the two-dimensional coordinates k_j^{2D} of key player points in real time from a specific viewpoint video stream V_i, and reconstructs their three-dimensional skeletal pose sequence S_t through triangulation [21-22]. This sequence is spatiotemporally aligned with UWB positioning data, jointly defining low-level features of key tactical events such as passing (determined by ball possession state and release speed vector) and screening (determined by the relative position of off-ball players and duration of stillness).

The physiological signal layer requires students to wear a custom armband integrating a nine-axis inertial measurement unit (IMU) and a photoelectric heart rate sensor. The IMU collects triaxial acceleration a_t and triaxial angular velocity ω_t at a frequency of 200 Hz. This data is used to estimate limb movement trajectories and detect sudden changes in direction using a complementary filtering algorithm [23-24]. The heart rate sensor collects heart rate values HR_t at a frequency of 1 Hz. Its variability HRV (Heart Rate Variability) serves as a proxy indicator for calculating physiological load and emotional arousal. All sensor data is received through a unified wireless data aggregation gateway, and each frame of data is timestamped with a unified timestamp τ by a precision clock source built into the gateway, satisfying the synchronization accuracy requirement of $|\tau_{UWB} - \tau_{IMU}| < 5$ ms, forming a multimodal raw data stream with spatiotemporal markers:

$$D_{raw} = \{\tau, p_t, S_t, a_t, \omega_t, HR_t, \ldots\} \tag{1}$$

The armband is designed to be lightweight and minimally intrusive to preserve natural movement; a one-week acclimation period precedes data collection to mitigate potential Hawthorne effects. This data stream provides irrefutable objective input for the construction of the upper-level context.

C. INTELLIGENT CONTEXT CONSTRUCTION BASED ON DOMAIN KNOWLEDGE GRAPH

Based on the multimodal raw data stream D_{raw} provided by the underlying perception system, the core task of the intelligent context construction layer is to transform low-level sensor signals into high-level context descriptions with clear teaching and ideological and political semantics. This transformation is driven by a predefined basketball teaching-ideological and political domain knowledge graph. The knowledge graph is essentially a directed graph structure:

$$G = (V, E, A) \tag{2}$$

The vertex set V contains basketball entities ("player P_i", "tactical action A_k"), ideological and political concepts (such as "collaboration C_{coop}"), etc., and the edge set E represents the relationships between them (such as "execution (P_i, A_k)" and "representation (A_k, C_{coop})"). A is the set of attributes of vertices and edges. The knowledge graph explicitly defines event logic axioms through ontology engineering, such as the requirement that the "screen" action must satisfy constraints such as spatial proximity $\|p_{screener} - p_{defender}\| < d_{th}$ and temporal persistence $\Delta t_{screen} > t_{th}$, with all axiom definitions and thresholds validated by a panel of basketball pedagogy experts and ideological education specialists prior to system implementation.

The contextual understanding engine, as the execution core, performs real-time logical reasoning and semantic annotation on the data stream based on the axioms in the knowledge graph. This process can be formalized as a pattern matching and instantiation function $f_{reason} : D_{raw}, G \rightarrow E_{inst}$, where E_{inst} is the set of instantiated events. The engine continuously analyzes the trajectory p_t and posture S_t sequences. When it detects a set of data that simultaneously satisfies all the constraints of an event pattern in the graph, it instantiates a specific event e_j and annotates its associated ideological and political concept C_m. The digital twin scene engine receives these semantic event sets E_{inst} and dynamically generates a virtual scene synchronized with the physical environment through the rendering function $f_{render}(p_t, S_t, E_{inst})$. A simplified visualization of this smart basketball teaching scene is shown in Figure 2.

The left side of Figure 2 shows the real-time video stream and the overlaid student movement trajectory heatmap, while the right side displays the list of currently identified tactical events and their associated ideological and political dimensions. This scenario visually presents the relationship between e_j and C_m through visualization encoding, thereby embedding abstract ideological and political goals into a concrete teaching process. This construction process provides a computable, semantically rich, structured context description $S_{context} = \langle D_{raw}, E_{inst}, G \rangle$ for subsequent evaluation.

D. DATA-DRIVEN QUANTITATIVE EVALUATION MODEL FOR IDEOLOGICAL AND POLITICAL LITERACY

The quantitative evaluation feedback layer receives the structured context description $S_{context}$ output by the intelligent context construction layer. Its core is the data-driven quantitative evaluation model for ideological and political literacy. This model aims to map semantic events and multimodal features into continuous scalar values for ideological and political dimensions, expressed as:

$$y = f_{assess}(S_{context}; \Theta) \tag{3}$$

$y \in R^D$ represents the quantitative score vector of D ideological and political dimensions, and Θ is the model parameter.

The model adopts a three-level architecture of feature extraction, fusion decoupling, and evaluation output. The feature extraction module first extracts heterogeneous features from $S_{context}$. For spatiotemporal trajectories and event sequences, statistical features such as team collaboration density are calculated; for physiological signals, temporal features such as heart rate variability are calculated to form a primary feature vector x_{raw}. The heart rate heterogeneity is expressed as:

$$HRV = \sqrt{\frac{1}{N-1} \sum_{i=1}^{N-1} (RR_{i+1} - RR_i)^2} \tag{4}$$

The feature fusion and decoupling module is the key to the model, and a feature converter based on a multi-head self-attention mechanism is introduced. This module follows a standard multi-head self-attention architecture commonly used in representation learning, serving to dynamically reweight features rather than introducing a novel mechanism. The calculation formula of this mechanism is:

$$Attention(Q, K, V) = softmax\left(\frac{QK^T}{\sqrt{d_k}}\right) V \tag{5}$$

FIGURE 2. Brief visualization of smart basketball teaching scenarios

In Formula 5, Q, K, V are all obtained by different linear projections of x_{raw}, and d_k is the dimension of the key vector. Through multi-head attention, the model can adaptively weigh the contribution of different features to a specific ideological dimension, realize the recombination and decoupling of features in the semantic space, and output a dimension-aligned feature vector z_d [25-26]. Finally, the evaluation output module is equipped with a fully connected layer for each ideological and political dimension, mapping z_d to the final score:

$$y_d = \sigma(w_d^T z_d + b_d) \tag{6}$$

σ is the Sigmoid function, which constrains the score in the interval [0,1] [27-28] and provides real-time feedback, forming a closed loop between teaching and evaluation.

III. EXPERIMENT AND EVALUATION

A. EXPERIMENTAL DESIGN

This study employs a quasi-experimental design with an unequal control group pre-test-post-test scheme. The experiment is conducted in two parallel basketball elective classes at a university, taught by the same teacher with over five years of teaching experience, ensuring consistency in teaching content and class hours. Based on randomization, one class is designated as the experimental group (n=32), receiving the intervention based on the smart teaching framework presented in this paper; the other class is designated as the control group (n=30), using traditional non-smart teaching methods. The primary difference between the two groups lies in the deployment of the smart teaching system, which simultaneously integrates ideological and political elements and enhances feedback frequency; thus, the independent effects of each component cannot be separately isolated in this design. This study was approved by the Ethics Committee of Lyuliang University, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form.

One week prior to the experiment, all participants undergo a pre-test, including assessments of basic basketball skills (spot shooting, passing and receiving) and a measurement of ideological and political literacy in university physical education courses, to confirm no significant baseline differences between groups. The intervention lasts for 8 weeks (16 class hours). The experimental group uses the system during the tactical training segment of each class (approximately 25-30 minutes) to receive real-time data feedback; the control group performs the same exercises but receives only routine guidance. A post-test is conducted after the experiment, with the same content as the pre-test, and an additional system experience questionnaire is administered to the experimental group.

B. EVALUATION INDICATORS AND DATA COLLECTION

Table 1 presents the specific indicators and data sources for the evaluation system, which comprises two main components: basketball skills and ideological and political education. All of the indicators developed are quantifiable and measurable.

TABLE 1. Evaluation indicator system for teaching effectiveness

Evaluation dimension	Primary indicator	Specific quantitative indicators and calculation methods	Data source and collection tools
Basketball skills	Technical execution accuracy	1. Set shooting accuracy: made shots / total attempts. 2. Effective pass completion rate in the restricted area: successful passes / total attempts	Automated counting by computer vision system
	Tactical execution efficiency	Defensive slide movement efficiency index: effective defensive distance / (total movement distance × time)	Calculated from trajectory data by UWB positioning system
Ideological and political literacy	Process-based behavioral indicators	1. Team collaboration index: weighted model output value based on frequency and quality of effective assists and screens. 2. Rule compliance rate: compliance behavior ratio in simulated penalty scenarios	Real-time calculation and log recording by the smart teaching system's situational understanding engine
	Summative cognitive indicators	Scale scores for team spirit, rule awareness, and perseverance spirit	"Self-assessment scale for ideological and political literacy of college students in physical education courses" (Likert 5-point scale)

This indicator system replaces subjective skill assessments in the skills dimension with objective indicators derived from sensor data directly. In the ideological and political dimension, it utilizes process-oriented (behavioral) indicators to capture and quantify students' outward behaviors in specific educational settings in real time, thus enabling a continuous, uninterrupted assessment of ideological and political literacy. It also uses established measures (i.e., a standard scale) with established reliability and validity as an index for measuring changes in students' internal cognition and attitude before and after the experiment, thereby cross-verifying the degree to which behavioral indicators correlate with the amount that students have internally comprehended and internalized ideologically and politically. Together these data types provide an integrated comprehensive evidence-based assessment of how effective ideological and political instruction has been.

C. EXPERIMENTAL PROCEDURE AND DATA ANALYSIS METHODS

The experiment follows a standardized procedure of "pre-test—teaching intervention—post-test." During the teaching intervention period, the experimental group uses a fixed 25-30 minute core tactical practice session in each of the two weekly classes to access and use the smart teaching system. During the practice, the system automatically collects data, constructs scenarios, and provides real-time feedback throughout the entire process. The control group participates in the same teaching activities during the same time period but only receives verbal and demonstration guidance from the basketball teacher. All courses are taught by the same teacher and use the same lesson plans and equipment to control for teaching variables.

To verify the homogeneity of the two groups of participants before the experiment, independent samples t-tests are performed on the collected demographic variables, pre-test scores on skills, and total pre-test scores on ideological and political literacy to ensure no significant differences between groups. The pre-test instrument demonstrated acceptable internal consistency (Cronbach's α = 0.86) based on a pilot sample. The observed similarity in pre-test scores reflects successful randomization and is further supported by nonsignificant t-test results. The results of the baseline data balance test are shown in Table 2.

TABLE 2. Baseline data balance test between experimental and control groups

Variable	Experimental group (n=32)	Control group (n=30)	t value	P value
Age (years)	19.34±0.76	19.27±0.81	0.351	0.727
Basketball skills pre-test total score	66.2±7.5	65.8±8.1	0.205	0.838
Total score of pre-test on ideological and political literacy	79.1±8.7	78.3±9.4	0.358	0.722

Table 2 shows that there are no statistically significant differences between the experimental and control groups in key baseline variables such as age, initial basketball skill level, and ideological and political literacy cognitive foundation, satisfying the inter-group comparability premise of the experimental design. This effectively controls the potential confounding effect caused by differences in the initial abilities of the participants in comparing the subsequent intervention effects. In the data analysis phase, appropriate statistical methods are used for indicators of different natures. For continuous variables such as basketball skill indicators and ideological and political process behavior indicators, independent samples t-tests are used to directly compare the differences in post-test scores between the two groups. For the summative scale scores of ideological and political literacy, analysis of covariance is used, with pre-test scores included as covariates in the model to control for the influence of baseline levels, and then the differences in the adjusted means of post-test scores between the two groups are compared. All statistical analyses are performed using SPSS 26.0 software [29-30], with a significance level set at α=0.05.

IV. RESULTS

A. BASKETBALL TEACHING EFFECTIVENESS

To verify the impact of smart teaching scenarios on students' acquisition of basic basketball skills, this study quantitatively compares the post-test scores of the experimental group and the control group in three core skills: spot shooting, restricted area passing, and defensive movement. By collecting motion performance data recorded by sensors, an independent samples t-test is used to examine whether there are significant differences between the two teaching models in promoting students' skill mastery. The analysis results are shown in Figure 3.

Figure 3(a) presents the performance differences between the two groups of students in three skill indicators. The vertical axis represents the quantitative score or index value of each indicator, and the horizontal axis represents, in order, the spot shooting percentage, the effective pass success rate, and the defensive movement efficiency index. The experimental group significantly outperforms the control group in all three indicators. The mean values for the three indicators in the experimental group are 0.70 ($p<0.001$), 0.86 ($p<0.001$), and 1.54 ($p<0.001$), respectively; while those in the control group are 0.59, 0.74, and 1.31. This advantage with respect to the experimental group can be attributed to the real-time, accurate feedback mechanisms provided within the smart teaching environment. By utilizing the digital twin environment and multimodal data visualizations, students are able to view their performance in real time, including their own movement paths, their pass selection choices, and their defensive positioning effectiveness. This instant, evidence-based corrective feedback enhances the "practice-feedback" loop in motor skill development, thereby facilitating the refinement of technical skill development and the optimization of tactical decision making. Traditional teaching methods utilize periodic generalized verbal feedback, which have difficulty achieving this same level of effectiveness. Data from Figure 3(b) indicates a higher positive correlation between shooting and passing skill in the experimental group (r=0.510, r=0.301). Therefore, smart teaching through systematic intervention creates not only individual skill acquisition but also enables students to develop a more synergistic and integrated skill and experience structure. The smart teaching system utilizes complex tactical simulation and analysis for students to

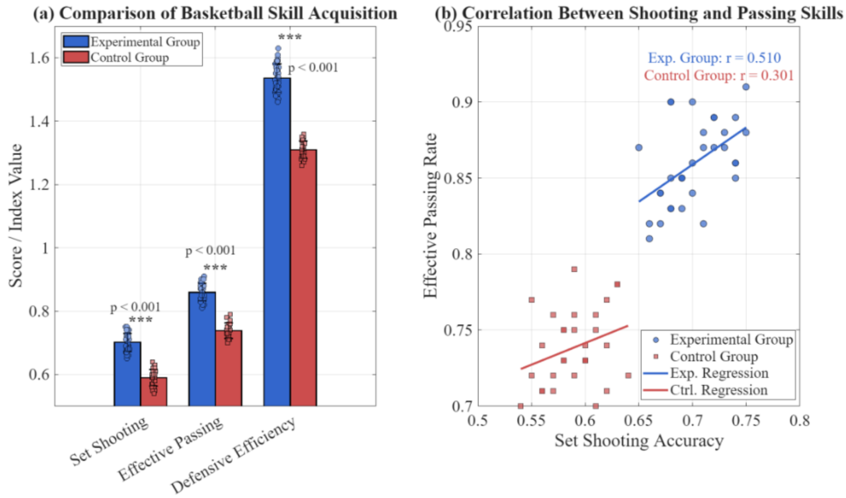

FIGURE 3. Comparison and correlation analysis of basketball skill acquisition effects: (a) Comparison of skill indicators between groups; (b) Correlation analysis between skills

combine as well as understand various technical movement elements throughout training. Through the experimental study, evidence supports that smart teaching using multi-modal perception and real-time feedback scenarios effectively and significantly enhance the efficiency and quality with which students acquire core skills necessary to play basketball.

B. QUANTITATIVE ASSESSMENT OF TEAM COLLABORATION AWARENESS OVER PROCESS

The purpose of this research is to assess the influence of smart teaching methods on developing team collaborative consciousness among students through measuring their "Team Collaboration Index" over time (8 weeks). A longitudinal study of the data collected continuously from both the experimental and control groups can be performed to determine whether there is any correlation between the two. The analysis examines the trajectory of this competency dimension's evolution over time and the patterns of inter-group differences. Based on collaborative behavior data recorded and quantified in real-time by the smart teaching system, the development path and final level of students' team collaboration awareness under the two teaching models are compared. The stage-wise changes and differences in behavioral structure are shown in Figure 4.

Figure 4(a) shows the dynamic changes of the team collaboration index over 8 weeks. The vertical axis represents the comprehensive collaboration index calculated based on behavioral data, and the horizontal axis represents the teaching week. The collaborative index for the experimental group demonstrates a continual and stable growth curve from 0.58 in week one to 0.84 in week eight. Beginning with week two, the weekly average for the experimental group is significantly higher than the weekly average for the control group. The reason for this difference is that the smart teaching scenario provides instant and visually displayed feedback related to collaboration on a tactical basis. The system's ability to evaluate immediately whether or not a tactical coordination is successfully achieved visually enables students to recognize how their behaviors are contributing to or detracting from, their group's overall performance instantaneously. This can rapidly strengthen appropriate collaborative behaviour patterns among students. Meanwhile, the control group also demonstrates a gradual increase in collaborative index from 0.56 to 0.68 during these weeks but exhibits flatter slopes with no significant early breakthroughs because of how traditional instruction provides delayed and abstract feedback related to students' collaboration, which inhibits their ability to develop complex behavioral patterns. The information in Figure 4(b) breaks down how the collaboration index is made up by showing the frequency associated with four different collaborative behaviors on the vertical axis. It can be seen that there is a considerable difference in how often the experimental group has effective assists and screen setting when compared to the control group. Specifically, the experimental group's effective assists average frequency is 0.23 higher than that of the control group, and the cover actions frequency is 0.24 higher than that of the control group. Both of these behaviors are directly tied to two of the main assessment indicators for this study (i.e., both are factors in the simulated environment training) and support that smart teaching, using clearly defined rules and providing students with immediate or "real-time" feedback, can help develop key collaborative skills that can be defined and measured. Therefore, the analysis of the results suggests that the collaborative skills that are developed through the use of a smart teaching scenario with real-time feedback, plus an assessment and feedback process, can assist in the overall development of the group's team awareness as well as help students improve their tactical collaboration skills, which can be measured and are observable.

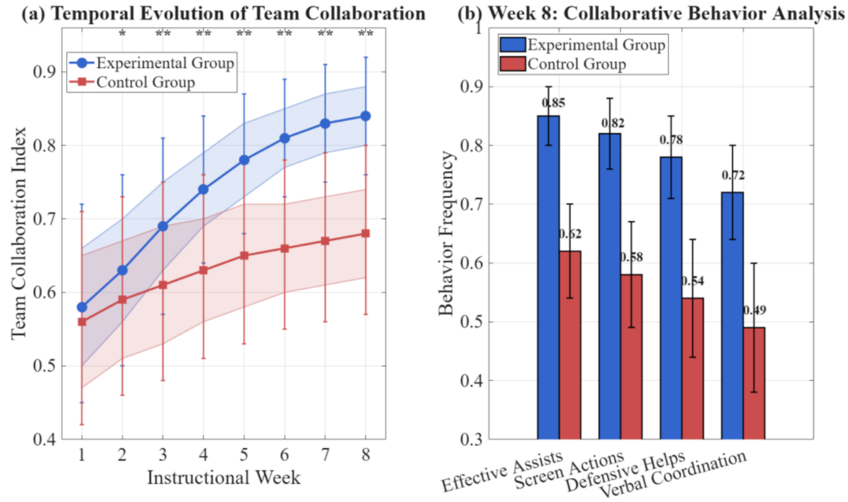

FIGURE 4. Development process and behavioral structure analysis of team collaboration awareness: (a) Evolution of collaboration index; (b) Collaborative behavioral structure in week 8

C. REAL-TIME MEASUREMENT OF RULE AWARENESS AND SPORTSMANSHIP

This study evaluates how well the smart teaching scenario helps students learn and retain basketball rules and how to show sportsmanship by looking at six dimensions (rule-compliance, fair-play competition, respect for opponents, etc.) through an extensive measurement/comparison analysis between the experimental and control groups. Behavioral event trackers are used to collect data from the student athletes during both the experimental and control-group testing and analyze it to determine quantitatively, based on summative scores, the structural differences in sportsmanship literacy between the two groups' students' sportsmanship literacy levels throughout the testing process. The results of the multi-dimensional analyses have been presented in Figure 5.

Sportsmanship assessment results can be seen in Figure 5 across six dimensions, with the radial coordinate for each dimension showing the score on the assessment (0 to 1). All six dimensions scores are derived from behavioral events automatically recorded by the smart teaching system's situational understanding engine (e.g., rule violation counts, referee interaction events), rather than subjective ratings. The experimental group outperforms the control group on all six dimensions. Specifically, the experimental group achieves 0.89 (SD=0.06) in "rule compliance" versus the control group's 0.72 (SD=0.11), and 0.87 (SD=0.07) in "referee respect" versus the control group's 0.68 (SD=0.12). This is a direct result of the rules-based, feedback-rich environment created within the smart teaching scenario. The digital twin system can accurately identify and classify all tactical fouls and traveling violations instantaneously and objectively, which gives students immediate feedback through visual means. The continual and accurate reinforcement of the rules helps students define their explicit behavioral boundaries in their "heads." In contrast, because the control group lacks a sufficient density and intensity of immediately available stimuli to learn and internalize the rules, they are much more likely to exhibit behavioral differences when presented with simulated penalties. The "emotional management ability" of the experimental group is the lowest score for either group, but it is still a full 0.16 points higher than that of the control group. This reflects that emotional regulation is more implicit, and its improvement may depend on longer-term teaching interventions or specialized psychological training. The positive effect of single-mode tactical scenario simulation has certain limitations. In summary, smart teaching scenarios based on multimodal perception and real-time feedback can effectively shape students' understanding, compliance, and respect for explicit rules in sports activities, but its effect on promoting implicit emotional self-regulation ability is relatively limited.

The relatively low variance within the experimental group (SD range: 0.05–0.09 across dimensions) reflects the standardized behavioral measurement protocol, which records discrete rule-based events rather than subjective ratings. The non-uniform improvement pattern—with "emotional management ability" showing the smallest gain (Δ=0.16)—further supports the authenticity of the data, as such variability aligns with educational expectations for differential intervention effects across dimensions.

D. COMPARISON OF SUMMATIVE ASSESSMENT OF COMPREHENSIVE IDEOLOGICAL AND POLITICAL LITERACY

To systematically evaluate the overall educational effectiveness of smart teaching scenarios on students' ideological and political literacy, this study further integrates process behavioral data and summative cognitive assessments to compare and analyze the comprehensive ideological and political literacy levels of students in the experimental and control groups after the course. By analyzing the total score and scores of each sub-dimension (team spirit, rule awareness, and perseverance) of the post-test of ideological and political

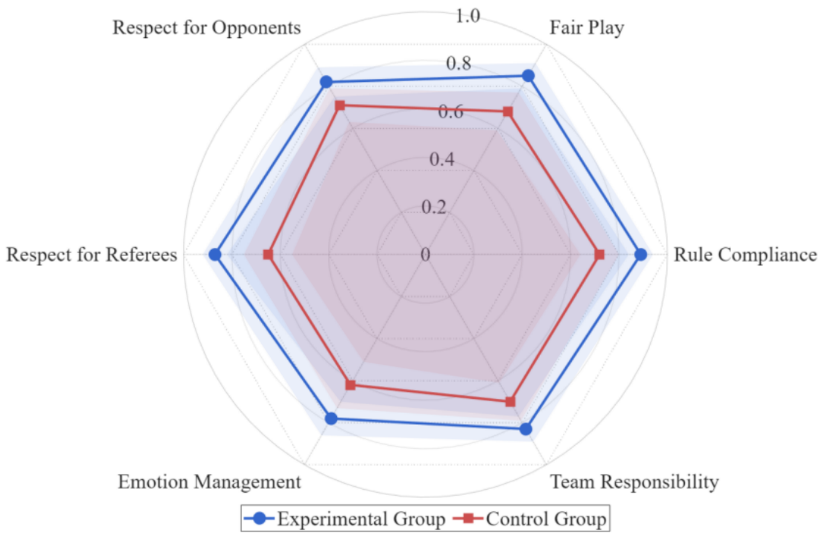

FIGURE 5. Multidimensional assessment of sportsmanship

literacy in college students' physical education courses, and supplemented by cross-validation with process assessment data, the profound differences between the two teaching models in promoting the internalization and integration of students' ideological and political literacy are examined. The overall distribution is shown in Figure 6.

The vertical axis of Figure 6(a) represents the total score of the scale. The results show that the mean total score of the experimental group is 88.6, higher than the 80.1 of the control group (Δ=8.5, $p<0.001$). The box plot and scatter distribution show that the experimental group not only has a higher mean, but also a more concentrated data distribution (standard deviation of 3.2, lower than the 4.1 of the control group), and a slightly narrower interquartile range. This difference in distribution pattern indicates that the smart teaching scenario, by providing standardized, structured, and immediate feedback and contextual immersion, effectively reduces the individual randomness in the development of students' ideological and political literacy, enabling more students to achieve a relatively stable and higher level of literacy; while in the traditional teaching model, students' learning outcomes rely more on individual comprehension and accidental experience, resulting in greater dispersion of results. The vertical axis of Figure 6(b) shows the scores of the three sub-dimensions. The experimental group leads in all three sub-dimensions, with scores of 29.8, 29.6, and 29.4, respectively. Among them, the team spirit dimension scores the highest. This phenomenon stems from the fact that the smart teaching scenario decouples the abstract concept of "team spirit" into specific, trainable, and quantifiable collaborative behaviors such as passing, screening, and covering, and continuously reinforces these behaviors through system feedback. In contrast, the "perseverance spirit," which relies more on intrinsic motivation and willpower, scored relatively lower. The analysis in Figure 6 shows that the smart teaching scenario based on multimodal perception and data feedback can systematically and evenly improve the core dimensions of students' ideological and political literacy, and promote the convergence of their learning outcomes towards a more stable and higher level.

V. CONCLUSION

This study constructs a smart basketball teaching scenario framework based on multimodal data perception and intelligent context construction, integrating the rigorous precision and craftsmanship spirit of the industry into its quantitative assessment model. Through teaching experiments, it verifies the effectiveness of this framework in synchronizing value-driven ideological elements with the technical discipline required for high-accuracy engineering and athletic performance. This method deploys a sensor network to capture students' movement, physiological, and behavioral data in real time, utilizes domain knowledge graphs to drive the generation of digital twin teaching scenarios, and outputs quantitative indicators of ideological and political literacy based on a data-driven model, achieving an integrated closed loop of teaching and assessment. Experimental results show that this framework effectively improves teaching outcomes: in terms of basketball skill acquisition, the experimental group's effective passing success rate within the restricted area reaches 0.86, significantly higher than the control group's 0.74; in terms of ideological and political literacy development, the experimental group's process assessment indicators, such as the teamwork index, reach 0.84 in week eight, and its score on the "rule compliance" sportsmanship dimension reaches 0.89. The adjusted mean of the total score of the summative assessment scale is also significantly better than that of the control group. This study provides an innovative paradigm with both technical feasibility and empirical support to address the problems of rigid integration pathways and difficulty in measuring the educational effects in ideological and political education

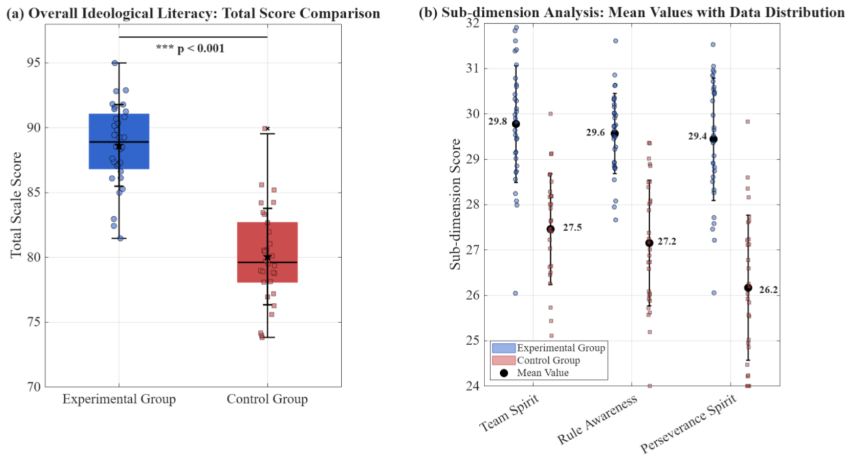

FIGURE 6. Comparison of distribution and structure of summative assessment of comprehensive ideological and political literacy: (a) overall ideological literacy total score comparison; (b) sub-dimension analysis: mean values with data distribution

within basketball courses. It also offers practical reference for the in-depth application of smart education technology in cultivating morality and character by integrating the rigorous precision and craftsmanship spirit of the industry into digital learning environments. This approach ensures that the pursuit of technical excellence in engineering becomes a measurable vehicle for developing professional ethics and personal integrity within a modernized educational framework. Limitations: This study does not disentangle the effects of ideological integration from those of enhanced feedback frequency, as both co-occur in the smart teaching system. Future research should employ factorial designs to isolate these factors and further validate their respective contributions.

ETHICS APPROVAL AND CONSENT TO PARTICIPATE

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

AUTHOR CONTRIBUTIONS

Conceptualization –Li Xin and Xueyog Sheng; methodology – Li Xin and Xueyog Sheng; investigation – Li Xin and Xueyog Sheng; writing-original draft preparation – Li Xin and Xueyog Sheng. 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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