International Journal of New Developments in Education
ISSN 2663-8169 Vol. 8, Issue 4: 105-112, DOI: 10.25236/IJNDE.2026.080415

Learning Behavior Representation, Process Tracking and Teaching Decision Optimization in PBL: A Learning Analytics Approach for Whole-Person Development

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Abstract: *The integration of Project-Based Learning (PBL) and whole-person development goals in art and design education at application-oriented universities faces practical dilemmas including the black-boxing of learning processes, the subjectivity of comprehensive quality assessment, and the lag in pedagogical intervention. Situated within China's Five-Education Integration policy framework, this study employs Learning Analytics to examine learning behavior representation and process tracking in PBL. A learning behavior analysis system was constructed comprising four layers: data collection, behavior modeling, predictive warning, and pedagogical application. Key modules include multimodal learning behavior representation, PBL process tracking and risk warning, and holistic competency assessment with teaching decision optimization. The system embeds holistic competency evaluation into the PBL workflow, enabling pre-class learner profiling, in-process pedagogical regulation, and post-class reflective improvement. It provides an operational technical solution for the transition from experience-driven to data-driven teaching reform, supporting the attainment of whole-person development goals encompassing moral, intellectual, physical, aesthetic and labor education.*

Keywords: *Learning analytics; PBL teaching; Learning behavior representation; Process tracking; Teaching decision optimization; Whole-person development*

1. Introduction

The deepening of digital transformation in higher education has created new imperatives for application-oriented universities, particularly in art and design programs where cultivating innovative thinking, collaborative competence, and comprehensive literacy is as critical as mastering technical skills. Project-Based Learning (PBL), with its problem-driven, inquiry-oriented, and outcome-focused pedagogy, has become an important direction for reform in art and design education. Nevertheless, the widespread implementation of PBL in studio classrooms confronts persistent challenges: the protracted, multi-phase, and highly individualized nature of design projects makes it difficult for instructors to trace student learning trajectories in fine granularity, resulting in assessment practices that remain overly reliant on final artifacts rather than developmental evidence. Moreover, the policy mandate for whole-person development—encompassing moral, intellectual, physical, aesthetic, and labor education—requires the integration of multidimensional goals into professional curricula, yet existing practices lack the behavioral indicators and evaluative tools necessary to operationalize these goals, leaving a pronounced gap between policy intent and classroom practice.

Learning Analytics (LA), defined as the measurement, collection, analysis, and reporting of data about learners and their contexts, offers a methodological foundation for addressing these dilemmas[3]. By representing, tracking, and modeling multimodal learning behaviors during PBL projects, instructors can anticipate cognitive obstacles, collaborative risks, and developmental needs, thereby enabling precision pedagogical intervention. However, extant LA research has concentrated predominantly on large-scale online courses or STEM laboratory instruction, with predictive models calibrated primarily for cognitive mastery rather than the nonlinear, creative workflows characteristic of art and design PBL[5]. Consequently, the multidimensional requirements of whole-person assessment remain largely unaddressed in the current LA literature.

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The concept of whole-person development resonates with the holistic education tradition articulated by scholars such as Ron Miller[9], yet in the Chinese higher education context, this ideal is operationalized through the specific policy framework of Five-Education Integration, which mandates the balanced cultivation of moral, intellectual, physical, aesthetic and labor competencies. Against this backdrop, the present study poses the following research question: How can a learning behavior representation and tracking system, grounded in Learning Analytics, be constructed to visualize learning processes, index whole-person development, and optimize teaching decisions within art and design PBL contexts? Situated within China's Five-Education Integration policy framework, this investigation explores the convergence of LA methodology and PBL pedagogy as a practical pathway toward data-driven teaching reform.

2. Research Foundation and Current Status

2.1 Application and Evaluation Dilemmas of PBL in Art and Design Education

PBL has a well-documented history in art and design education. International research demonstrates its efficacy in fostering critical thinking, problem-solving abilities, and interdisciplinary collaboration[1]. The 'learning by doing' ethos of PBL aligns closely with the discipline's emphasis on practical innovation. In the Chinese context, scholars have noted that introducing PBL in application-oriented art and design programs helps break the limitations of traditional skill-training models and strengthens the alignment between curriculum and industry demands. Despite this consensus on PBL's value, its assessment mechanisms remain under-theorized.

Current PBL assessment confronts three interrelated dilemmas. First, process evidence is routinely absent. Art and design projects typically span problem definition, research, concept generation, scheme development, physical prototyping, and exhibition; each phase generates rich behavioral data reflecting capability development, yet conventional evaluation fails to capture these processual traces systematically[2]. Second, assessment dimensions are narrowly conceived. Most evaluations center on the aesthetic and technical quality of final artifacts, effectively collapsing the assessment space into the intersection of intellectual and aesthetic education, while neglecting ethical conduct, collaborative integrity, physical exertion, and labor engagement. Third, feedback mechanisms are temporally delayed. Instructors typically render summative judgments only after project completion, missing the critical windows for early identification of learning risks and adaptive strategy adjustment.

2.2 Advances in Learning Analytics for Educational Assessment

Learning Analytics has emerged as a cross-disciplinary field integrating data mining, psychology, and educational theory to illuminate learning behavior patterns and inform instructional optimization[3]. Early LA studies relied heavily on clickstream data, submission logs, and forum interaction frequencies from Learning Management Systems, employing statistical regression or machine learning to predict academic performance and attrition risk. More recent work has incorporated multimodal data streams—including eye-tracking, facial expressions, voice interactions, and software operation logs—to construct richer portraits of learner cognition and affect[4].

In the domain of educational assessment reform, LA has been mobilized for early warning systems that flag at-risk students for personalized intervention, and for learning dashboards that render student trajectories visible to support self-regulation and instructor decision-making[6]. Nevertheless, applications of LA to whole-person development assessment remain incipient. Most existing systems build predictive models around cognitive variables, with insufficient attention to the behavioral representation and data modeling of moral, physical, aesthetic, and labor dimensions[7]. Furthermore, LA tools tailored for creative disciplines such as art and design are notably scarce, owing to the highly contextualized and individualized nature of design learning behaviors, which resist reduction to standardized data-collection frameworks[8].

2.3 Research Gaps and Positioning of This Study

Synthesizing the foregoing analysis, three gaps are identified. First, scene adaptability is deficient: prevailing learning behavior prediction systems are designed for online general-education courses or STEM laboratory settings, lacking targeted configurations for the nonlinear project workflows of art and design PBL. Second, evaluative dimensions are incomplete: most predictive indicators concentrate

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on cognitive achievement, failing to establish multidimensional behavior analysis models commensurate with whole-person development goals, thereby creating a disconnect between technical tools and educational values[6]. Third, the loop between behavior representation and teaching decision optimization is broken: prior research typically halts at the visualization of prediction results, without translating learning analytics into actionable pedagogical strategies[7].

This study is positioned to address these gaps by constructing a learning behavior analysis system that integrates representation, tracking, multidimensional evaluation, and decision optimization for PBL in art and design education. By anchoring the investigation in Learning Analytics methodology and situating it within the policy context of China's Five-Education Integration, the research explores a practical pathway from experience-driven to data-driven teaching reform.

3. System Design and Construction

3.1 Requirements Analysis

The requirements analysis derives from an integrated examination of PBL instructional characteristics in art and design and the evaluative demands of whole-person development. From the perspective of instructional workflow, art and design PBL follows a nonlinear progression of problem discovery, analytical cognition, practical resolution, and individual expression, with each phase entailing substantial implicit cognitive activity alongside explicit operational behavior. The system must penetrate the surface of final artifacts to represent and mark learning behaviors across the entire process, enabling instructors to monitor both collective rhythm and individual trajectories in real time.

From the perspective of evaluative dimensions, whole-person development transcends narrow intellectual assessment to incorporate moral, physical, aesthetic, and labor education. The system must establish mapping associations between learning behaviors and developmental goals: moral education is represented through responsibility assumption, conflict negotiation, and academic integrity in team collaboration; intellectual education through the complexity of design cognitive strategies and knowledge transfer capability; physical and labor education through physical exertion, hands-on practice frequency, and craftsmanship manifested in iterative refinement; aesthetic education through the accuracy of aesthetic judgment and the distinctiveness of creative expression. From the perspective of instructional decision-making, the system must not merely describe current states and track process trajectories, but also predict developmental trends and optimize pedagogical decisions, providing instructors with early signals of learning risk and capability deficit at critical project nodes.

3.2 Overall Architecture Design

In response to these requirements, the system adopts a four-layer architecture—data collection, behavior modeling, predictive warning, and pedagogical application—forming a complete information chain from raw data to instructional decision optimization. The data collection layer captures multimodal behavioral data across the PBL workflow. Three data sources are integrated: first, clickstream, resource access, discussion interaction, and version submission records from digital learning platforms; second, design software operation logs and artifact iteration data reflecting students' technical pathways and creative evolution; third, structured classroom observation and instructor-student interview data supplementing collaborative behaviors and affective states not captured by platforms. Cross-validation among these three sources constitutes a stereoscopic portrait of student learning behavior.

The behavior modeling layer performs data cleaning, feature extraction, and dimensional classification. It maps raw behavioral data onto four process domains—problem discovery, analytical cognition, practical resolution, and outcome expression—according to the PBL workflow. Simultaneously, it maps behavioral features onto five developmental domains—moral, intellectual, physical, aesthetic, and labor—according to the whole-person development framework, yielding a two-dimensional 'process domain × developmental domain' behavior analysis matrix. Through this matrix, instructors can intuitively identify students' capability performance and developmental balance at specific project phases. The predictive warning layer builds dual prediction mechanisms for learning process and learning outcomes based on structured features output by the behavior modeling layer, as shown in Figure 1.

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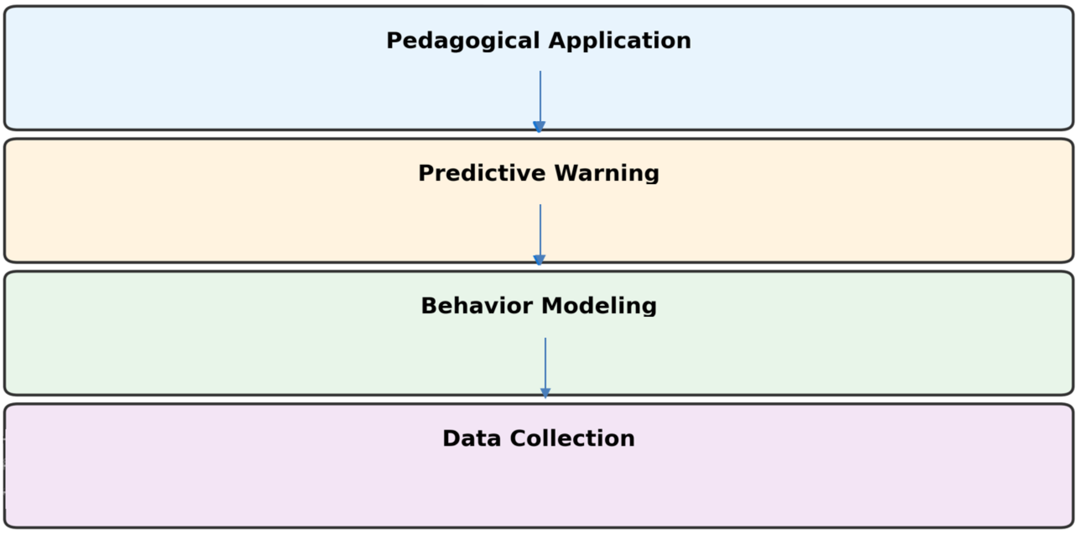

Fig. 1 System four-layer architecture

Process prediction evaluates whether students can advance smoothly to the next project node, identifying potential cognitive bottlenecks or collaborative obstacles; outcome prediction synthesizes whole-process behavioral features to estimate final artifact quality, whole-person development balance, and curriculum goal attainment. The warning mechanism pushes differentiated pedagogical decision recommendations to instructors according to risk levels. The pedagogical application layer serves as the interface between the system and instructional practice, translating predictive warnings into operational decision support: at the micro level, individualized intervention plans and group collaboration adjustment suggestions for instructors; at the meso level, data reports for curriculum scheme optimization and teaching method improvement for teaching and research offices; at the macro level, effectiveness evaluation for whole-person development education reform at the departmental level, as shown in Figure 2.

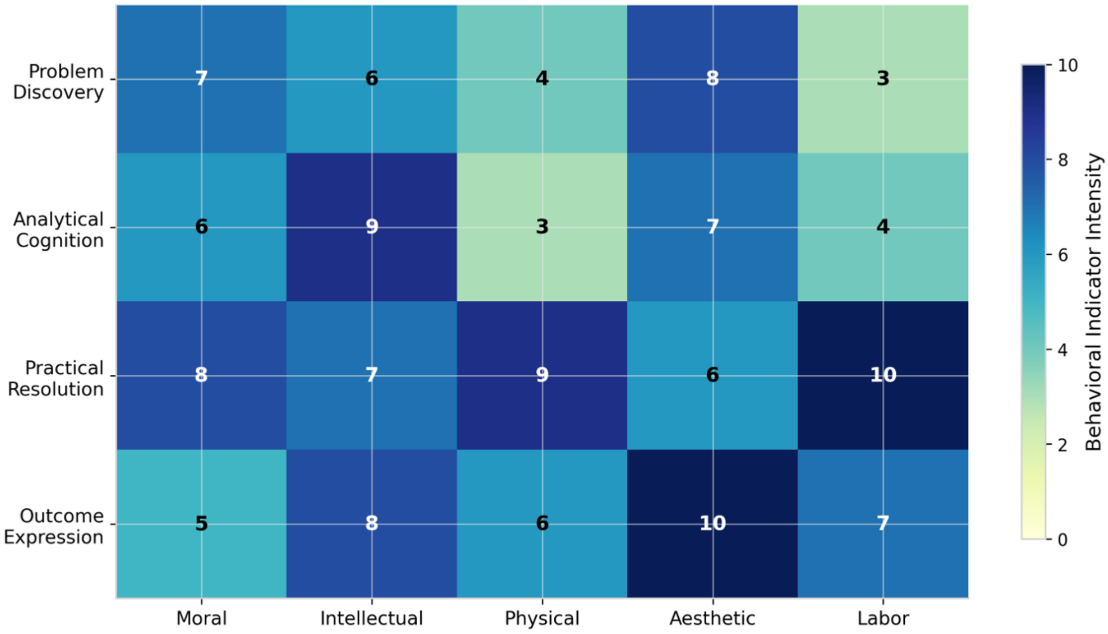

Fig. 2 Two-dimensional behavior analysis matrix (process domain × development domain)

3.3 Core Module Design

3.3.1 Multimodal Learning Behavior Representation Module

This module designs differentiated collection and representation strategies for each PBL phase.

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During the problem-discovery phase, the system captures students' information retrieval paths, problem formulation texts, and knowledge association networks, thereby encoding problem awareness and knowledge activation levels. During the analytical-cognition phase, the system records discussion frequencies, opinion adoption and revision trajectories, and reference resource types through an embedded collaborative design platform, reflecting analytical strategies and cognitive processing depth. During the practical-resolution phase, the system collects design software operation logs, temporal distributions of artifact version iterations, and modification depths, integrating instructor and peer evaluation feedback to form a stereoscopic characterization of creative practice behaviors[8].

Given the emphasis on diversified teaching methods in art and design, the system supports pedagogical method tagging. When instructors implement differentiated strategies—demonstration, guidance, heuristics, coaching, or customized innovation—the system tracks student behavioral response patterns under each method, accumulating data foundations for subsequent teaching decision optimization.

3.3.2 PBL Process Tracking and Risk Warning Module

This module transforms collected behavioral data into visualized tracking and diagnostic information for PBL instruction. It incorporates project node templates consistent with art and design PBL workflows, allowing instructors to adjust node parameters according to specific course configurations. At each node, the system automatically calculates behavioral indicators for both class aggregates and individual students, including node dwell time, resource utilization rates, interaction density, and cognitive strategy richness, generating process-oriented evaluation reports.

A specially designed 'project advancement risk index' synthesizes schedule deviation, behavioral activity decay rates, and collaborative participation trends to identify early signs of project delay or learning burnout. When the system detects that a student's behavioral activity at a critical node falls continuously below personal baseline levels with significantly decreased collaborative utterances, it triggers a warning prompting the instructor to adopt targeted guidance or coaching strategies; if the risk index continues to escalate, the system recommends initiating one-on-one customized tutoring. Additionally, the module supports network analysis of group collaboration, visualizing information flow and role distribution among team members to help instructors identify structural collaboration imbalances and adjust grouping strategies or task allocations accordingly.

3.3.3 Holistic Competency Assessment and Teaching Decision Optimization Module

This module constitutes the key component supporting the attainment of whole-person development goals. It establishes an association rule library linking behavioral indicators to whole-person developmental dimensions, translating learning behavior data into interpretable and comparable holistic competency indices. The moral dimension is primarily associated with responsibility fulfillment records, conflict negotiation behaviors, academic integrity markers, and value-related discussion participation in project teams. The intellectual dimension is associated with knowledge transfer applications, complexity of design cognitive strategies, and optimization of problem-solving pathways. The physical and labor dimensions are associated with physical exertion duration, hands-on practice frequency, material operation records, and iterative refinement behaviors. The aesthetic dimension is associated with the accuracy of aesthetic judgment, distinctiveness of creative expression, and the balance between formal beauty and functional rationality.

The module employs radar charts combined with trend line graphs to generate dynamic whole-person development portraits for each student. Instructors can rapidly identify students' strength and deficit areas, while the system generates optimization pathways for balanced development based on predictive models. For instance, for students with prominent aesthetic indicators but weak labor education indicators, the system recommends assigning more physical model-making or field investigation tasks in subsequent projects to strengthen hands-on practice and engineering literacy. Simultaneously, the module supports class-level aggregation analysis of whole-person development; if multiple cohorts show consistently low performance in a particular dimension, the system alerts the teaching and research office to increase corresponding practical instructional components in the curriculum scheme, thereby realizing data-driven and scientific teaching decision optimization, as shown in Figure 3.

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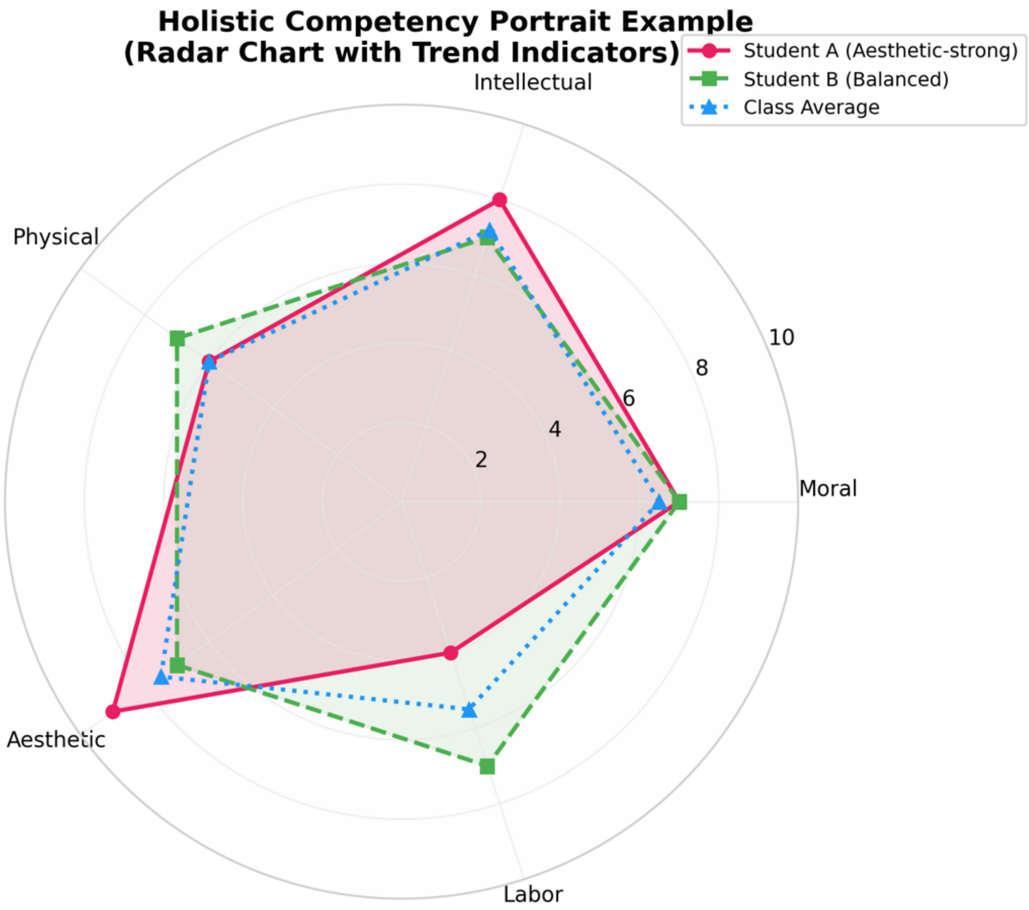

Fig. 3 Example of holistic competency portrait (radar chart)

4. Practical Application Path and Expected Effectiveness

4.1 Application Process of the System in PBL Courses

The system is embedded into PBL courses in art and design foundation programs through three stages: pre-class, in-class, and post-class. During the pre-class stage, instructors review behavioral representation data and whole-person development characteristics from previous cohorts in analogous PBL projects, combining these with current cohort learner profiles to optimize project topic selection and group formation strategies. Based on students' prior knowledge levels and behavioral preferences, the system recommends adaptable combinations of diversified teaching methods—for example, suggesting guidance and heuristic methods as primary strategies with lecturing as supplementary support for groups with weak foundations but high creative activity, thereby balancing knowledge supplementation and creative stimulation, as shown in Figure 4.

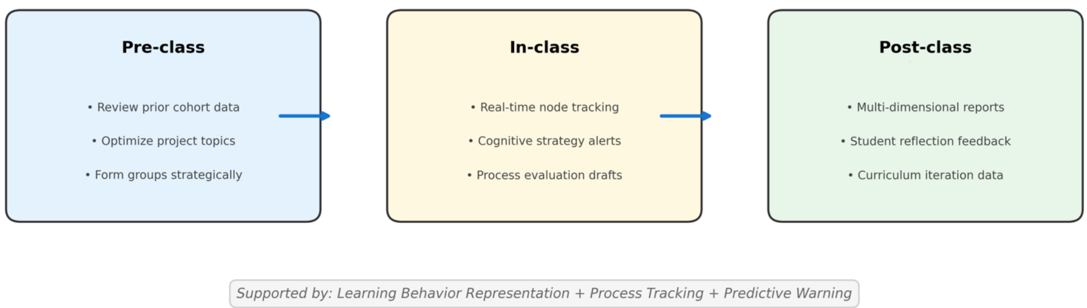

Fig. 4 System application workflow in PBL courses

During the in-class stage, the system tracks group advancement status at PBL project nodes in real time. At the problem-definition node, it analyzes the quality of student-proposed problems and their knowledge association depth, assisting instructors in determining whether intervention is necessary. At the scheme-development node, it monitors students' design cognitive strategy selections, pushing extension resources to those overly reliant on single technical pathways. At the outcome-refinement node, it integrates whole-process behavioral data to generate draft process evaluations, providing instructors with reference points for summative assessment and mitigating the contingency effects of final artifact presentation quality on evaluation outcomes. During the post-class stage, the system outputs multidimensional evaluation reports based on whole-process data, including individual learning behavior representation analysis reports, group collaboration effectiveness reports, whole-person development attainment reports, and teaching decision optimization recommendation reports. These reports are fed back to students to support attributional reflection and autonomous improvement, while also being aggregated at the teaching and research office level as data foundations for instructional case accumulation and curriculum scheme iteration, supporting the paradigm shift from experience-based summary to evidence-driven reform.

4.2 Analysis of Expected Effectiveness

From the perspective of instructional process optimization, the system's introduction transforms the traditionally passive pattern of 'instructor judgment by experience and post-hoc adjustment' into active 'data-driven, process-regulated' instructional management. Instructors can implement differentiated teaching strategies at critical nodes based on predictive warning information, enhancing the precision and timeliness of pedagogical intervention and thereby alleviating the instructional (loss of control) risks caused by process invisibility in PBL.

From the perspective of student development, whole-process behavior representation and immediate feedback encourage students to focus on their learning trajectories and capability evolution rather than merely fixating on the superiority or inferiority of final artifacts. The introduction of whole-person development portraits helps students establish self-awareness of balanced development across moral, intellectual, physical, aesthetic, and labor dimensions, stimulating intrinsic motivation to address deficits. Particularly in the balanced development of aesthetic and labor education, the system can provide timely reminders and improvement suggestions for students with strengths in aesthetic expression but relative weaknesses in hands-on practical ability.

From the perspective of teaching decision optimization, multi-round PBL instructional data accumulated by the system supports instructors in reflective improvement of their own teaching behaviors. By comparing student behavioral response patterns under different teaching methods, instructors can more scientifically evaluate the effectiveness of their instructional strategies and optimize their personal pedagogical repertoires. At the community-of-practice level, curriculum scheme adaptability reports output by the system provide objective evidence for teaching seminars and collective lesson preparation, promoting the organizational migration of teaching experience from individual to collective levels and achieving group-level optimization of teaching decisions.

From the perspective of educational model innovation, the holistic competency assessment and teaching decision optimization module translates abstract whole-person development goals into collectible, analyzable, and predictable behavioral indicators, effectively resolving the dilemma of 'difficult integration, difficult evaluation, and difficult implementation' that whole-person development goals face in professional classrooms. With system support, whole-person development ceases to be a task parallel to professional instruction and becomes a natural outcome embedded throughout the PBL project process, thereby realizing an art and design education model centered on aesthetic education with mutual penetration among moral, intellectual, physical, aesthetic, and labor dimensions.

5. Conclusion and Prospect

This study addresses the practical needs of PBL teaching reform in art and design programs at application-oriented universities, focusing on the implementation challenge of whole-person development goals. Grounded in Learning Analytics methodology, the research constructs a learning behavior representation, process tracking, and teaching decision optimization system for PBL instruction. By systematically reviewing advances in PBL instructional assessment and LA technology, the study establishes three core requirements—process-oriented data collection, multidimensional capability mapping, and precision teaching decision-making—and designs a four-layer system architecture. Key modules including multimodal behavior representation, PBL process tracking, holistic competency assessment, and teaching decision optimization are elaborated in terms of design rationale and application pathways. The findings indicate that the system can provide whole-process data support for art and design PBL, spanning pre-class learner profiling, in-process pedagogical regulation, and post-class reflective improvement, thereby facilitating the transition from experience-driven to data-driven reform and offering an operational technical solution for the attainment of whole-person development goals encompassing moral, intellectual, physical, aesthetic, and labor education.

It should be noted that the current study has completed the overall system design and functional planning; however, the core analytical models and prediction algorithms require large-scale data training and parameter tuning in actual instructional scenarios. Furthermore, the scientific rigor and comprehensiveness of the whole-person development behavioral indicator system need to be examined and refined through multiple rounds of teaching practice. Future research will proceed in three directions: first, conducting teaching experiments spanning two or more semesters to validate the system's actual contributions to instructional process optimization and whole-person development goal attainment in authentic PBL courses; second, expanding cross-course adaptability by extending the system to landscape design, interior design, digital media art, and other professional courses to examine its transferability across diverse PBL contexts; third, exploring data interfacing with extracurricular practice platforms and discipline competition management systems to construct a whole-person development tracking system covering 'classroom—campus—society' scenarios, providing more comprehensive digital support for the cultivation of compound talents in art and design at application-oriented universities.

Acknowledgements

This research was supported by Anhui Provincial Higher Education Quality Project Teaching Research Initiative, NO.2023jyxm0947 and Landscape Teaching Team NO.2023cxtd127 and Product Design Professional Development Program NO.2023xjzlts108, also support by Wanjiang University of Technology's University-Level Quality Project, NO.zl202215, also support by Wanjiang University of Technology's "Outstanding Program in Environmental Design" at the institutional level, NO.ylzy013,also support by Teaching and Research Project of Nanjing Institute of Technology, NO.JXZN20253073.

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