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Identifying Structural Barriers in the Digital-Intelligent Integration of Construction-Engineering Education

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Abstract: This study examined how data-driven and intelligent technologies are embedded across the core instructional processes of the Intelligent Construction program, including curriculum design, classroom delivery, learning assessment, and quality enhancement. Although tools such as BIM platforms, IoT systems, digital twins, and AI-based learning analytics have been introduced, their pedagogical value remains limited. The findings indicate three structural constraints: insufficient alignment between curriculum objectives and digital-intelligent competencies, fragmented technology deployment with low inter-platform interoperability and limited data feedback loops, and inconsistent use of process-based evidence in learning evaluation. Additionally, institutional support and data governance frameworks remain underdeveloped, restricting the depth of integration. In response, this study proposes a coordinated improvement pathway emphasizing conceptual renewal, institutional support, capacity building, and technological synergy. The work provides an empirical foundation for constructing an integrated, industry-linked talent cultivation model in intelligent construction.

Keywords: Intelligent construction; Digital-intelligent technologies; BIM; IoT; Digital twin; Learning analytics; Instructional assessment; Evidence-based teaching.

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1. Introduction

The rapid digital-intelligent turn of the Architecture, Engineering and Construction (AEC) sector is reshaping competency requirements and pushing higher education beyond basic informationization toward embedded, data-driven pedagogy. In intelligent-construction programs, Building Information Modeling (BIM), the Internet of Things (IoT), digital twins, and learning analytics are increasingly positioned not as add-on tools but as integrated elements across curriculum design, classroom delivery, assessment, and continuous quality enhancement [1–3]. Recent syntheses and cases show how digital twins and cyber-physical infrastructures can scaffold authentic, scenario-based learning and system-level feedback, although institutionalization remains uneven [4,5].

Despite policy attention and substantial investment, evidence points to persistent integration gaps along the instructional cycle. In curriculum design, digital-intelligent competencies are often under-specified, narrowing objectives to software operation rather than higher-order abilities such as systems thinking, collaborative decision-making, and data-informed judgment [2,6]. In delivery, fragmented platform ecosystems and weak interoperability interrupt data flows and limit continuous, authentic learning experiences, even in well-equipped labs and simulations [3,7]. In assessment, practice remains dominated by summative approaches [8,9]. The systematic use of process evidence and formative feedback is still emergent in engineering education [4,10]. Parallel developments in learning analytics suggest strong potential for scalable formative support, yet current implementations concentrate on surface-level behavioral measures rather than multi-dimensional engagement and timely instructional action [11–13]. At the governance layer, European benchmarking shows institutions still converging on coherent data standards, quality frameworks, and cross-program coordination, which constrains depth and consistency of technology integration [14–16].

1.1. Structural challenge

The presence of digital-intelligent technologies does not guarantee pedagogical absorption or transformative impact. What is needed is a system view tracing how technologies are embedded across all instructional stages and how multi-actor dynamics (faculty, students, industry mentors) shape integration depth and effectiveness. Building on the above literature, this study focuses on intelligent-construction education to delineate where integration is working, where it stalls, and why.

1.2. Research aims and questions

The study aims to identify current integration patterns and principal bottlenecks of digital-intelligent technologies across the core instructional processes of the School of Intelligent Construction, Qingdao Hengxing University of Science and Technology, and to develop evidence-based directions for improvement. Specifically, it asks:

(1) To what extent are digital-intelligent technologies embedded across different stages of the instructional process?

(2) What key obstacles constrain the depth and effectiveness of this integration?

(3) Which stages possess the greatest potential for scalable and systematic improvement?

2. Methods

2.1. Research design and setting

This study followed a process-oriented design aligned with the core instructional cycle of intelligent-construction education: curriculum design, instructional delivery, learning assessment, and quality improvement. Data were collected within the School of Intelligent Construction, Qingdao Hengxing University of Science and Technology.

2.2. Data sources and participants

This study combined four sources of evidence: questionnaires, semi-structured interviews, classroom observations, and document analysis (syllabi, teaching guidelines, evaluation records). The sample comprised faculty (N = 58), students (N = 326), and industry mentors (N = 21), complemented by interviews (N = 26) and classroom observations (N = 14).

2.3. Focal technologies

Five families of digital-intelligent technologies were examined given their prevalence in intelligent-construction curricula: Building Information Modeling (BIM), the Internet of Things (IoT), Digital Twins (DT), AI-enabled learning analytics, and smart-classroom systems.

2.4. Operationalization of embeddedness

At the instructional-unit level, embeddedness was defined as the proportion of sessions within a course or module that made substantive use of a focal technology. Three levels were specified:

(1) Embedded

≥ 0.70 with procedure based, stable use

(2) Partially embedded

0.30–0.70 with intermittent or instructor dependent use

(3) Not yet embedded

< 0.30 or occasional demonstrations without procedural integration

2.5. Instruments and procedures

Questionnaires captured exposure, frequency and mode of use, alignment with intended learning outcomes, and perceived barriers. Interview protocols were role-specific to surface adoption mechanisms, interoperability issues, and evidence use. Classroom observations followed a structured rubric (lesson phase; technology function—visualization, simulation, data capture, feedback; evidence flow—collection, interpretation, action). Document analysis mapped course outcomes to technology-enabled activities and assessment artifacts.

2.6. Analysis

This study first produced stratified descriptive statistics by instructional stage and technology. Cross-tabulations compared distributions across stakeholder reports and observation records. For categorical contrasts we examined association strength; for Likert-type items, non-parametric tests were used when needed. Qualitative data from interviews and open-ended responses were thematically coded and triangulated with quantitative patterns and documentary evidence.

3. Results

3.1. Stratified distributions of embeddedness

Table 1 presents the share of units at each embeddedness level by stage and technology based on questionnaires and observations.

Table 1. Proportions at each embeddedness level by instructional stage and technology

Stage	Technology	Embedded	Partially embedded	Not yet embedded
Curriculum design	BIM	0.04	0.7	0.27
	IoT	0.22	0.65	0.13
	DT	0.64	0.07	0.29
	AI learning analytics	0.2	0.33	0.47
	Smart-classroom	0.54	0.08	0.38

Table 1 (Continued)

Stage	Technology	Embedded	Partially embedded	Not yet embedded
Instructional delivery	BIM	0.74	0.07	0.19
	IoT	0.74	0.01	0.25
	DT	0.74	0.06	0.2
	AI learning analytics	0.73	0.04	0.23
	Smart-classroom	0.44	0.35	0.2
Learning assessment	BIM	0.17	0.49	0.34
	IoT	0.22	0.16	0.62
	DT	0.54	0.14	0.32
	AI learning analytics	0.24	0.44	0.32
	Smart-classroom	0.5	0.22	0.29

Note: Minor deviations from unit sums reflect rounding and reporting precision.

3.1.1. Interpretation

Embeddedness is highest in instructional delivery, where BIM, IoT, and DT each reach ≥ 0.70 in the "Embedded" category. This indicates stable operational mechanisms in practice-oriented sessions (e.g., simulations, labs), with BIM–DT coupling enabling high-level visualization and data linkage for virtual construction, site simulation, and modeling drills.

By contrast, curriculum design shows limited embeddedness for most technologies. Except for DT, "Embedded" proportions are generally < 0.30 and "Partially embedded" shares are high, suggesting exploratory or auxiliary use at the design stage rather than systematic integration into learning outcomes and course architecture. Notably, AI learning analytics and smart-classroom systems exhibit high "Not yet embedded" shares (0.47 and 0.38), indicating that intelligent analysis and behavioral tracking remain at an early stage of adoption.

In learning assessment, usage is structurally uneven. BIM and DT have a foothold in product- and task-based evaluation, whereas IoT and AI learning analytics remain largely confined to data capture or statistical feedback. Smart-classroom systems show a 0.50 "Embedded" share, implying gradual uptake of formative, process-based evidence, though a systematic data-to-decision feedback loop is not yet established.

Overall pattern. The portfolio reveals practice-led integration, design lag, and an assessment gap. This imbalance constrains end-to-end digital continuity across the instructional cycle. Strategic improvement should therefore front-load integration in curriculum design and strengthen data-driven feedback in assessment to move from localized digital use toward systemic, program-level governance.

3.2. Aggregate embeddedness scores

To summarize across stages, this study computed average embeddedness scores by technology. BIM and DT rank highest (1.65 and 1.45), reflecting mature use in delivery, especially labs and simulations; smart-classroom systems score 1.30, indicating stable use for classroom interaction and formative checks. IoT and AI learning analytics trail (1.05 and 1.10), typically in pilot or auxiliary modes without comprehensive integration into design and assessment. The trend confirms a BIM-/simulation-centric pattern with delivery outpacing design and assessment, consistent with a transitional, partially integrated state. (Refer **Figure 1**)

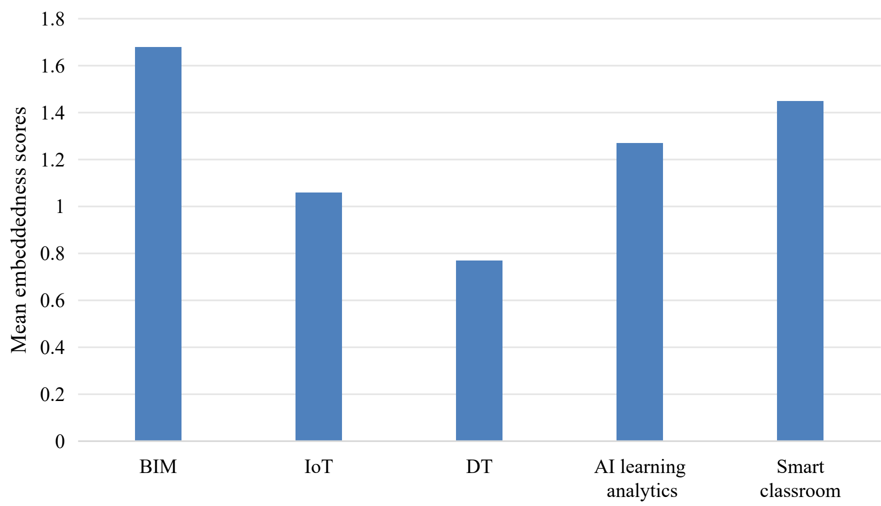

Figure 1. Mean embeddedness scores by technology.

3.3. Curriculum design: Status and diagnostics

Syllabi and standards show explicit targets for BIM and smart-classroom use; targets for IoT and DT are weaker, and AI learning analytics is mostly positioned as supportive tooling. DT scenarios are scarce in lab manuals; the resource-management platform is not yet connected to evaluation systems, dispersing evidence trails.

At the instructor level, heterogeneity in design mindset, tool fluency, and data literacy translates into unequal embeddedness. A correlation analysis indicates a strong positive association between course-design capability and embeddedness depth (r = 0.72): below a design-capability score of 60, embeddedness clusters around 40–55 (auxiliary, single-tool use); above 75, embeddedness commonly exceeds 70 with multi-tool fusion and data-informed design. Some high-scoring instructors already form BIM–IoT–smart-classroom loops at the course level. (Refer **Figure 2**)

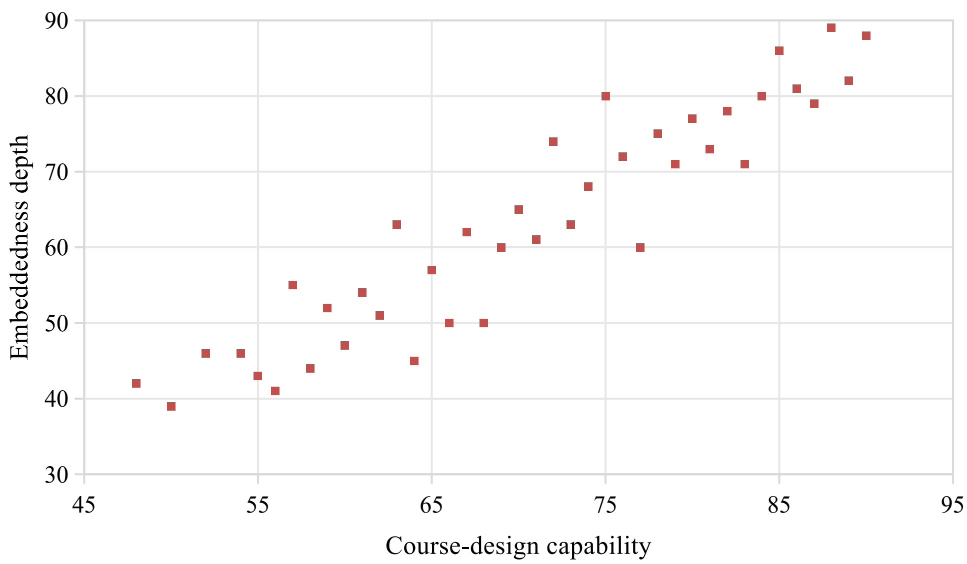

Figure 2. Relationship between instructors' design capability and embeddedness depth (r = 0.72).

3.4. Instructional delivery: Classroom and lab integration

Classroom observations show frequent use of smart-classroom functions for attendance, polling, and in-class quizzes, yet learning analytics and personalized feedback are used far less, indicating shallow data use at the point of instruction. (Refer **Figure 3**)

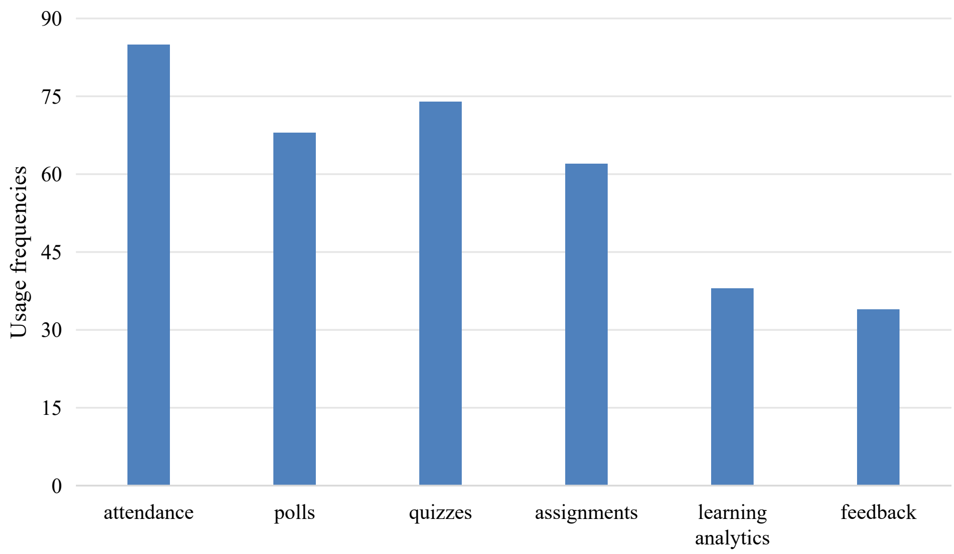

Figure 3. Usage frequencies across smart-classroom functions (attendance, polls/quizzes, assignments vs. analytics/ feedback).

In labs and practicums, BIM–IoT integration underpins "smart site" simulations and "equipment condition monitoring". However, data exchange stability is undermined by device maintenance and access-control issues. Application intensity varies by activity: highest in construction simulation and safety monitoring (= 0.82 and 0.79), lower in materials testing and equipment O&M (= 0.56 and 0.48), partly due to uneven IoT module updates and interface standards. Project management/progress control is moderate (= 0.52), reflecting limited experience with end-to-end BIM–IoT instructional flows. (See **Figure 4**)

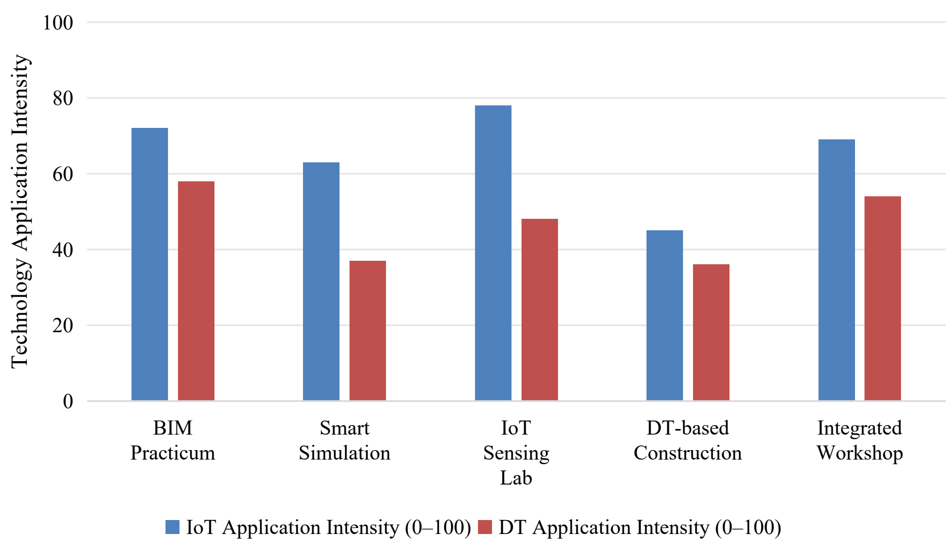

Figure 4. Application intensity of BIM–IoT across five practicum activities.

Implication. Collaboration exists but a full "virtual–physical" teaching ecosystem is not yet in place. Gaps in data standardization, interface compatibility, and task-chain coupling keep the system at a "local integration → systemic coordination" transition.

3.5. Learning assessment: Structure and attitudes

Assessment practice remains summative-heavy. Final products and staged assignments constitute roughly 60% of total weight; classroom performance and process evidence account for around 15% each; written tests are about 10%. Although platforms can record process data, these data are not consistently translated into formal evidence. (Refer **Figure 5**)

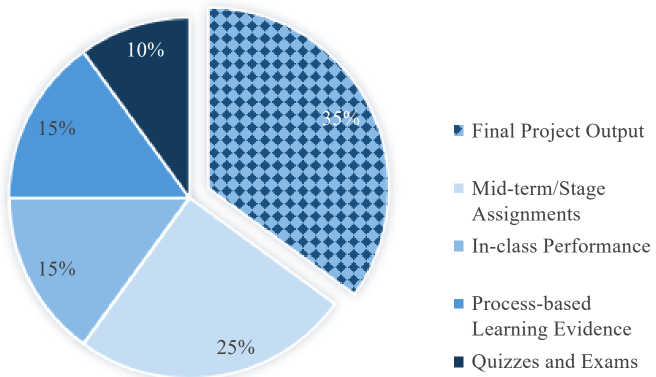

Figure 5. Assessment weight structure.

Stakeholder attitudes also diverge. Faculty show the highest trust (accuracy 78%; value for improvement 80%; reservations on feedback timeliness 68%). Students rate timeliness higher (75%) but are less convinced about transparency and improvement value (around 68%). Industry mentors are lowest across indicators (≤ 70%), especially on transparency and alignment with job competencies (around 60%).

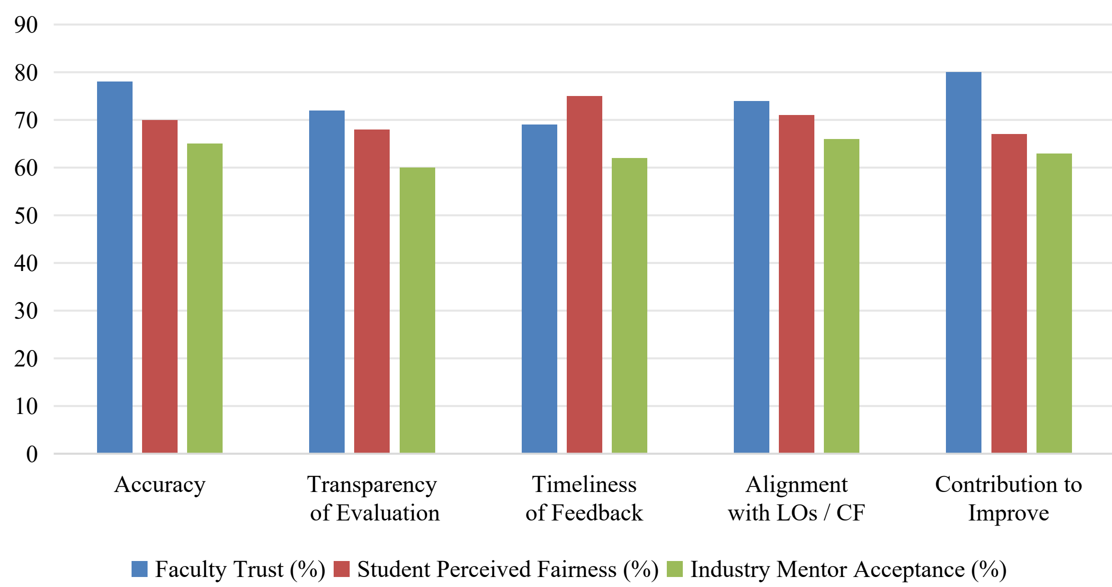

Figure 6. Attitudes toward intelligent assessment among faculty, students, and industry mentors.

Implication. Without shared templates and visual analytics, data interpretability and credibility remain concerns. The system has the conditions for data-informed assessment but has not yet shifted from "result judging" to "process diagnosis".

3.6. Management support: Enablers and bottlenecks

Five governance elements were rated: policy framework, faculty development, platform interoperability, data governance, and performance incentives. Curriculum-reform policy scored highest (82), indicating clear strategic direction, but implementation lags. Incentives are moderate (76) and skewed to research/competitions rather than classroom digitalization. Faculty training (65) and data governance (60) are weak, reflecting sporadic workshops and missing standards; platform interoperability is lowest (58), a key bottleneck for BIM/IoT/smart-classroom coupling.

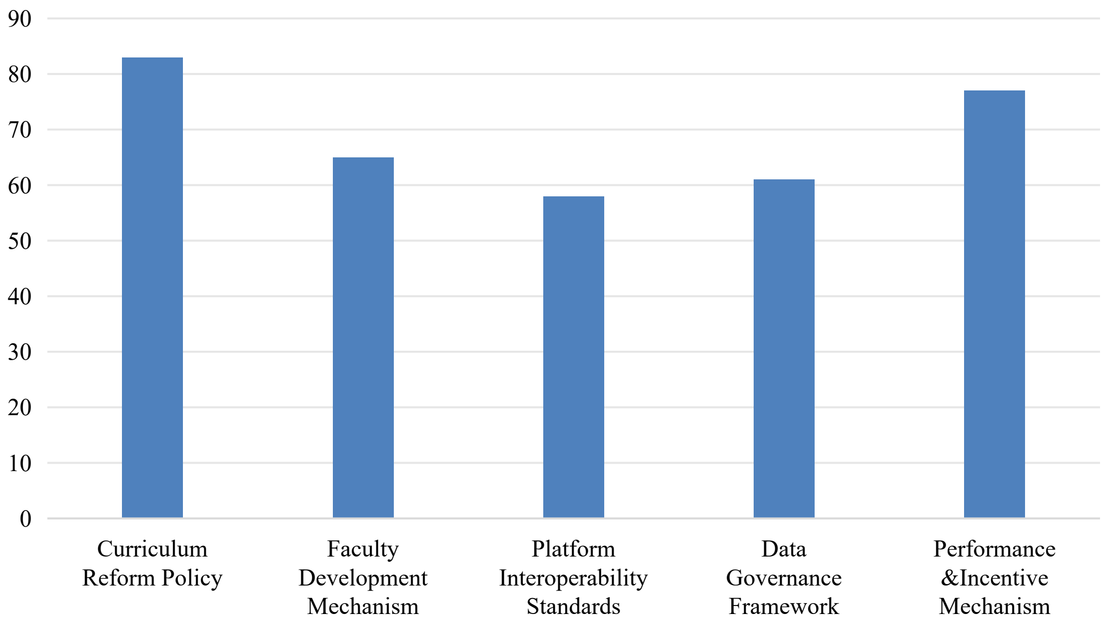

Figure 7. Scores for management support elements (0–100).

Implication. A coherent "policy–platform–people" linkage is not yet established. Fragmented standards and discontinuous training limit depth and sustainability of integration.

4. Directions for quality improvement and model proposition

This study proposed a four-pronged pathway, conceptual renewal, institutional support, capacity building, and technological synergy, to rebalance the portfolio:

(1) Shift from "tool use" to data-enabled pedagogy, strengthening learning-analytics literacy and evidence-oriented design;

(2) Establish cross-unit curriculum update mechanisms, a unified data dictionary, and evidence-governance norms;

(3) Deliver joint training on task-based design + learning analytics to enhance course integration and data

interpretation;

(4) Advance interoperability across key platforms so that teaching, administration, and assessment systems function as a coordinated whole.

Building on these, a Scenario–Task–Data–Competency (STDC) coupling model was proposed. Real-world scenarios seed problems; project-based tasks organize learning; process data steer feedback; competency profiles guide outcomes—forming a dynamic loop from goals → teaching → assessment → improvement. This structural frame makes the data flow explicit and actionable for iterative course redesign.

5. Limitations and future work

Sample scope and depth limit generalization. Planned next steps include controlled comparisons and longitudinal tracking to validate the STDC model and to operationalize data-informed assessment pipelines in intelligent-construction programs.

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Disclosure statement

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