

Exploring Practical Pathways of Data-Intelligence Decision Making Empowering Project-Based Course Construction

Zhiming Tang

School of Management, Chongqing University of Science and Technology, Chongqing, China

Abstract: Project-based courses have become a common way to develop applied competences in higher education, yet their construction is often decided by experience rather than evidence, and difficulties appear in topic selection, process monitoring, and outcome evaluation. This study explores how data-intelligence decision making can empower the construction of project-based courses and what practical pathways make the empowerment work. Starting from the design principles of project-based learning and the shift from experience-based to evidence-based management, the paper identifies three dilemmas in current practice: project topics that are disconnected from industrial demand data, process monitoring that depends on teacher observation, and evaluation that relies on single-source final products. It then proposes three pathways. Demand-driven topic selection combines graduate employment data, enterprise recruitment records, and student learning profiles to generate project candidates. Process monitoring uses learning analytics to collect milestone, teamwork, and resource-use indicators and to trigger adjustments during the course rather than after it. Multi-dimensional evaluation integrates product quality, process performance, and competence gain, and feeds the results back into the next cycle of course revision. Evidence from published studies supports the direction, including significant gains in collaboration skills in a project-based course taken by thousands of graduate students and improved student outcomes in applied interdisciplinary project programmes. The paper further discusses platform construction, data governance, teacher data literacy, and human-in-the-loop safeguards, and concludes that data-intelligence decision making changes project-based course construction from a one-off design into a continuously revised process.

Keywords: Project-Based Learning; Data-Intelligence Decision Making; Course Construction; Learning Analytics; Higher Education Management

1. Introduction

Project-based courses occupy a growing share of undergraduate and graduate programmes in Chinese universities. In these courses students work on a real or simulated task over several weeks, produce an artefact, and are assessed on both the product and the process. The pedagogical case for this format is well established: projects give learners a driving question, require sustained inquiry, and place responsibility for planning and revision on the student group [1, 2]. Universities have adopted the format for reasons that go beyond pedagogy as well, since employers ask for graduates who can work in teams and handle ill-structured problems [3].

Course construction, however, has not kept pace with the number of project-based courses being offered. Most teaching teams select project topics from their own experience and industrial contacts, arrange milestones by intuition, and evaluate results mainly through a final presentation and report. Three problems follow. Topics drift away from what the labour market currently requires, and students notice the gap when they enter internships. Process problems, such as a group losing direction in week three or one member carrying the workload of four, are discovered late or not at all. Evaluation concentrates on the final artefact, which says little about the competences the course was designed to build. Teaching teams revise the course once a year, mostly by discussing impressions at a semester meeting.

Meanwhile universities have accumulated data that could inform each of these decisions. Course platforms record participation and submission timelines, teamwork platforms record task allocation, internships and

employment systems record what graduates do after leaving, and recruitment platforms publish the skills employers list. The problem is no longer data scarcity but the absence of a decision routine that turns these records into course design choices. This paper addresses that gap. Section 2 reviews the design logic of project-based courses and the shift toward data-based decision making. Section 3 analyses the dilemmas of current construction practice. Section 4 proposes three practical pathways. Section 5 discusses safeguards and supporting evidence, and Section 6 concludes.

2. Theoretical Basis

2.1 Design Logic of Project-Based Learning

Project-based learning is organised around a question or problem that has more than one defensible solution, and it expects students to produce a tangible artefact that answers the question. Blumenfeld and colleagues described the approach as sustained effort in which the driving question, the artefact, and the classroom culture jointly support student inquiry, and they emphasised that teachers must scaffold the process rather than leave groups to sink or swim [1]. Krajcik and Blumenfeld later systematised the design elements into learning goals, a driving question, scientific or professional practices, collaboration, scaffolding, and assessment that matches the goals [3]. Research on problem-based variants adds a complementary point: students develop self-directed learning and collaborative skills when the problem forces them to identify what they do not know and to distribute the work of finding out [2]. Two implications follow for course construction. First, topic quality determines learning quality, because an artificial or outdated question produces artificial inquiry. Second, process support and assessment must be designed together with the topic, since a course that scaffolds the process but grades only the product sends contradictory signals.

2.2 From Experience-Based to Data-Intelligence Decision Making

Education management has gradually adopted data-based decision making as a working method rather than a slogan. Schildkamp reviewed the field and observed that data use improves school outcomes mainly when teachers and leaders work through an explicit cycle of

problem definition, data collection, interpretation, action, and evaluation, and that the cycle breaks down without shared routines and time [6]. Mandinach and Gummer argued that the binding constraint is data literacy, meaning the ability to transform raw records into instructional and curricular decisions rather than merely reading dashboards [7]. What the term data-intelligence adds to this picture is the analytical layer. Topali and colleagues reviewed 47 empirical studies of human-centred learning analytics and artificial intelligence in education and reported a pattern worth noting: more than two thirds of the solutions involved stakeholders in some part of the design, but fewer involved them during ideation and prototyping, and most reported no evaluation of impact, which limits trust and adoption [8]. A similar review of 130 articles on artificial intelligence in curricula concluded that the technology matters less than the design decision about which competences the curriculum should build, in particular critical thinking and interdisciplinary problem solving [9]. Taken together, the literature suggests that data-intelligence decision making in course construction is best understood as a structured routine that links data, professional judgement, and curriculum revision, not as an automated system that replaces teachers.

3. Dilemmas in Current Project-Based Course Construction

3.1 Topic Selection Separated from Demand Data

Most teaching teams build a topic pool from previous years' projects and personal industrial contacts, then repeat it with minor updates. The advantage is familiarity; the cost is lag. Employment and recruitment data that describe current skill demand sit in the career centre and in public recruitment platforms, disconnected from curriculum meetings. The result is familiar to both students and employers: a project portfolio that trains skills the market valued several years ago, while emerging needs, such as data-supported decision making in operational roles, appear in job postings but not in project briefs. Because the mismatch is invisible inside the classroom, it persists until internship feedback arrives, and internship feedback arrives too late to change the current cohort's experience.

3.2 Process Monitoring Based on Observation

Once a course starts, monitoring depends on what the instructor can see and hear. Groups that meet visibly and speak up in class appear to be working; quiet groups may be failing quietly. Attendance and submission data exist in the platform, but they are usually consulted for grading at the end of the term rather than for adjustment during it. Milestone data, if collected at all, are recorded as completed or not completed, without information on workload distribution or revision effort. The practical consequence is that intervention happens after the deadline, when the only remaining options are late penalties or lowered standards. Published evidence on project courses points in the opposite direction: outcomes depend heavily on group-level dynamics, and course format choices such as accelerated pacing influence specific skills such as conflict management [4]. Those findings are actionable only if the dynamics are visible while the course is running.

3.3 Evaluation Concentrated on Final Products

Assessment in project-based courses frequently reduces to a presentation score, a report score, and a peer evaluation with generous ratings. Product quality is visible and therefore overweighted, while competence gain, which is the actual learning goal, is inferred rather than measured. Students read this weighting accurately and allocate effort accordingly: they polish the deliverable in the final week and minimise engagement in the earlier inquiry stages. Evaluation data also stay inside the course. Scores are submitted, the course ends, and the next cohort meets a similar set of problems, because nothing from the assessment was converted into a design revision. Evidence from a large applied project programme showed that skill development, mentoring relationships, and even graduation outcomes can be affected by how such programmes are organised [5], which suggests that evaluation should be designed to capture these dimensions rather than only artefact quality.

4. Practical Pathways of Data-Intelligence Empowerment

4.1 Demand-Driven Topic Selection

The first pathway replaces experience-based topic generation with a demand-driven procedure that draws on three data sources.

Employment and internship records show where graduates actually work and which tasks they perform in their first year. Recruitment data from enterprise platforms show which skills employers request, weighted by the number of postings in the target region and industry. Student learning profiles show which competences the current cohort already has, which prevents the course from repeating content covered elsewhere. The procedure has four steps: extract skill demand terms from the first two sources; map them against the programme's competence framework; screen candidate topics against feasibility criteria such as data availability, duration, and supervision capacity; and rank the candidates by the strength of demand evidence. Teaching teams do not lose authority in this process. They retain the judgement about which topics are pedagogically sound, and the data simply make the demand side explicit. A topic pool built this way also has a practical benefit for industry cooperation, because the brief can state which employer skills it addresses, which makes enterprises more willing to provide cases and data.

4.2 Learning Analytics for Process Monitoring

The second pathway turns process monitoring into a routine supported by learning analytics. Three indicator groups are sufficient to start. Milestone indicators track whether each group has completed agreed deliverables on schedule, using platform timestamps rather than self-reports. Collaboration indicators track task allocation and contribution balance across group members, taken from document editing histories, task board assignments, and communication records. Resource indicators track the use of laboratories, equipment, and data sets, which matters when shared resources constrain project scope. These indicators feed a weekly review rather than a final report. Weekly review is deliberate: the published evidence indicates that group-level dynamics dominate individual characteristics in project courses [4], so problems that appear at group level can be addressed in days if they are detected in days. The review produces one of three actions for each flagged group: an adjustment of scope, a change in task allocation, or a mentoring session with the supervisor. Recording which action was taken, and what happened next, creates the process data that the evaluation pathway

described below requires.

4.3 Multi-Dimensional Evaluation and Course Iteration

The third pathway restructures evaluation so that it measures the competences the course claims to build and returns its results to the design cycle. Four dimensions cover the learning goals: product quality, assessed against a rubric aligned with the professional standard for the domain; process performance, assessed from the milestone and collaboration indicators described above; competence gain, assessed through a short pre-post measurement of the target skills, which converts the course from a claim into evidence; and reflection quality, assessed from individual reflective notes that record what the student would do differently. The four dimensions produce a course-level profile rather than a single average, and the profile is reviewed by the teaching team at the end of each delivery. Three questions guide the review: which competences produced the weakest gain, which process indicators predicted that weakness, and which design element should change in the next cycle. The answers are recorded and carried into the next topic selection round, which closes the loop between evaluation and construction. Table 1 summarises the three pathways.

Table 1. Practical Pathways from Data-Intelligence Decision Making to Course Construction

Construction Stage	Data Basis for Decision	Practical Pathway and Output
Topic selection	Employment and internship records, recruitment skill demand, student profiles	Demand term extraction, competence mapping, feasibility screening, ranked topic pool
Process monitoring	Milestone timestamps, task allocation records, resource usage logs	Weekly indicator review, group-level alerts, scope or allocation adjustments
Outcome evaluation	Rubric scores, process indicators, pre-post skill measurement, reflective notes	Four-dimensional course profile, revision questions, updated next-cycle design

5. Implementation Safeguards and Supporting Evidence

5.1 Platform, Governance, and Data Literacy

The pathways above need a modest technical

base and a stronger institutional base. On the technical side, the requirement is not a new system but an integration layer that pulls milestone, collaboration, and employment data into one working view, since the records already exist in separate platforms. On the institutional side, three safeguards matter. Data governance must specify what student data may be used for course construction, who may see it, and how long it is retained, because process monitoring can drift from support into surveillance if the boundary is not written down. Teacher data literacy must be developed deliberately, in line with the argument that decisions improve when educators can transform records into curriculum choices rather than merely read dashboards [7]. The decision cycle must be scheduled into the academic calendar, with fixed review points, since data-based practice fails when it is added to an already full workload as an extra task [6]. Reviews of learning analytics implementation reach a related conclusion: solutions that ignore stakeholder needs and pedagogical context are adopted slowly or not at all, and most published cases still lack evidence of impact [8].

5.2 Human-in-the-Loop and Evidence from Practice

Data-intelligence decision making in course construction should keep teachers and students in the decision. The indicators identify where attention is needed; the supervisor decides what to do, and the students involved know that indicators are reviewed and why. This arrangement matches the human-centred direction of recent analytics research [8] and avoids two common failures: decisions made from incomplete data without professional judgement, and decisions made from habit while data is collected but ignored. Evidence from large-scale project programmes supports the general direction of the three pathways. In an applied project programme that integrated project work into interdisciplinary research teams, a matched-pairs analysis found measurable gains in research, teamwork, and critical thinking skills, closer student-faculty relationships, and a higher likelihood of graduating with distinction, with team organisation, layered mentoring, and applied research identified as the factors that made replication possible [5]. In a project-based graduate course taken by roughly 3,300 students annually, collaboration skills improved

significantly from the start to the end of the course, and the accelerated format had a positive effect on conflict management skills, while differences in outcomes were associated with student groups rather than with individual characteristics such as gender or prior achievement [4]. Both findings point to the same operational conclusion: what happens inside the group during the course determines the result, so process data deserve the same design attention as the final product. Reviews of curriculum-level artificial intelligence applications add that the design question is which competences the curriculum intends to build, with critical thinking and interdisciplinary problem solving named as central [9].

5.3 Limitations and Further Work

Two limitations qualify the proposals. The pathways were derived from the literature and from construction practice rather than from a controlled trial, so their effects on learning outcomes require evaluation in real courses. Data availability also varies: employment records are held by career centres that may not link them to course-level use, and collaboration data depend on the platforms a teaching team happens to adopt. Further work can proceed in two directions. One is a multi-cohort comparison of courses that adopt the full pathway set against courses that adopt only demand-driven topic selection, which would separate the contribution of each pathway. The other is the development of indicators for competence gain that are short enough to administer inside a normal course week, since long instruments will not survive contact with a real semester.

6. Conclusion

This study examined how data-intelligence decision making can empower project-based course construction and proposed three practical pathways. Demand-driven topic selection connects course design to employment and recruitment evidence, so that project briefs reflect the competences graduates are actually expected to have. Learning analytics based process monitoring shifts attention to group-level dynamics while a course is running, when adjustment is still possible. Multi-dimensional evaluation measures product, process, competence gain, and reflection, and returns its findings to the next design cycle. Two conclusions follow from the analysis. First, the

pathways depend more on routine and governance than on sophisticated algorithms, because the required data already exist in universities and the main obstacle is that no one is assigned to interpret them in a scheduled cycle. Second, teachers remain the decision makers, and the role of data is to make the demand side and the group dynamics visible. Evidence from large project programmes and project-based courses indicates that group process and course organisation shape outcomes strongly, which is precisely where these pathways focus attention. For teaching teams beginning this work, a reasonable sequence is to build the topic pool from demand data in one semester, add weekly process indicators in the next, and introduce competence-gain measurement once the first two routines are stable.

References

- [1] Blumenfeld P C, Soloway E, Marx R W, et al. Motivating project-based learning: Sustaining the doing, supporting the learning. *Educational Psychologist*, 1991, 26(3-4): 369-398.
- [2] Hmelo-Silver C E. Problem-based learning: What and how do students learn? *Educational Psychology Review*, 2004, 16(3): 235-266.
- [3] Krajcik J S, Blumenfeld P C. Project-based learning. In: Sawyer R K, ed. *The Cambridge Handbook of the Learning Sciences*. New York: Cambridge University Press, 2006: 317-334.
- [4] Johnsen M M W, Sjølie E, Johansen V. Learning to collaborate in a project-based graduate course: A multilevel study of student outcomes. *Research in Higher Education*, 2024, 65(3): 439-462.
- [5] Balleisen E J, Howes L, Wibbels E. The impact of applied project-based learning on undergraduate student development. *Higher Education*, 2024, 87(4): 1141-1156.
- [6] Schildkamp K. Data-based decision-making for school improvement: Research insights and gaps. *Educational Research*, 2019, 61(3): 257-273.
- [7] Mandinach E B, Gummer E S. *Data Literacy for Educators: Making It Count in Teacher Preparation and Practice*. New York: Teachers College Press, 2016.
- [8] Topali P, Ortega-Arranz A, Rodríguez-Triana M J, et al. Designing human-centered learning analytics and artificial intelligence

- in education solutions: A systematic literature review. Behaviour & Information Technology, 2025, 44(5): 1071-1098.
- [9] Jaramillo J J, Chiappe A. The AI-driven classroom: A review of 21st century curriculum trends. Prospects, 2024, 54(3-4): 645-660.