Electronic Supplementary Material

S.1 Case Study 1: Java Object-Oriented Programming Course Reform

S.1.1 Context and Background

This case study details a curriculum reform within a core Java object-oriented programming (OOP) course, exemplifying the application of several framework principles within a higher vocational institution context, as shown in Figure 4. Target student cohort, computer-related majors with foundational Java syntax knowledge, but limited OOP and algorithm experience, aligns with the need for developing AI literacy and skills, as discussed in Section 2.3.2. Reform addressed the imperatives, highlighted in Section 3.1, to move beyond theoretical knowledge towards applying principles to solve complex and realistic problems.

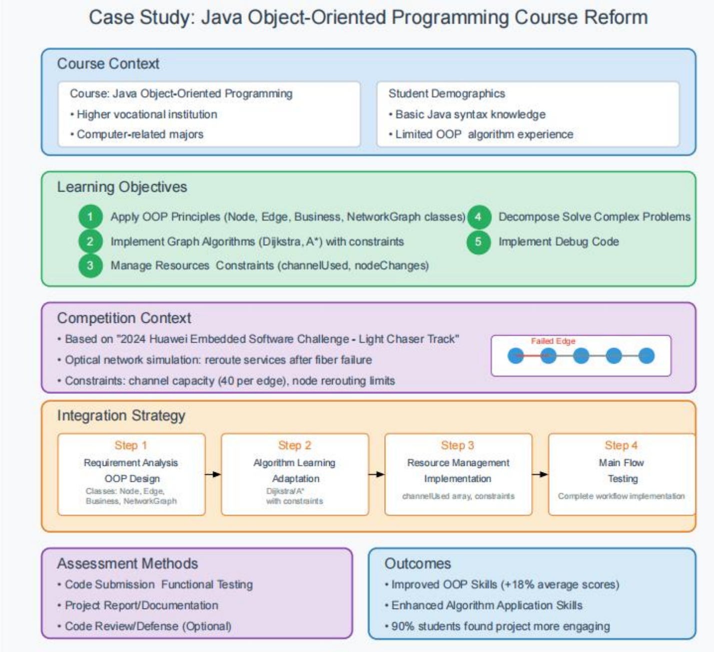
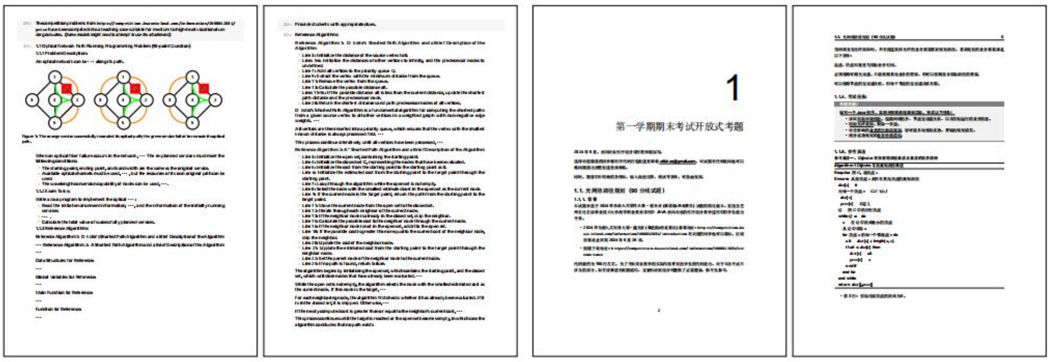


Figure 4 Overview of the Java object-oriented programming course reform case study.

Core learning objectives, as shown in Figure 4, were designed to foster five practical competencies, including applying OOP for system modeling, implementing and adapting graph algorithms (e.g., Dijkstra and A*) under constraints, managing resources programmatically, decomposing complex problems, and enhancing coding and debugging skills. This focus on application, adaptation, and problem decomposition directly targets the cultivation of higher-order thinking skills central to the framework presented in Section 3.1. To ground these objectives in a realistic context and enhance engagement, aligning with the value of authentic assessment in Section 5.4, the curriculum integrated a project derived from a real-world industry challenge—Huawei Embedded Software Challenge 2024. This optical network simulation problem, requiring service rerouting under capacity and node constraints, provided a complex, constrained graph path finding and resource allocation task. Leveraging such industry contexts also reflects the benefits of AI Partnerships discussed in Section 4.2.1.

S.1.2 Algorithm-Centric Content and Integration Strategy

While this case doesn't heavily feature GenAI creating content for students, it exemplifies using externally sourced, algorithm-centric materials as structured guidance, akin to how AI may be prompted to generate detailed scenarios as shown in Figure 5. The competition provided the detailed problem descriptions, recommended algorithm frameworks (Dijkstra and A* pseudocode), and implicit data structure guidance, serving as scaffolding for student learning.



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第一学期期末考试开放式考题

(a) Huawei Competition Context (b) Chat for Course Case Details (c) Real-world Example Snippet 1 (d) Real-world Example Snippet 2

Figure 5 Conceptual use of GenAI and competition context to construct and detail the course example for Case Study 1. (a) Shows the competition basis; (b) illustrates prompt engineering for refining case details; and (c, d) show analogous real-world snippets (actual prompts/outputs not shown here).

The integration strategy in Figure 4, employed a multi-week project structure characteristic of PjBL (Section 3.2.2), a key active learning approach (Section 3.2). The four stages guided students progressively: The first step is requirement analysis and OOP design, which focuses on problem interpretation and OOP application. The second step is algorithm learning and adaptation, which moves beyond rote algorithm understanding, demanding critical adaptation to handle specific constraints (e.g., contiguous channel availability), thereby engaging higher-order thinking skills (Section 3.1). The third step is resource management implementation, which requires precise coding for resource tracking and updating.The fourth step is main flow and testing, which integrates all components into a functional workflow, emphasizing testing and debugging. Standard Java development tools and version control facilitated this process.

S.1.3 Assessment Methods and Observed Outcomes

The assessment strategy employed multiple methods (Section 5.4) to evaluate student learning against the objectives in Figure 4. The primary method, functional testing of submitted code, served as an authentic assessment (Section 5.4) of their ability to solve the constrained problem. Project reports, requiring explanation of design rationale and problem-solving approaches, enabled a process-oriented assessment (Section 5.4), evaluating depth of understanding beyond just the final code. Optional code reviews provided further insight into individual comprehension.

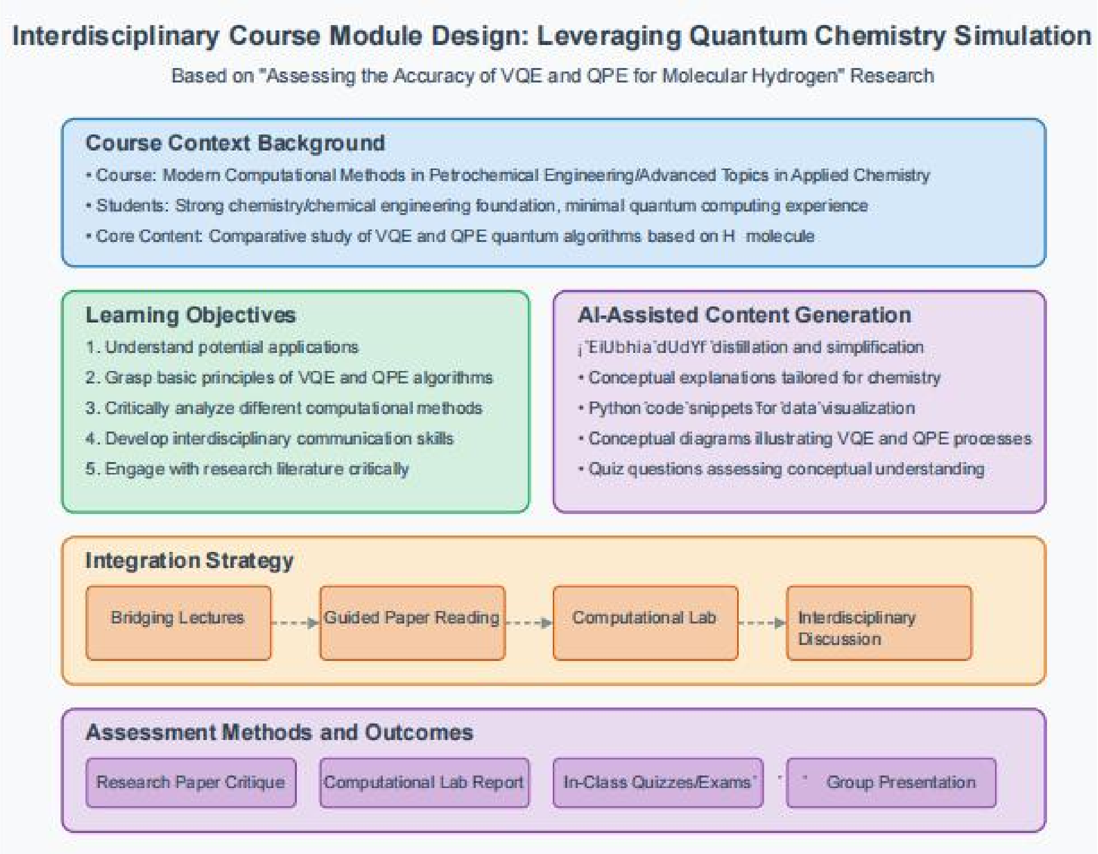
The observed outcomes strongly support the effectiveness of this approach, aligning with the benefits anticipated from active learning (Section 3.2) focused on problem-solving (Section 3.1). As highlighted in Figure 4, students showed significant improvements in practical OOP and algorithm application skills, notably learning to adapt algorithms under constraints. Their ability to tackle complex problems improved, and crucially, student engagement and motivation increased markedly, with over 90% finding the project more engaging. This outcome reinforces the value of using authentic, challenging tasks derived from real-world contexts. The curriculum's enhanced alignment with relevant professional skills further underscores the benefit. Challenges related to student unfamiliarity and task complexity were addressed through pedagogical scaffolding (lectures, milestones, hints, and support sessions), reflecting the need for adaptable teaching practices discussed implicitly in relation to faculty support (Section 5.1.2).

S.2 Case Study 2: Interdisciplinary Module Design Leveraging Quantum Chemistry Research

S.2.1 Module Context and Pedagogical Design

This case study exemplifies the principles of interdisciplinary AI education (Section 3.3) by detailing an advanced module designed for chemistry or chemical engineering students with minimal prior quantum computing knowledge. Integrated within upper-level courses as shown in Figure 6, the module aimed to introduce cutting-edge quantum simulation concepts relevant to future research and development roles, addressing the challenge of bridging significant disciplinary knowledge gaps. This aligns with the goal of fostering adaptability and engaging students with emerging technologies, even those outside their primary specialization.

The learning objectives as shown in Figure 6, were crafted to promote higher-order thinking skills (Section 3.1) and interdisciplinary competence, rather than deep technical mastery. Objectives included understanding potential quantum computing applications in their field, grasping conceptual principles of variational quantum eigensolver (VQE) and quantitative precipitation estimation (QPE), critically analyzing computational methods via research outputs, developing interdisciplinary communication, and enhancing information literacy (Section 4.4.1) by engaging critically with scientific literature.



Interdisciplinary Course Module Design: Leveraging Quantum Chemistry Simulation

Based on "Assessing the Accuracy of VQE and QPE for Molecular Hydrogen" Research

Course Context Background

- Course: Modern Computational Methods in Petrochemical Engineering/Advanced Topics in Applied Chemistry
- Students: Strong chemistry/chemical engineering foundation, minimal quantum computing experience
- Core Content: Comparative study of VQE and QPE quantum algorithms based on H molecule

Learning Objectives

1. Understand potential applications
2. Grasp basic principles of VQE and QPE algorithms
3. Critically analyze different computational methods
4. Develop interdisciplinary communication skills
5. Engage with research literature critically

AI-Assisted Content Generation

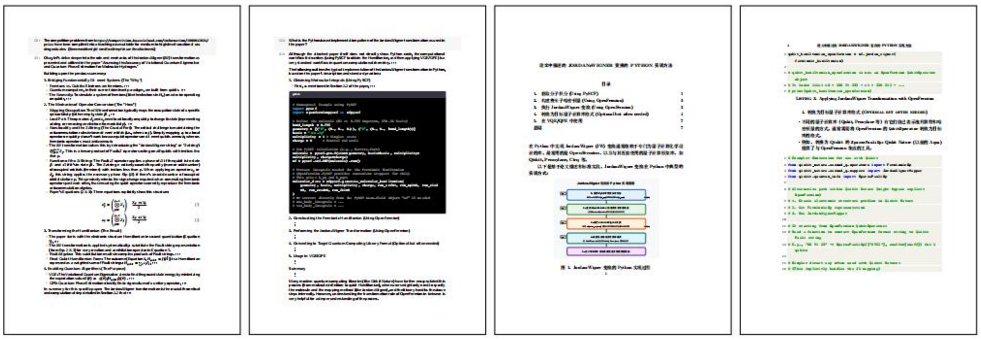
¡˜EiUbhia˜dUdYf ˜distillation and simplification
- Conceptual explanations tailored for chemistry
- Python˜code˜snippets˜for˜data˜visualization
- Conceptual diagrams illustrating VQE and QPE processes
- Quiz questions assessing conceptual understanding

Integration Strategy

Assessment Methods and Outcomes

Figure 6 Overview of the interdisciplinary course module design. VQE: variational quantum eigensolver, QPE: quantitative precipitation estimation.

To anchor these objectives, the module centered on a real research paper comparing VQE and QPE for H_2. This provided an authentic context for analysis. Significantly, the instructor, primarily a chemistry expert, utilized generative AI as an assistant as shown in Figure 7, to bridge their own knowledge gaps and generate accessible learning materials. This highlights the practical need for and potential of AI tools in supporting faculty development and enablement in Section 5.1, when tackling interdisciplinary teaching.



(a) Build interdisciplinary knowledge (b) Detail interdisciplinary knowledge (c) Real-world snippet (Illustrative) 1 (d) Real-world snippet (Illustrative) 2

Figure 7 Illustrative concept: Chemistry and engineering instructors using GenAI to explain unfamiliar computer science concepts, facilitating the creation of interdisciplinary teaching cases. (a, b) Depict using AI for knowledge building and detailing; (c, d) represent analogous real-world snippets (actual prompts/outputs not shown).

S.2.2 AI-Assisted Content Generation and Integration Strategy

The core scientific content was drawn directly from the VQE and QPE research paper. AI's crucial role, as suggested under AI-assisted content generation as shown in Figure 6, was as an instructor's assistant, facilitating the interpretation and translation of complex, interdisciplinary information into effective teaching resources. This process exemplifies leveraging AI for Content Creation support related to Section 2.4.2. The instructor used advanced language models to generate simplified explanations of quantum concepts tailored for the target audience, draft conceptual algorithm summaries, and formulate clarifying questions. AI also aided in creating supplementary materials like Python visualization snippets, conceptual diagrams, and draft quiz questions, demonstrating AI's utility in preparing materials that bridge communication gaps discussed in Section 3.3.

The module's integration strategy as shown in Figure 6, involved sequential activities designed to scaffold learning. AI-assisted Bridging

Lectures introduced concepts and motivation. Guided Paper Reading sessions fostered critical engagement with research literature. A computational analysis lab, focusing on data analysis and interpretation using provided scripts, offered hands-on engagement without requiring deep coding skills. The concluding interdisciplinary discussion encouraged students to synthesize knowledge and consider collaborative potential, aligning with the goals of interdisciplinary AI education in Section 3.3. Instructor use of AI for preparation and student use of Python tools reflect the blended technology integration discussed throughout the paper.

S.2.3 Assessment Methods and Observed Outcomes

Assessment for this module as shown in Figure 6 deliberately prioritized conceptual understanding and analytical skills, aligning with the principles of assessing higher-order thinking rather than technical implementation. Methods included a research paper critique, a computational lab report focused on interpretation, and in-class quizzes assessing conceptual grasp. Optional group presentations further encouraged application and communication skills.

The observed outcomes demonstrated the value of this interdisciplinary, AI-assisted approach. Students exhibited increased awareness of advanced computing's relevance to their field and enhanced critical reading skills when engaging with complex literature in Section 3.1. They developed a conceptual grasp of sophisticated methods by analyzing results, stimulating interest in further computational studies. Critically, the AI assistance empowered the instructor in Section 5.1 to confidently deliver challenging interdisciplinary content. The primary challenge, the conceptual difficulty, was managed through strategies like

AI-powered simplification, focusing on concepts over technical depth, scaffolding activities, and explicitly connecting quantum methods to relevant domain problems which are practical approaches to overcoming implementation challenges related to Section 5.1.2.

S.3 Case Study 3: Student-Led Curriculum Reform Design with AI Assistance

S.3.1 Module Context and Pedagogical Framework

This case study outlines a scenario where students themselves engage in AI-assisted curriculum redesign, moving beyond the traditional instructor-led model. As illustrated in Figure 8, this approach is envisioned within contexts like advanced undergraduate seminars, capstone projects, or dedicated modules focusing on pedagogy and technology. Such modules could be offered across various disciplines, empowering students to shape the future of learning within their own fields. The target participants are typically senior undergraduate or postgraduate students who possess solid domain knowledge, a foundational level of AI literacy enabling interaction with generative tools, and an interest in educational innovation or the application of AI within their discipline’s learning environments.

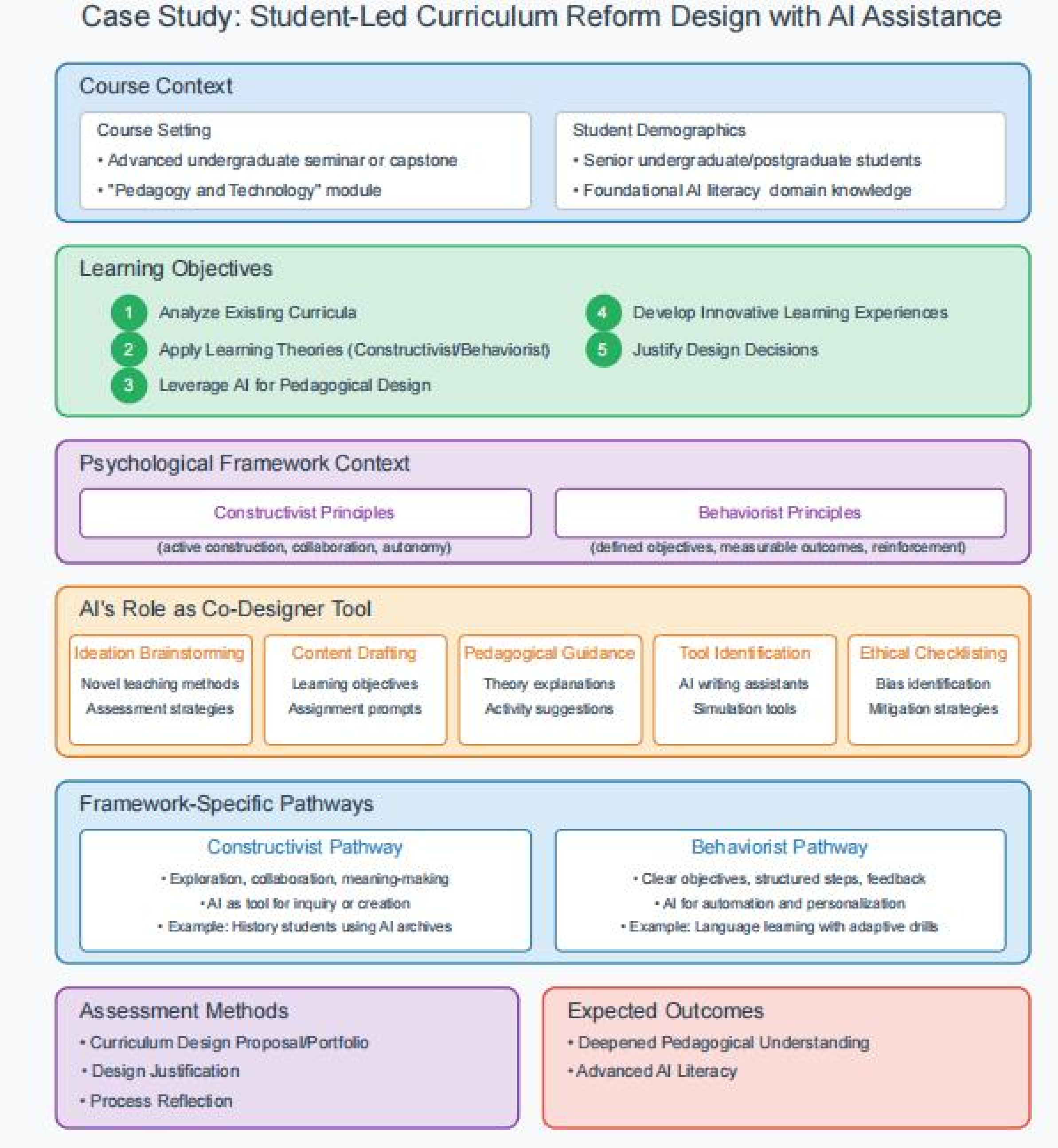


Figure 8 Overview of the student-led curriculum reform design case study.

The central learning objective is for students to actively experience and comprehend the curriculum design process, specifically enhanced by AI capabilities, through distinct pedagogical lenses. Key objectives, summarized in Figure 8, include enabling students to critically analyze existing curricula for AI integration opportunities, differentiate and apply principles from constructivist and behaviorist learning theories, leverage generative AI ethically and effectively throughout the design process (for ideation, content drafting, tool identification, and ethical review), develop innovative AI-integrated learning experiences, and rigorously justify their design choices based on their chosen learning theory and an understanding of AI's potential and limitations.

The pedagogical foundation for this case study involves exploring two distinct design pathways supported by AI: first, one guided by constructivist principles emphasizing active construction, collaboration, and autonomy. Second, another followed by behaviorist principles focusing on defined objectives, measurable outcomes, and reinforcement. This dual-pathway approach, depicted in Figure 8, allows students to explore how AI can serve as a versatile co-design tool adaptable to fundamentally different educational philosophies.

S.3.2 AI-Assisted Student Design Process and Pathway Integration

In this scenario, students transition from learners to active curriculum designers. Tasked with reforming a familiar course or module, they should explicitly adopt either a constructivist or behaviorist framework and utilize generative AI as a co-design partner. As outlined under AI's role as co-designer tool in Figure 8, AI assists across the design life cycle. Students can leverage AI for ideation and brainstorming (generating AI integration ideas, novel methods, and assessment strategies), content drafting (initial versions of objectives, activities, prompts, and rubrics), seeking pedagogical guidance (explaining learning theories and suggesting aligned activities), tool identification (suggesting relevant AI tools for learners and instructors), and performing an ethical checklist function (identifying potential biases or integrity issues and brainstorming mitigations).

The integration strategy manifests through framework-specific pathways, illustrated in Figure 8. Students following the constructivist pathway might design experiences emphasizing exploration and collaboration, using AI for inquiry or creation. Examples include using LLMs to brainstorm complex problems for project-based learning, suggesting collaborative projects involving AI tools, designing assessments requiring critical evaluation of AI output within authentic tasks, or scripting AI-driven ethical simulations. A potential output could be a module where history students use AI archives to collaboratively investigate alternative narratives. Conversely, students on the behaviorist pathway might focus on structured learning with clear objectives and feedback, using AI for automation and personalization. Examples include using AI to break down skills into measurable steps, generating adaptive quiz banks, designing AI tutors for immediate feedback, or outlining personalized learning plans based on pre-assessments. An output might be an AI-enhanced language learning module with automated feedback and adaptive drills. Students would typically employ readily available AI tools like LLMs, potentially augmented by specialized tools for image generation, coding, or research exploration relevant to their design.

S.3.3 Assessment Methods and Anticipated Outcomes

Assessment in this student-led design context, detailed in Figure 8, centers on evaluating the quality and rationale of the proposed curriculum reform. The primary method is the submission of a comprehensive curriculum design proposal or portfolio, outlining the reform’s rationale, objectives, alignment with the chosen learning theory (constructivist or behaviorist), specific AI-integrated activities, assessment plan, and ethical considerations. Students would also engage in design justification and presentation, defending their pedagogical choices and explaining AI’s role. A process reflection requires students to analyze their design journey, including their use and critical evaluation of AI assistance. Optional peer review can further enhance learning by providing structured feedback on proposals.

The anticipated outcomes of this approach as shown in Figure 8, extend beyond traditional content knowledge. Engaging students directly in AI-assisted design is expected to lead to deepened pedagogical understanding through active application of learning theories. It fosters advanced AI literacy, particularly in sophisticated prompting and critical evaluation of AI outputs for pedagogical purposes. This process can also surface novel educational innovations tailored to specific disciplinary contexts. Furthermore, it promotes student ownership and meta-cognition regarding learning design and effectiveness, while explicitly highlighting the trade-offs inherent in different pedagogical frameworks, especially when integrating AI.

Potential challenges include managing students’ varying prior knowledge of pedagogy and mitigating the risk of superficial designs overly reliant on uncritical AI generation. These can be addressed by providing foundational resources on learning theory, structuring the task with clear milestones requiring explicit justification referencing the chosen framework, emphasizing critical AI use in assessment rubrics, and potentially incorporating peer feedback mechanisms. Detailed rubrics focusing on design coherence, appropriate AI integration, feasibility, and ethical thoughtfulness are crucial for fair evaluation.