

Design and Evaluation of an AI-Supported Structured Project-Based Learning Model in an Undergraduate Deep Learning Technology Course

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Abstract: Generative artificial intelligence (AI) can support project-based learning (PBL), but without instructional structure, it may facilitate task completion without sustained analytical engagement. This study developed and implemented an AI-supported structured project-based learning (AI-SPBL) model in an undergraduate Deep Learning Technology course. The model treated AI as part of a structured project process and required a project proposal at the midterm assessment to make students' reasoning visible before implementation. A historical cross-cohort comparison examined 61 software engineering students across 18 group projects. Compared with the 2025 comparison cohort, which used conventional PBL, the 2026 intervention cohort produced technical reports showing broader analytical practices, while project-level scores were modestly higher and less dispersed. These findings suggest that embedding AI within a structured project process may shift its role from a task-efficiency tool toward a scaffold for more visible, evidence-based project reasoning.

Keywords: Generative artificial intelligence; Structured project-based learning; Deep learning technology

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1. Introduction

Generative artificial intelligence (AI) tools such as ChatGPT, Claude, and DeepSeek are changing teaching and learning in higher education. This shift is especially relevant to courses that use project-based learning (PBL). In the PBL process, projects can strengthen problem-solving and engineering competence. They can also promote self-directed learning while supporting project management and teamwork. AI can not only provide personalized feedback and help students generate ideas, but also streamline research and support

complex problem-solving that reflects professional practice. Therefore, the integration of AI into PBL has emerged as a growing area of educational research and curriculum reform ^[1].

AI-supported PBL does not guarantee meaningful or sustained learning without instructional structure or scaffolding ^[2]. Conventional PBL may provide a project brief and assess final project outcomes while offering limited support for intermediate decisions ^[3]. In an undergraduate deep learning course, this gap is amplified by abundant datasets, code repositories, and AI-generated solutions. Students can produce technically fluent outputs without sustained analytical engagement. AI support lowers barriers to project completion. However, students may rely on AI assistance rather than learn from it. Without instructional structure, students may accept the first plausible response or begin implementation prematurely. They may also delegate comparison and verification to AI rather than reflect on these decisions themselves. The central question is therefore not whether students should use generative AI but how its use should be organized to support project learning. Two recent studies provide complementary design principles. Kestin *et al.* studied structured AI tutoring and emphasized sequenced activities alongside targeted feedback ^[4]. For project work, the Project-Work Artificial Intelligence Integration Framework (PAIIF) positions AI as co-intelligence throughout the project lifecycle, from conception and design to implementation and operation ^[5]. Together, these studies suggest that AI support should be embedded in a visible activity structure and evaluated through both outcomes and the decisions that produce them. They also support incorporating instructional scaffolding and instructor guidance into PBL to enhance its educational value and foster student agency.

We developed and implemented an AI-supported structured project-based learning (AI-SPBL) model in an undergraduate Deep Learning Technology course in 2026. The AI-SPBL model treated AI as one element of an integrated project lifecycle rather than as a stand-alone intervention. The reform began with AI-assisted proposal development and project-focused literature review. Students then completed technical implementation and explicit testing before preparing a standardized technical report and oral presentation. These linked activities provided continuous support from problem formulation to final reflection. The proposal required students to articulate consequential decisions before implementation, while AI supported early clarification and exploration. Together, these components were intended to accelerate topic formulation while sustaining student agency. They were also designed to strengthen metacognitive engagement and higher-order thinking. We evaluated the 2026 reform using a historical cross-cohort comparison with the 2025 comparison cohort, which used conventional PBL. We first assessed differences in overall project outcomes. We also evaluated whether students in the intervention cohort showed greater student agency during complex project exploration.

2. Current problems in project-based learning in the Deep Learning Technology course

2.1. Course background

Deep Learning Technology is a bilingual major elective for software engineering undergraduates. The syllabus covers three areas, including basic principles, classical models, and technical applications. The course aims to familiarize students with the development of deep learning and to help them understand its basic theories, important models, and applications. It also focuses on cultivating students' ability to apply deep learning technologies to practical problems, work in teams, and communicate effectively through presentations. The 2025 class used a conventional PBL approach. For the final project assessment, teams

selected a topic and formulated a problem based on relevant literature. After implementing a model, they presented their work and submitted a technical report with source code. This arrangement links theory with practice and creates opportunities for teamwork and communication. It also produces several artifacts that make the project lifecycle visible and support performance evaluation.

2.2. Problems in the conventional project lifecycle

A review of the course identified several problems in the 2025 class. Thirty students formed seven groups and completed final projects. The project topics ranged from image classification and text generation to air-pollution forecasting. Many tasks used toy datasets or largely reproduced existing projects based on publicly available code. Some outcomes remained technically basic and lacked in-depth exploration of a meaningful question or a new deep learning model. This may have occurred because topic selection consumed substantial time, leaving limited time to develop a strong project proposal. In addition, participation and contributions within groups were uneven, making it difficult to complete and improve the project outcomes. Although the midterm assessment required team formation and topic selection, it did not require all groups to submit a midterm report. Some groups may not have begun developing their project proposals until the final project assessment period. Students could therefore begin implementation without receiving collective feedback on their initial plans. They might also fail to schedule the work and assign tasks among team members.

As generative AI makes coding and report production easier, conventional PBL designs face additional limitations. PBL requires critical problem-solving and often draws on knowledge from multiple disciplines. Without scaffolding, a group can rely on an available repository or dataset. It may also adopt an existing architecture and use generative AI to produce an application narrative after implementation. This approach leaves educationally important decisions implicit. The AI-SPBL reform therefore integrated generative AI assistance into a structured project process. Its purpose was to make the reasoning chain visible before implementation and improve project outcomes.

3. Integrated AI-SPBL reform

3.1. Conceptual framework of the AI-SPBL model

The AI-SPBL model combines an open project lifecycle with a common project-framing scaffold. It retains open topic selection and technical implementation. Students must also present their work and submit a technical report. A common structure can support these open project components by constraining the process and evidence chain across the project lifecycle. For each deep learning project, groups were asked to submit a proposal at the midterm assessment. The proposal must explain the research background and define the problem. It must also identify candidate datasets and methods, as well as suitable evaluation metrics. This additional project-framing scaffold follows a problem–data–metrics–constraints (PDMC) framework that provides the core logic for project framing. The AI-SPBL model also embeds AI support in a visible activity structure. Generative AI serves as co-intelligence throughout the project lifecycle, from conception and design to implementation and operation.

3.2. Study design

The intervention cohort in 2026 used the AI-SPBL model and included 31 students who completed 11 projects (mean group size, 2.82). The comparison cohort in 2025 used conventional PBL and included 30

students who completed seven projects (mean group size, 4.29). Both cohorts conducted a literature review and completed a self-selected group project. The AI-SPBL model was the intended instructional difference between the cohorts. The same instructor taught both cohorts under the same syllabus.

3.3. Implementation procedures

The implementation followed the 16-week course calendar, with the midterm assessment in week 7 and the final project assessment in week 16. During weeks 1–6, the instructor explained the course requirements and project-based assessment procedures. Both classes received project-driven instruction covering basic principles and classical deep learning models.

The 2026 AI-SPBL reform moved project conception and experimental planning to a mandatory midterm assessment. The week-7 midterm assessment distinguished the reformed 2026 class from the 2025 class. In 2025, students were asked to begin topic selection and submit a paper translation at the group level, without submitting a project proposal. By contrast, the 2026 midterm assessment comprised two compulsory components. First, initial literature review and paper translation were required. Second, students were required to assign tasks to individual members of the final-project team and submit a structured project proposal. Students first used generative AI to search the literature and support translation. They also used it to explore topics and prepare the proposal before full implementation. Each group remained responsible for verifying and submitting its work.

The 2026 AI-SPBL reform was structured at two levels. At the milestone level, the week-7 midterm assessment placed the literature review and project planning before implementation. This fixed sequence was designed to prevent topic selection from extending late into the semester. At the task level, the proposal template required students to specify seven forms of evidence: (1) a project title; (2) team roles; (3) research background explaining why the problem should be studied; (4) a research task stating the problem to be addressed; (5) a candidate dataset description including the number of samples, examples, and label distribution; (6) candidate deep learning models; and (7) an experimental plan specifying the data-partition strategy and evaluation metrics. The milestone-level scaffold organized when major decisions had to be made, while the task-level scaffold, supported by generative AI, specified what each decision had to contain. Together, this two-level scaffold defined the AI-SPBL reform implemented in 2026.

During weeks 8–15, advanced deep learning models, such as large language models (LLMs), and typical applications were taught. Meanwhile, both classes developed their projects alongside continued instruction. In week 16, final project outcomes from both classes were evaluated using the same broad components: presentation and defense, technical report, source code, and paper translation. A standardized technical report preserved evidence showing whether the proposed plans had been implemented, revised, and evaluated.

4. Results

Following implementation of the AI-SPBL model, project-level scores in the 2026 intervention cohort differed from those in the 2025 comparison cohort. At the project level, the mean score increased from 82.86 to 84.64. The median rose from 80 to 85. The minimum likewise increased from 75 to 80. In contrast, the standard deviation decreased from 7.00 to 3.89. At the student level in 2026, seven students (22.58%) scored between 90 and 100. Twenty-two students (70.97%) scored between 80 and 89. The remaining two students (6.45%) scored between 70 and 79. These descriptive differences are consistent with modestly

higher and less dispersed project-level scores in 2026. Together with the observed differences in the quality of technical reports and code, the project artifacts suggest that students connected theory more coherently to model implementation. They also communicated the resulting technical work more coherently. One possible explanation is that the structured proposal encouraged group members to enter the project lifecycle earlier, thereby increasing the time available for implementation and analysis. The proposal also enabled the instructor to identify unclear goals or mismatched elements. Feedback could therefore be provided before implementation, which may have contributed to the improved outcomes.

Following implementation of the AI-SPBL reform, we observed evidence of research-oriented problem-solving in the students' project artifacts. Within the AI-SPBL model, students first formulated the problem and investigated the literature. They then developed and evaluated a model before communicating the results. Compared with those in the 2025 comparison cohort, projects in the 2026 intervention cohort covered a broader range of topics, ranging from interpretable classification, image generation, medical image segmentation, graph-data caching, quantitative investment, and parameter-efficient fine-tuning. Several groups moved beyond implementing and reporting the performance of a single model. The 2026 technical reports compared models and included ablation studies. Some groups used grouped cross-validation or out-of-distribution evaluation. Others reported negative results and analyzed errors. This pattern suggests that students used AI and disciplinary knowledge to explore alternative solutions. One representative project in 2026 proposed an end-to-end quantitative investment system that connected stock-price prediction with asset allocation. The group designed an adaptive dual-model ensemble framework with a composite loss and evaluated it experimentally. This project was subsequently developed into a manuscript for journal submission. Taken together, these outcomes suggest that aligning AI use with a structured project process may strengthen students' ability to formulate and investigate complex research problems. In this model, AI may function less as a task-efficiency tool. Instead, it may scaffold deeper learning while supporting responsible, evidence-based practice.

5. Conclusion

This study developed an AI-SPBL model and implemented the associated reform in an undergraduate Deep Learning Technology course. The model embedded generative AI within a two-level scaffold that combined a mandatory midterm assessment focused on project planning with explicit structural requirements for project proposals. The observed differences were consistent with a shift away from task-efficient AI use toward a scaffold for deeper PBL grounded in responsible, evidence-based practice. Project artifacts also suggested greater student agency in investigating complex research problems, while project-level scores were modestly higher and less dispersed. These findings suggest that generative AI may better support open-ended technical projects when its use is tied to explicit project stages and decision requirements. Evidence requirements and output verification remain essential, as does timely instructor feedback. These conditions distinguish structured AI use from reliance on a general-purpose answer generator.

Disclosure statement

The authors declare no conflict of interest.

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