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WIP: Transforming Engineering Labs through AI-Powered Project-Based Learning

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Work-in-Progress: Intersegmental AI-Powered Project-Based Learning Engineering Labs

Abstract

Engineering laboratories are central to developing students' technical competence, professional skills, and engineering identity, yet they are often experienced as prescriptive, procedure-driven environments. This work-in-progress paper presents an intersegmental implementation of an AI-powered Project-Based Learning (AI-PBL) framework, aligned with ABET outcomes, across engineering laboratories at a community college, a comprehensive university, and an R1 institution.The project integrates artificial intelligence tools to scaffold learning while preserving instructor authority, disciplinary rigor, and assessment validity.

Introduction

Engineering laboratories are essential for connecting theory and practice, yet traditional lab instruction often emphasizes procedural completion over inquiry, limiting authentic engineering engagement. Persistent challenges in student engagement, equity, and retention—particularly for women, underrepresented minority (URM), and first-generation students—have been well documented in STEM education [1, 2, 3]. Active and inquiry-based learning approaches have demonstrated significant improvements in student learning and performance in laboratory and large-enrollment STEM contexts [4, 5, 6, 7], with Discipline-Based Education Research underscoring the importance of discipline-specific instructional design [8].

Gold Standard Project-Based Learning (PBL) addresses these challenges by engaging students in sustained, authentic engineering problems aligned with engineering design practices and ABET student outcomes [9, 10]. Equity-oriented PBL course redesigns have been shown to reduce achievement gaps while improving learning outcomes for all students [11]. Building on these foundations, this work-in-progress paper presents an intersegmental AI-powered Project-Based Learning (AI-PBL) framework that integrates artificial intelligence into laboratory instruction while preserving pedagogical intent, assessment validity, and equity, responding to the accelerating adoption of AI in education [12].

AI-PBL Framework Overview

The AI-PBL framework is grounded in learning science principles including constructivism, metacognition, and formative feedback [13, 14, 15], with structured reflection, peer interaction, and iterative sense-making embedded throughout the project cycle. It adapts Gold Standard

Project-Based Learning [10] for engineering laboratories by emphasizing authentic, complex problems, student agency, engineering design, and public products aligned with ABET student outcomes. The framework is implemented intersegmentally across a comprehensive university, community college, and R1 institution, enabling examination of AI-PBL across diverse student populations and institutional contexts.

AI-PBL follows a three-stage instructional progression: Skills → Design → Innovation, explicitly grounded in Backward Design [16], with project activities and assessments mapped directly to ABET outcomes. AI use is deliberately separated into instructional scaffolding, assessment, and student-designed bot development to ensure AI augments, rather than replaces, student reasoning and instructor judgment. Custom GPT-based bots function as adaptive tutors supporting inquiry, design iteration, and reflection, while an AI-Driven Evaluation (ADE) bot aligns assessment with Bloom's Taxonomy and AAC&U VALUE rubrics. Shared infrastructure (Google Drive, GitHub, Jupyter) supports reproducibility, and an IRB-compliant equity lens enables longitudinal analysis of anonymized student interactions, DFW rates, grade distributions, and demographic trends, positioning AI-PBL as a replicable model for enhancing laboratory-based engineering education.

PBL in Labs

AI-enhanced Project-Based Learning (AI-PBL) was implemented across three laboratory-centered courses: Mechanics of Materials, Applied Electromagnetics, and Computer Science Data Structures, to replace traditional procedure-driven instruction with cohesive, design-centered learning experiences situated in authentic engineering and computing contexts. Across all courses, students engaged in sustained projects integrating theory, experimentation, design, and communication, aligned with ABET Student Outcomes related to complex problem solving (SO1), design (SO2), experimentation (SO6), teamwork (SO5), and communication (SO3).

In Mechanics of Materials, students integrated multiple experimental investigations into the iterative design and testing of a small-scale emergency shelter, using laboratory data to inform engineering decisions rather than completing isolated experiments. In Applied Electromagnetics, students addressed an emergency communications challenge by designing, simulating, fabricating, and measuring an antenna using professional tools and instrumentation. In Computer Science Data Structures, students connected classical algorithms to machine learning workflows through an anchor project linking computational complexity to empirical performance and ethical considerations.

Across all implementations, AI tools functioned as adaptive scaffolds supporting inquiry, data interpretation, simulation analysis, and reflection, while faculty maintained control over learning goals, assessment, and experimental rigor. These implementations demonstrate the potential of AI-PBL to enhance laboratory-based instruction, promote authentic engineering practice, and support higher-order technical competencies.

External industry advisors propose or mentor projects, reinforcing authenticity and professional relevance. High-performing students from prior offerings serve as Teaching Assistants (TAs), supporting data organization and preliminary analysis under faculty supervision.

Class Bots for Learning Scaffolding

Custom GPTs were developed for three laboratory courses using the ChatGPT GPT Builder following a structured, reproducible design process. Each GPT was configured through system-level instructions to function as a course-specific learning support tutor, grounded exclusively in instructor-curated laboratory manuals and Open Educational Resources (OER). Laboratory content was segmented into individual, descriptively named files and uploaded as the sole authoritative knowledge base, enabling fixed Retrieval-Augmented Generation (RAG) and reducing hallucinations. Web and computational tools were selectively enabled to support simulation workflows and contextual guidance.

To preserve academic integrity, the GPTs were explicitly constrained to scaffold inquiry rather than provide solutions. System instructions enforced a professional, instructor-like tone, restricted responses to course-relevant laboratory content, and avoided direct answers, completed calculations, or full lab reports. Interaction settings emphasized guided questioning, reflection, and design reasoning aligned with Gold Standard PBL, AAC&U VALUE rubrics, and Reading Apprenticeship principles [17]. A scaffolded "chain-of-thought–style" prompting approach guided students through goal clarification, identification of key concepts, and actionable planning without exposing internal reasoning or final answers.

This structured guidance approach aligns with evidence that scaffolded active learning produces stronger learning gains than unstructured discovery [18, 19]. Collectively, these design choices enable AI-PBL bots to function as adaptive laboratory learning guides that support inquiry, iteration, and reflection while maintaining instructor authority and assessment integrity.

ADE Bot for Assessment

The AI-Driven Evaluation (ADE) bot is a custom GPT built using OpenAI's GPT Builder interface, configured to function exclusively as an assessment tool for researchers and instructors. It does not interact with students. Instead, ADE analyzes transcripts of student–AI interactions generated during project work.

The bot operates through two components: behavior instructions and a curated knowledge base. The behavior instructions direct ADE to treat all user input as student conversation logs and to produce structured evaluation reports without prompting for clarification or generating instructional dialogue. The knowledge base consists of two documents: (1) detailed ADE bot specifications that define scoring rubrics and output structure, and (2) a PBL assessment rubric aligned with ABET outcomes.

ADE outputs five analytic dimensions for each transcript: Bloom's taxonomy level [19] (1–6 scale), critical thinking and problem-solving depth using a modified VALUE rubric (1–4 scale)[20], metacognitive skills (1–4 scale), creativity and inquiry (1–4 scale, when evidence exists), and a qualitative discourse and sentiment summary. Each score is accompanied by a brief justification grounded in direct quotations from the student's language.

The goal is not to evaluate correctness but to characterize inquiry quality over time. All analysis must reference observable student behavior; the bot is instructed never to infer intent unless explicitly stated in the transcript. The bot is currently redesigned to improve assessment using human scored assignments on the same rubrics.

To triangulate findings, ADE analytics are complemented by established survey instruments including the Student Assessment of Learning Gains (SALG) [21], CLASSE [22], and self-efficacy measures adapted from prior work [23]. Prior research has shown that self-efficacy is a key mediator of performance gains in active-learning environments, particularly for URM students [6].

Preliminary Observations and Lessons Learned

Initial analysis indicates measurable growth across all assessed skills, with the most pronounced gains occurring during the phase in which students propose and justify solutions to the RFP. This milestone appears to catalyze higher-order reasoning, as students integrate technical knowledge, constraints, and design trade-offs into a coherent proposal. The analysis also suggests that sustained engagement in this inquiry-driven process elevates overall performance profiles, particularly for students who already demonstrate strong mastery on traditional assessments such as midterms and quizzes.

Quantitative data were collected using pre- and post-semester Student Assessment of Learning Gains (SALG) surveys, modified for the AI-PBL project, to capture students' self-reported perceptions of learning related to critical thinking, problem solving, communication, collaboration, and metacognition [24]. Qualitative data were collected concurrently through student focus groups designed to explore how students experienced AI use during open-ended project work and to provide explanatory context for survey responses.

Descriptive analyses compared combined pre-semester modified SALG responses from fall classes (N=37) with combined post-semester responses (N=41).

Using the SALG instrument, which captures perceived learning aligned with course design [24], descriptive pre/post responses (N=41) results showed higher post-survey ratings—particularly for metacognition, critical thinking, and problem solving—though findings are interpreted as indicative patterns due to the unpaired design.

Inductive thematic analysis of focus groups revealed that students used AI as a cognitive scaffold, developed greater confidence and metacognitive awareness in open-ended tasks, and recognized AI's limitations, providing explanatory context for the observed SALG survey patterns.

Lessons learned emphasize the importance of explicit AI boundaries, early student orientation to AI limitations, and sustained faculty collaboration.

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