

## PAPER

# Personalized and Scalable Problem-Based Learning in Soft Skills Education: The Role of AI Agents in Multidisciplinary Contexts

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## ABSTRACT

Soft skills development remains a critical challenge in higher education, especially in large, multidisciplinary learning environments where students vary in background, motivation, and self-regulatory capacity. Although problem-based learning (PBL) is broadly acknowledged as a successful method for developing critical skills and abilities such as planning, collaboration, and reflective thinking, traditional implementations often face constraints in personalization, coordination, and formative assessment. This study introduces an enhanced PBL model augmented by artificial intelligence (AI) Agents to support soft skills acquisition in blended learning contexts. The AI Agent, leveraging natural language processing (NLP) and automation via the n8n platform, functioned as a virtual assistant to facilitate task planning, peer coordination, self-monitoring, and timely feedback. A quasi-experimental study was carried out involving three groups of students (N = 263) participating in a course focused on developing soft skills, comprising one group using AI-supported PBL, another group using traditional PBL, and a control group taught through standard instructional methods. A mixed-methods analysis demonstrated that the group utilizing AI support exhibited statistically notable enhancements in their outcomes across six soft skill domains, particularly in planning, group work, and reflective learning ( $p < 0.001$ ). Behavioral data from LMS logs and product assessments further validated enhanced collaboration, consistency, and accuracy in self-assessment among AI-supported learners. The findings demonstrate that integrating AI Agents into PBL not only reduces instructor workload and enhances instructional equity but also empowers learners through personalized, data-driven scaffolding. This approach offers promising implications for scalable, technology-enhanced soft skills education across disciplines.

## KEYWORDS

soft skills, artificial intelligence (AI) agent, blended learning, problem-based learning (PBL), personalization

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## 1 INTRODUCTION

In the context of an increasingly competitive and dynamic global labor market, soft skills have become one of the key factors determining students' success after graduation [1]. According to the *Future of Jobs Report 2023* by the World Economic Forum [2], Current employers highly value candidates who demonstrate essential abilities, including effective time management, collaborative teamwork, strong communication skills, and sharp critical thinking. Beyond employability, these competencies are also fundamental for graduates to participate effectively in lifelong learning and to adapt to rapid technological and societal transformations [3]. This reality highlights not only education but also a societal demand for universities, especially in technical fields, to ensure that all students are systematically equipped with soft skills training as part of their formal curricula.

However, implementing soft skills teaching still faces numerous challenges, particularly in large, multidisciplinary classes where differences in students' academic backgrounds, as well as constraints in time and resources, have hindered the effectiveness of instruction [4]. Problem-based learning (PBL) is a well-established educational method celebrated for its success in fostering essential 21st-century skills, such as critical thinking, problem-solving, and collaborative teamwork. This effectiveness has been validated through various empirical studies, including research conducted at a leading technical university in Vietnam [5], where the application of PBL demonstrated significant improvements in students' behavior and academic performance.

Nevertheless, scaling up PBL exposes inherent limitations, especially in terms of personalized learning. In large classes, it is difficult for instructors to monitor and provide timely, detailed feedback to each student. Meanwhile, the rapid advancement of artificial intelligence (AI), particularly intelligent agent systems (AI Agents), offers a promising solution to this issue. With the ability to process natural language, AI Agents can automatically and individually monitor, analyze, and respond to students' learning processes. These systems can act as virtual assistants, accompanying and supporting students throughout their problem-solving journey, thereby optimizing the application of PBL in large-scale and blended learning environments. Thus, the integration of AI into PBL is not only a pedagogical innovation but also a way to promote more equitable and scalable access to high-quality soft skills training in higher education. Building up from this earlier work [5], this paper sets out the following research objectives:

- Design a model that integrates AI Agents into the PBL process in soft skills instruction.
- Implement this model as a trial within the subject of "Time Management Skills" as part of a soft skills training program.
- Assess the influence of AI Agents on students' learning behaviors and their progress in cultivating effective time management abilities.

Based on these objectives, the central research hypothesis is that integrating AI Agents into PBL can significantly enhance the development of students' soft skills by providing personalized support, timely feedback, and improved coordination. Through this study, the authors hope to contribute a teaching model that combines PBL and AI technology, aligned with the characteristics of modern classrooms, thereby improving the effectiveness of soft skills development programs in higher education.

## 2 LITERATURE REVIEW

### 2.1 Theoretical foundation of PBL in soft skills training

Problem-based learning is a student-focused teaching method that promotes exploration, analysis, and resolution of real-world situations by learners [6], [7], [8]. Instead of merely delivering academic knowledge, PBL creates an environment where students can practice communication, teamwork, critical thinking, and adaptability [9], [10]. The PBL process typically follows five recurring stages:

- Problem presentation: The instructors or materials introduce an open-ended scenario that encourages students to ask guiding questions.
- Learning objectives identification: Students discuss, assess existing knowledge, recognize knowledge gaps, and set in-depth learning goals.
- Information search planning: Tasks are distributed, sources are identified, and time management skills are developed.
- Data collection and synthesis: Searching for materials, conducting interviews or surveys, then sharing and synthesizing findings, and practicing communication and analytical thinking.
- Presentation and feedback: Student teams share their solutions and gain input from both classmates and teachers, nurturing abilities in delivering presentations and providing constructive feedback [6], [11].

Recent studies have demonstrated that PBL significantly contributes to the development of students' soft skills across multiple dimensions. In particular, learners engaged in PBL frequently report substantial gains in communication, teamwork, and conflict resolution. For instance, an experimental study conducted in Pakistan showed that PBL fostered more effective information sharing and collaborative problem-solving, thereby enhancing both communication and conflict management abilities [12]. Likewise, research at Vietnam National University, Hanoi, indicated that the majority of participants experienced increased confidence in public speaking, greater willingness to articulate ideas, and more active engagement in group discussions, which collectively strengthened their presentation and communication competencies [13], [14].

In addition to communication-related outcomes, PBL has been found to reinforce collaboration, leadership, and problem-solving. Through coordinating or assuming leadership roles within groups, students practice task delegation, negotiation, and team management—activities that directly nurture leadership capacity and analytical problem-solving. Quantitative evaluations of PBL cohorts confirm significant improvements in leadership and problem-solving scores following course completion [15]. These findings align with broader evidence that PBL encourages cooperation, structured role distribution, and shared responsibility in group contexts, thereby cultivating essential interpersonal and managerial competencies [10], [11].

At the individual level, PBL consistently enhances critical thinking, self-directed learning (SDL), and self-regulation. Comparative studies demonstrate that students exposed to PBL outperform their peers in critical thinking assessments and produce more innovative solutions than those taught through traditional methods [13]. Large-scale meta-analyses further substantiate that PBL not only promotes SDL and problem-solving but also strengthens cognitive flexibility and reflective learning practices [15], [16]. Through its iterative cycle of problem analysis, self-study, and group synthesis, PBL enables learners to independently acquire knowledge, adapt proactively to novel situations, and assume greater responsibility for their own learning trajectories.

At HUST, the focus on developing soft skills is not only a trend but also a key educational policy. In study [5], the PBL method was piloted in a “Soft Skills” course involving 140 students from various majors. Results indicated that PBL outperformed traditional teaching methods in enhancing soft skills, particularly in three aspects:

- (RQ1) PBL demonstrates a notably beneficial impact on teaching soft skills when compared to traditional approaches.
- (RQ2) PBL substantially improves students’ collaboration and teamwork skills in a multidisciplinary learning environment.
- (RQ3) The integration of educational technology into PBL significantly supports students’ soft skill development.

## 2.2 Technologies supporting PBL implementation: From LMS to AI agents in higher education

The adoption of PBL in higher education is progressively bolstered by digital platforms and technological tools. Among them, Learning Management Systems (LMS) serve as foundational tools, followed by the rise of AI Agents as more sophisticated and personalized solutions.

**Applications and limitations of LMS in PBL implementation.** Learning management systems such as Moodle, Canvas, and Blackboard have become essential tools in contemporary education, functioning as hubs for coordinating and storing project-related resources. Basically, LMSs support PBL implementation through the following key features:

- Centralized resource repository: Instructors can upload and organize all project documents, including prompts, rubrics, reference materials, and implementation guides. This ensures consistent and timely access for all students [17].
- Group collaboration spaces: LMSs offer tools for forming workgroups, discussion forums, wikis, and private file-sharing spaces for each team, facilitating idea exchange, task delegation, and collaborative project creation [18].
- Progress tracking and assignment submission: Instructors can set milestones with deadlines, enabling students to submit deliverables in stages. This feature helps monitor class-wide progress and ensures systematic submission tracking [19].
- Assessment support: LMS platforms integrate tools for assessments, including multiple-choice tests for background knowledge, peer reviews, and instructor feedback via grading systems [20].

However, relying solely on traditional LMS platforms for PBL reveals significant limitations. Chief among them is the system’s passive nature and lack of personalization [21]. LMSs function more as administrative and content repositories rather than proactive learning support tools [22]. Specific challenges include:

- Delayed and impersonal feedback: Instructors often provide feedback only after assignments are submitted, resulting in slow error correction. Feedback is usually general to the group rather than tailored to individual needs and knowledge gaps [23].
- Difficulty in tracking individual contributions: LMS platforms struggle to track and evaluate each student’s actual participation in group work, leading to potential grading inequities [24].

- Lack of real-time support: Students often encounter unexpected issues during projects, but LMSs cannot provide “timely, on-demand help” without instructor intervention.

These issues regarding interaction, personalization, and timely support have driven the development of a more advanced generation of technology: AI Agents.

**AI agents: Intelligent and personalized solution for PBL.** AI Agents are automated systems powered by AI, designed to overcome LMS limitations by offering proactive, real-time, and personalized support in teaching, assessment, and learning guidance [25], [26]. Unlike static applications, AI Agents continuously adapt based on data collected from learners, thereby creating unique learning experiences for everyone.

Architecturally, an AI Agent consists of three main components: Sensors that collect data on learning behaviors and performance (e.g., access frequency, review time, and accuracy rates); Processors that analyze this data to build learner profiles and predict needs and difficulties; and Actuators that deliver suggestions, feedback, or adapt learning pathways by recommending materials, generating customized quizzes, or issuing study reminders [27], [28]. Through this continuous feedback loop, AI Agents provide timely, personalized assistance—an advantage over traditional education tools. In practice, AI Agents are deployed in various forms, each serving a specific pedagogical function within the PBL context:

- Educational Chatbots: Interact with students via natural language to answer questions 24/7, provide instant academic guidance and information, enhance active study environments, and reduce instructor workload [29], [30].
- Intelligent Tutoring Systems (ITS): Monitor students’ problem-solving processes in detail, diagnose errors, and offer step-by-step hints, simulating one-on-one tutoring [31], [32]. Using models such as Bayesian Knowledge Tracing, ITS can identify students’ weak areas and recommend appropriate review activities to strengthen competencies before undertaking more complex tasks in the project.
- Recommender Systems: Personalize learning resources by suggesting lectures, videos, or references tailored to each learner’s profile, pace, and preferences, helping students search for information more effectively [33], [34].
- Automated Feedback Agents: Offer immediate, detailed feedback on structured tasks like multiple-choice tests or programming exercises, enabling instant error correction [32]. For essays or project reports, these agents use natural language processing (NLP) to analyze and comment on structure, coherence, and writing style, facilitating the development of academic writing skills [35].
- Simulation Agents: Develop engaging virtual settings, such as laboratories or business simulations that enable students to practice and apply their knowledge in a secure, highly interactive, and lifelike context, minimizing risks compared to implementation in the real world [27].

In general, when AI Agents detect decreased engagement or declining performance, they can automatically alert instructors or notify students via email, SMS, or LMS notifications [29]. They also track assignment completion, provide timely reminders, and issue alerts when students show signs of falling behind [30]. Research in the field of AI in education has demonstrated the potential of AI agents to enhance education quality by enabling flexible, adaptive, and learner-centered ecosystems [36].

Importantly, within the PBL framework, these functions directly address limitations in soft skills development. For example, automated reminders and group

coordination features strengthen planning and teamwork skills; real-time feedback on reports and presentations enhances academic communication and reflective decision-making; and personalized resource recommendations foster self-regulated learning. Thus, AI Agents are not only general educational tools but also act as catalysts for cultivating core soft skills—planning, collaboration, communication, and reflection—when embedded into the PBL process.

**Nodemation (n8n): A workflow automation platform for personalized learning.** While AI Agents (as described in Section “AI agents: Intelligent and personalized solution for PBL”) offer a vision of personalized education, in reality their implementation often faces two major barriers: technical complexity and system integration. Universities typically operate across fragmented ecosystems, including LMS platforms (e.g., Moodle), productivity tools (Google Workspace, Microsoft 365), communication platforms (email, Zalo, Telegram), and dedicated AI models. Integrating these systems into a seamless data flow that can trigger intelligent, real-time actions requires significant development resources [37].

In this context, open-source automation platforms have emerged as strategic solutions. N8n is a standout tool that acts as a flexible intermediary layer, enabling the connection and orchestration of various digital services without requiring advanced programming skills [38]. Instead of building complex AI Agents from scratch, educators and edtech administrators can use n8n’s visual drag-and-drop interface to design automated learning scenarios, turning pedagogical ideas into executable workflows. Though research on n8n in education is still emerging, the role of automation and “low-code” platforms in democratizing technology and promoting innovation has been widely acknowledged [39].

### 3 METHODOLOGY

The study model proposes integration between the traditional PBL cycle and an automated AI Agent system to support students throughout the process of scenario-based assignments while simultaneously providing real-time data to instructors. Figure 1 illustrates the traditional PBL cycle, which consists of three main stages: (1) Problem presentation – Problem analysis, (2) Information search – Solution planning, and (3) Discussion – Solution presentation – Evaluation.

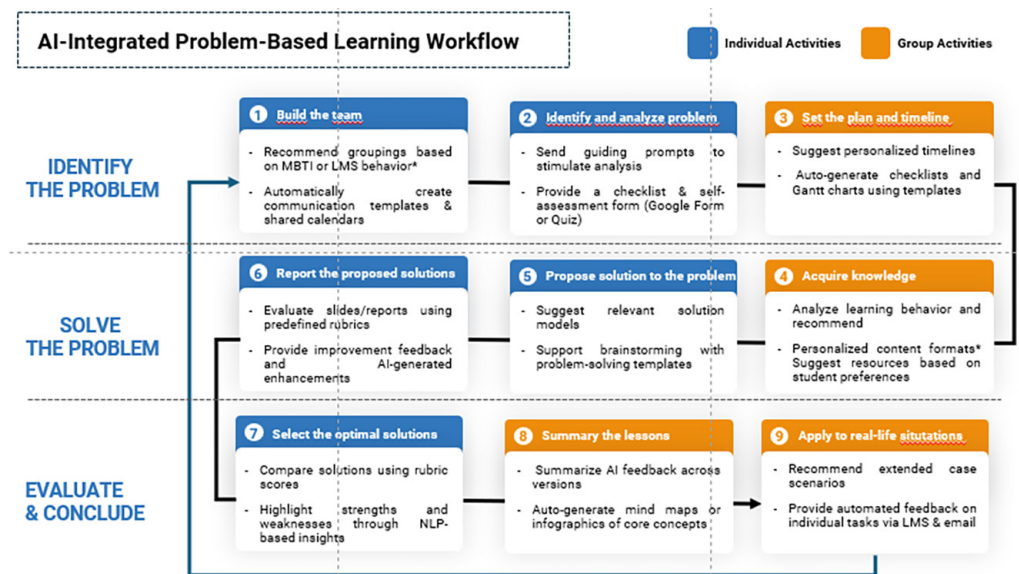


Fig. 1. AI-integrated PBL model

### 3.1 Problem identification

In the initial step, the goal is to create problem-based scenarios that stimulate students' analytical thinking and learning motivation. Since this was a soft skills course, students were asked to complete a short online Myers–Briggs Type Indicator (MBTI) inventory (approximately 10–15 minutes) at the beginning of the semester as part of their career orientation and teamwork preparation. Participation was voluntary, and only students who consented to share their results were included in the dataset. The MBTI results were used solely to support diverse team formation, ensuring that groups represented different working and communication styles, and had no impact on course grades. During this stage, the AI Agent system provides initial prompts and analytical guidance to foster learners' critical thinking. The specific learner activities and system support in this stage are outlined in Table 1, which describes the Problem Identification Process.

**Table 1.** Explanation of the process for identifying problems

Process	Student Tasks and Engagements	AI System Support
1. Team Formation	<ul style="list-style-type: none"> <li>– Form teams and assign roles.</li> <li>– Use templates and schedules to set up a workspace.</li> </ul>	<ul style="list-style-type: none"> <li>– Suggest team formation based on MBTI or behavior on LMS.</li> <li>– Automatically generate communication templates and shared work schedules.</li> </ul>
2. Problem Identification & Analysis	<ul style="list-style-type: none"> <li>– Analyze the assigned group problem.</li> <li>– Complete self-assessment forms to clarify evaluation criteria.</li> </ul>	<ul style="list-style-type: none"> <li>– Provide prompts and guiding questions to stimulate analysis.</li> <li>– Supply checklists and self-assessment templates.</li> </ul>
3. Planning & Scheduling	<ul style="list-style-type: none"> <li>– Develop a work schedule and delegate responsibilities to team members.</li> <li>– Use automatically generated charts to track progress.</li> </ul>	<ul style="list-style-type: none"> <li>– Suggest personalized milestones.</li> <li>– Automatically generate task lists and Gantt charts from available templates.</li> </ul>

### 3.2 Problem solving

At the second stage, learners are required to equip new knowledge to address the identified problem. The AI Agent system supports the personalized learning process, recommending collaborative strategies and providing templates to help organize tasks effectively. The detailed sequence of learner activities and corresponding AI support is presented in Table 2, which describes the problem-solving process.

**Table 2.** Explanation of the approach to resolving issues

Process	Student Tasks and Engagements	AI System Support
4. Knowledge Acquisition	<ul style="list-style-type: none"> <li>– Study learning materials (videos, documents) on the LMS.</li> <li>– Apply knowledge to practical tasks.</li> </ul>	<ul style="list-style-type: none"> <li>– Analyze learning behavior to recommend personalized content formats.</li> <li>– Suggest learning resources based on student preferences.</li> </ul>
5. Solution Proposal	<ul style="list-style-type: none"> <li>– Analyze problems of the assigned group.</li> <li>– Complete self-assessment forms to clarify evaluation criteria.</li> </ul>	<ul style="list-style-type: none"> <li>– Recommend appropriate solution models.</li> <li>– Support brainstorming using problem-solving templates.</li> </ul>
6. Problem-Solving Solution Report	<ul style="list-style-type: none"> <li>– Showcase and justify the team's product.</li> <li>– Gather and integrate feedback to enhance the result.</li> </ul>	<ul style="list-style-type: none"> <li>– Automatically evaluate and review presentations or reports using established criteria.</li> <li>– Provide improvement feedback and AI-generated advanced content.</li> </ul>

### 3.3 Evaluation and summary

At this stage, the emphasis is placed on evaluating the correctness, real-life applicability, and optimality of the proposed solutions. Upon submission, the AI Agent conducts automatic content analysis, generates immediate feedback, and synthesizes data to support instructors in tracking student performance. These processes are documented in Table 3, which describes the evaluation and summary phase.

**Table 3.** Overview of the assessment and conclusion

Process	Student Tasks and Engagements	AI System Support
7. Choosing the Best Solution	<ul style="list-style-type: none"> <li>– Discuss to evaluate and choose the group's final solution.</li> <li>– Provide critiques on other groups' solutions.</li> </ul>	<ul style="list-style-type: none"> <li>– Compare solutions using rubric-based scoring.</li> <li>– Highlight strengths and weaknesses through NLP.</li> </ul>
8. Lesson Summary	<ul style="list-style-type: none"> <li>– Review and refine the product while evaluating its thoroughness.</li> <li>– Organize and structure the knowledge gained.</li> </ul>	<ul style="list-style-type: none"> <li>– Summarize AI-generated feedback versions.</li> <li>– Automatically generate mind maps or infographics of core concepts.</li> </ul>
9. Practical Application	<ul style="list-style-type: none"> <li>– Independently practice solving newly suggested problems.</li> <li>– Apply results to different scenarios.</li> </ul>	<ul style="list-style-type: none"> <li>– Suggest extended real-world scenarios.</li> <li>– Provide automated feedback on individual tasks via LMS or email.</li> </ul>

The proposal to integrate an AI Agent system into the PBL process stems from the desire to enhance teaching and learning effectiveness in large-scale classrooms. This model positions the AI Agent as a learning companion capable of intervening and supporting students at every stage of the learning process. For individual activities, the AI supports personalized learning by analyzing learner behavior, recommending relevant content and resources, and providing automated feedback via LMS or email. For group activities, the AI not only assists with organizational aspects—such as suggesting group formations or providing working templates—but also engages in the cognitive process by offering solution models and supporting brainstorming activities. A primary characteristic of this model is its capacity to automatically evaluate. The AI can analyze student learning products (e.g., reports, presentations) based on predefined rubrics, deliver instant feedback, and compile data on progress and quality work for instructors. Through an automated workflow connecting the LMS, AI Agent, and reporting system, the entire data flow is streamlined, reducing manual effort and enabling instructors to monitor and intervene promptly when needed.

## 4 EXPERIMENT

### 4.1 Experimental design

The experimental teaching tasks were embedded in the official Soft Skills course, with a primary focus on the topic of time management skills. Within this context, students worked in groups on scenario-based assignments that required them to (i) analyze the given problem, (ii) search for and synthesize relevant information, (iii) design and implement a project plan, (iv) propose and present solutions, and (v) provide peer critiques and reflections. These tasks were deliberately aligned with the PBL cycle and supported by AI Agents at different stages to ensure timely

guidance and feedback. The expected learning outcomes were two-fold: (1) personal skills such as planning, time management, and self-regulated learning, and (2) collaborative skills such as teamwork, academic communication, presentation, and reflective decision-making. These outcomes also served as the criteria for evaluating the effectiveness of the intervention.

To assess the effectiveness of the AI-integrated PBL model (PBL-AI) on students' skill growth and academic performance, the research team carried out a controlled study involving three groups of participants. A total of 300 students were randomly chosen and equally distributed across the three groups (100 students per group). The experiment took place over an 8-week summer semester, comprising a total of 45 class periods dedicated to the "Soft Skills" course. The content and official curriculum objectives were predefined and covered two main categories:

- Core personal skills: Positive thinking and personal values; effective time management.
- Collaborative personal skills: Effective teamwork; effective communication; effective presentation; art of persuasion.

Table 4 presents a detailed illustration of the experimental structure, including task allocation and the conditions under which the PBL-AI model was applied to each group. The experimental structure is outlined in Table 4.

**Table 4.** Experimental design

Group	No. of Students	Teaching Method	Support Tools	Notes
Group 1 (Experimental PBL-AI)	100	PBL with AI Agent Integration	None	Students work on projects and interact with the AI Agent for feedback.
Group 2 (Control A PBL)	100	Project-Based Learning	PBL materials and question sets	Students work on projects and group discussions; no AI Agent involved.
Group 3 (Control B)	100	Traditional teaching	Automated support from AI Agent	Lecture-based instruction, no use of PBL.

The experimental procedure was structured into three stages: Pre-test, Instructional Delivery, and Post-test. The workflow is depicted in Figure 2. The study was carried out across three primary phases, lasting a total of nine weeks. The Pre-test phase (Week 0) focused on establishing a standardized baseline across all three study groups. During this phase, all participating students completed a pre-test survey to assess their initial competencies in core soft skills (addressing challenges, collaboration, analytical thinking, and independent learning). They also took a diagnostic test to evaluate their foundational knowledge related to the learning topic. Simultaneously, the research team finalized the preparation of learning materials and a shared PBL project scenario for Groups 2 and 3, as well as completing the technical configuration of the AI Agent system for integration into the LMS for Group 1.

The Experimental Instructional phase (Weeks 1–7) was carried out simultaneously across all three groups, all of whom studied the same topic to ensure content consistency. Group 1 (Experimental group) applied the AI-integrated PBL model (PBL-AI), with comprehensive system support from group formation, planning suggestions, instant feedback on project outputs, personalized learning resources, and automated

rubric-based assessment. Meanwhile, Group 2 (Control group A) also implemented the PBL model, but without AI support. Students self-managed the learning process, while instructors provided manual feedback on a scheduled basis. Group 3 (Control group B) followed the traditional lecture-based method. Throughout the process, a multi-source data collection system was used, recording learning progress and interactions on the LMS, student group outputs, qualitative feedback from instructors, and activity reports automatically generated by the AI Agent.

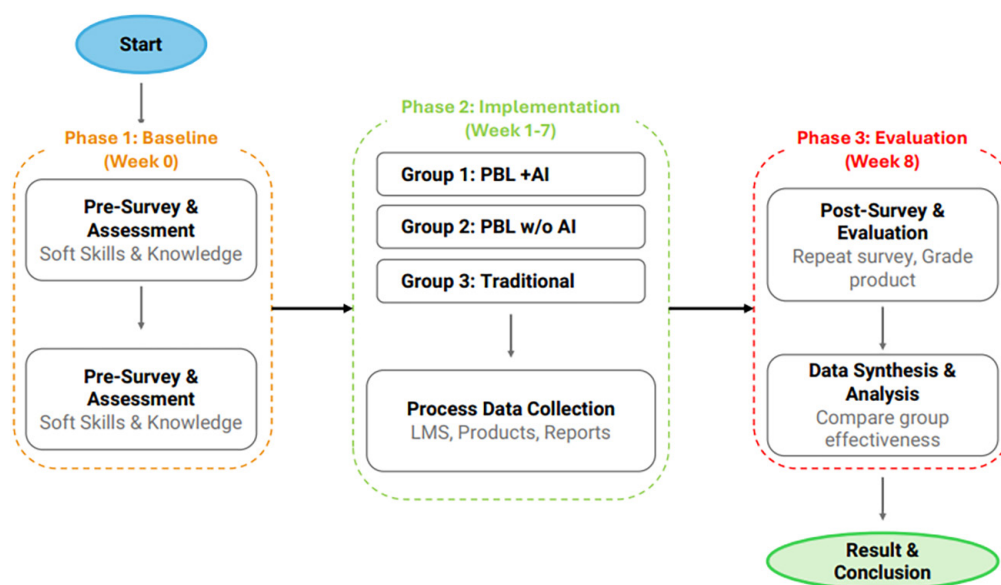


Fig. 2. Experimental process flowchart

The final phase, evaluation and data analysis (Week 8 onward), focused on measuring outcomes and synthesizing results. The primary tasks involved administering a post-test survey to all three groups to evaluate the enhancement of soft skills in comparison to the pre-test outcomes. Instructors also evaluated students' final project submissions using a standardized rubric to ensure objectivity. The resulting data were then compiled for comparative analysis. Quantitative analysis employed statistical tests (e.g., ANOVA or independent t-test) to identify significant differences in performance across the groups. In parallel, qualitative analysis of instructor observations and comments was conducted to better understand the strengths and limitations of each learning experience. The objective was to formulate thorough conclusions regarding the efficacy of the PBL-AI model in comparison to traditional PBL and standard teaching approaches.

Together, these three phases constitute the study's research instruments: a pre-test survey of soft skills, a diagnostic test of topic knowledge, and a post-test survey complemented by rubric-based product evaluations.

## 4.2 Application of AI agents in PBL instruction based on n8n

The experimental phase titled "Application of AI to Support PBL Instruction" was implemented through three main steps, corresponding to three initial stages of the overall instructional process as illustrated in Figure 3. The goal of this phase was to evaluate students' initial responses and the preliminary effectiveness of integrating AI into specific PBL activities before expanding to more complex phases.

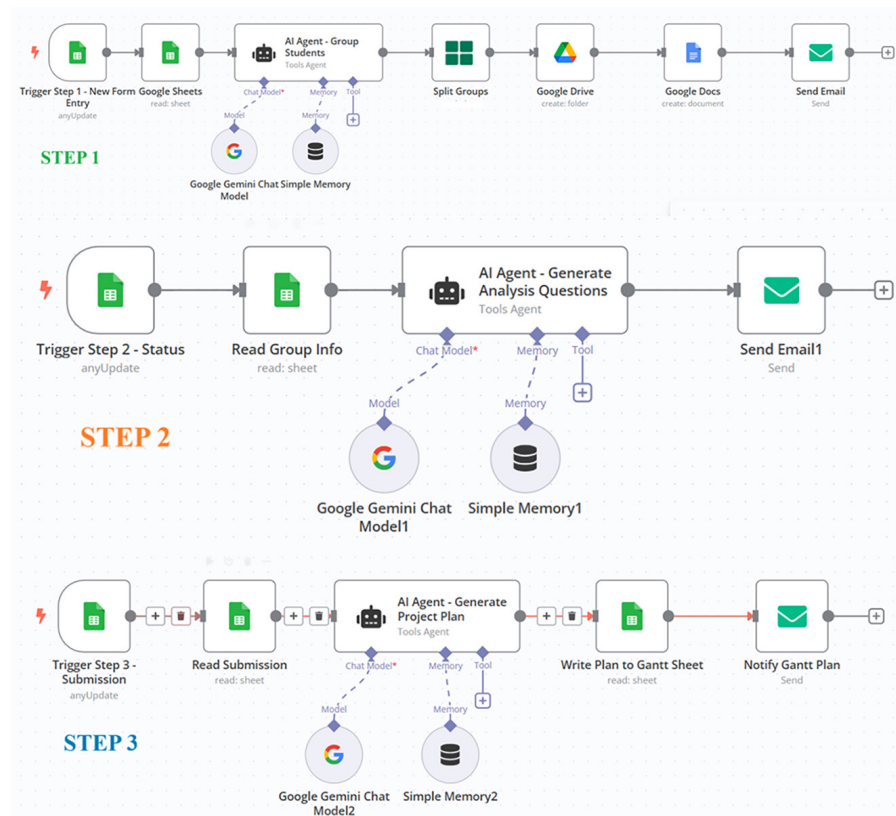


Fig. 3. AI-enhanced PBL: The first 3 steps

Step 1: Automated Student Grouping (AI-Grouping)

- Trigger Scenario: Whenever the instructor inputs a student list (including emails, MBTI results, and LMS behavioral data) into Google Sheets and marks the status as “New,” the workflow is automatically triggered.
- AI Processing: The node “AI Agent – Group Students” processes all input data with a prompt such as “Group students into teams of 4–5, prioritizing MBTI diversity and varying activity levels.” The system returns a JavaScript Object Notation (JSON) response with group assignments.
- Outcome: Each group is named “Group 1,” “Group 2,” etc., and includes a list of members’ emails. Sequential nodes then create a shared Google Drive folder, initiate a group project planning document, and send email notifications to all group members.
- Purpose: To ensure all groups start simultaneously with high diversity while minimizing manual setup time, enabling students to quickly begin their PBL tasks.

Step 2: Sending Problem Analysis Prompts (AI-Problem Analysis)

- Trigger Scenario: The instructor (or system) marks “✓” in the status column of the “Groups” sheet once Step 1 is complete.
- AI Processing: The node “AI – Generate Analysis Questions” takes the group’s project topic and uses the prompt “Generate 5 critical thinking questions for root-cause analysis.”
- Outcome: The AI returns five deep, relevant guiding questions, which are sent via email to the group along with a link to a checklist and a self-assessment form stored in Google Drive.

- Purpose: To guide students in systematically analyzing the problem, stimulating critical thinking, and ensuring no essential aspects are overlooked before designing solutions.

Step 3: Suggesting a 4-Week Plan and Updating the Gantt Chart (AI Project Plan)

- Trigger Scenario: When a group submits a preliminary problem description and goals (marked “SUBMITTED” in the relevant column of the “Submissions” sheet), the Step 3 workflow is triggered.
- AI Processing: The node “AI – Generate Project Plan” processes the group’s submission using the prompt “Propose a 4-week project plan with milestones and specific tasks” and outputs a JSON structure: {task, assignee, start\_date, end\_date}.
- Outcome: The plan data is automatically recorded in the “Gantt” sheet to generate a Gantt chart, and an email with the chart link is sent to the group.
- Purpose: To provide students with a clear timeline from the start, facilitate early task allocation, and allow instructors to monitor and preliminarily assess the group’s planning abilities.

### 4.3 Findings and discussion

Similar to the approach adopted in study [5], which had previously established content validity, factor structure, and acceptable reliability, data processing in this study was carried out through three main steps: pairing pre-survey and post-survey records, checking completion levels, and excluding invalid data. The questionnaire used in this study was adapted from previously validated instruments in soft skills research and further refined through expert review to ensure content validity. Table 5 shows that Cronbach’s alpha values for all scales were above 0.68, confirming acceptable reliability. A student record was retained only when all of the following conditions were met: (i) the participant had a valid identifier and was clearly assigned to one of the three groups; (ii) both the pre-survey and post-survey were completed; (iii) at least 80% of items within each scale were answered; and (iv) no signs of careless responding or unreasonable completion time were detected. As a result, out of the 300 initially assigned students, 263 were retained for the final analysis (PBL-AI group: 88/100; PBL group: 85/100; traditional teaching group: 90/100). Students who completed only one of the two surveys (n = 37) were excluded from paired-sample analyses. For questionnaires with a small number of missing responses (< 20% of items within a scale), missing values were treated using within-scale mean imputation.

Table 5. Cronbach’s alpha reliability coefficients for scales

Criteria	Reliability Coefficient for Group 1 (N = 88)		Reliability Coefficient for Group 2 (N = 85)		Reliability Coefficient for Group 3 (N = 90)	
	Pre Test	Post Test	Pre Test	Post Test	Pre Test	Post Test
P1 – Planning	0.821	0.834	0.842	0.826	0.722	0.741
P2 – Time management	0.741	0.778	0.814	0.802	0.703	0.695
P3 – Self-regulated learning	0.689	0.792	0.782	0.773	0.681	0.702
P4 – Teamwork	0.762	0.807	0.801	0.788	0.709	0.721
P5 – Academic communication	0.754	0.803	0.821	0.808	0.729	0.738
P6 – Reflection & decision-making	0.773	0.824	0.832	0.813	0.718	0.732

On this validated dataset, an ANOVA was conducted using pre-test scores on the soft skills scales to confirm baseline equivalence across the three groups before the intervention, and the results indicated no significant differences ( $p > .05$ ).

**Quantitative analysis: Evaluation based on soft skills scale.** Quantitative data was collected using a soft skills questionnaire, covering six core competencies: (P1) Planning, (P2) Time Use, (P3) Self-regulated Learning, (P4) Teamwork, (P5) Academic Communication, and (P6) Reflection and Decision-making. A total of 263 students were incorporated into the evaluation: 88 students in Group 1 (PBL-AI), 85 students in Group 2 (Traditional PBL), and 90 students in Group 3 (Traditional Teaching Method).

Table 6 displays the ANOVA test outcomes for the pre-test scores of the three groups. The findings show no statistically significant variations among the groups across all six criteria ( $p > 0.05$ ), confirming the baseline equivalence of participants before the intervention.

**Table 6.** Comparison of pre-test scores among groups (ANOVA)

Criterion	F-Value	p-Value	Conclusion
P1	1.82	0.165	No significant difference
P2	0.97	0.381	No significant difference
P3	1.13	0.322	No significant difference
P4	0.74	0.489	No significant difference
P5	1.05	0.351	No significant difference
P6	1.67	0.192	No significant difference

Table 7 presents a comparison of the average Pre-test and Post-test scores for each group, highlighting a significant improvement in Group 1 (PBL-AI), with score increases ranging from 0.9 to 1.2 points. Notably, the criteria P1, P4, and P6 show very high levels of change, with strong statistical significance ( $p < 0.001$ ).

**Table 7.** Analysis of average pre- and post-test scores across groups

Criterion	Group	Pre-Test (M $\pm$ SD)	Post-Test (M $\pm$ SD)	t	p-Value
P1	Group 1	3.12 $\pm$ 0.45	<b>4.31 <math>\pm</math> 0.42</b>	18.02	< 0.001
	Group 2	3.09 $\pm$ 0.41	3.78 $\pm$ 0.44	11.56	< 0.001
	Group 3	3.08 $\pm$ 0.47	3.15 $\pm$ 0.49	1.32	0.19
P4	Group 1	3.20 $\pm$ 0.52	<b>4.22 <math>\pm</math> 0.50</b>	15.84	< 0.001
	Group 2	3.15 $\pm$ 0.49	3.80 $\pm$ 0.55	9.76	< 0.001
	Group 3	3.18 $\pm$ 0.51	3.27 $\pm$ 0.53	1.09	0.28
P6	Group 1	3.01 $\pm$ 0.58	<b>4.10 <math>\pm</math> 0.46</b>	14.17	< 0.001
	Group 2	3.00 $\pm$ 0.55	3.52 $\pm$ 0.50	8.11	< 0.001
	Group 3	2.99 $\pm$ 0.57	3.05 $\pm$ 0.52	0.88	0.37

Table 7 demonstrates that the PBL-AI model produced comprehensive and superior impacts across most of the assessed criteria. In contrast, the traditional PBL model only yielded significant improvements in a few aspects, while the conventional teaching method showed virtually no effect.

From a theoretical perspective, this reinforces the argument that technology—particularly AI—functions not merely as a support tool but as a “catalyst” for guided self-directed learning. These results align with findings from previous studies, such as Belland [40], who argued that AI reduces the burden of group coordination, thereby freeing up students’ cognitive resources to focus on higher-order thinking skills.

**Qualitative analysis: Team activities and learning outcomes.** Table 8 presents the quality of group products based on a four-level evaluation rubric (Excellent, Good, Average, and Weak). The results show that 85% of the groups in Group 1 achieved Good or Excellent ratings, whereas this proportion in Group 2 was only 50%. Group 3 did not participate in group-based activities and therefore had no data available.

**Table 8.** Quality of group products after the course

Group	Number of Groups	Excellent (%)	Good (%)	Average (%)	Weak (%)
Group 1	13	38.5%	46.1%	15.4%	0%
Group 2	12	16.7%	33.3%	41.7%	8.3%
Group 3	–	–	–	–	–

Table 8 clearly demonstrates the positive impact of AI in supporting planning, progress reminders, and group data analysis, enabling students to focus more on subject-specific content rather than organizational issues.

Table 9 continues to present the results from observing group work processes and analyzing meeting minutes, indicating that Group 1 held more meetings, had higher participation rates, and utilized AI support almost consistently.

**Table 9.** Comparison of group activities between group 1 and group 2

Criterion	Group 1	Group 2
Average number of meetings/ weeks	2.7	1.9
Full member participation rate	92.4%	75.8%
Use of AI support	100%	0%
Quality of meeting minutes	Detailed and complete	Inconsistent
Observational notes	Focused on academic discussion	Time-consuming group organization

These qualitative findings strongly support the above quantitative data and further clarify the mechanisms through which AI exerts its influence: by reducing the burden of coordination, increasing timely feedback, and maintaining group discipline.

**Discrepancy between instructor evaluation and self-assessment.** Table 10 presents the difference between students’ self-assessment scores and the objective evaluations provided by instructors. The data shows that Group 1 had the smallest gap (0.11 points), indicating that students had a more realistic perception of their own competencies—thanks in part to the continuous feedback provided by the AI system.

**Table 10.** Comparison between student assessment and instructor evaluation

Group	Self-Assessment (Out of 5)	Instructor Evaluation	Discrepancy
Group 1	4.32	4.21	<b>0.11</b>
Group 2	4.18	3.75	0.43
Group 3	4.05	3.26	<b>0.79</b>

Table 10 highlights a potential risk in traditional education: students often overestimate their own abilities when there is a lack of objective feedback. This is a factor that can negatively impact the long-term development of soft skills.

**Awareness and behavioral change in learning.** Table 11 illustrates the degree of shifts in students’ awareness and learning behavior following the course. The data shows that Group 1 had the highest proportion of students achieving the “Sustained behavioral change” level (42%). While students in Group 2 mostly remained at the “Enhanced awareness” level (55%), and the majority of Group 3 only reached the “Basic awareness” level (61%).

**Table 11.** Levels of awareness after the course

Group	Basic Awareness	Enhanced Awareness	Behavioral Change Awareness
Group 1	14%	44%	<b>42%</b>
Group 2	20%	<b>55%</b>	25%
Group 3	<b>61%</b>	30%	9%

Table 11 provides additional evidence that technology integration influenced not only the development of soft skills but also learners’ motivation and learning behaviors. Specifically, students in the PBL-AI group demonstrated higher engagement, more consistent participation, and developed more positive and sustainable learning habits. While these results were not part of the central hypothesis, they represent exploratory findings that highlight potential broader benefits of integrating AI into the PBL process.

**Discussion of findings in relation to previous research.** The quantitative results revealed that the PBL-AI group achieved the strongest improvements, particularly in planning (P1: +1.19 points), teamwork (P4: +1.02 points), and reflection/decision-making (P6: +1.09 points), all with high statistical significance ( $p < 0.001$ ). By comparison, the traditional PBL group achieved smaller gains of around 0.6–0.7 points, while the lecture-based group showed almost no significant changes ( $p > 0.05$ ). These findings suggest that AI acted as a catalyst by reducing the burden of group coordination through automated scheduling, reminders, and resource suggestions, and by providing timely formative feedback, thereby allowing students to allocate more cognitive resources to higher-order skills such as critical thinking and problem solving. This interpretation is consistent with Belland et al. [35], who demonstrated through a meta-analysis that scaffolding technologies enhance higher-order cognition by alleviating organizational load. Moreover, our results resonate with Deep et al. (2019), who observed significant yet moderate improvements in teamwork and communication among engineering undergraduates using PBL; in our study, 85% of PBL-AI teams produced outputs rated as Good or Excellent, compared to only 50% in the traditional PBL group, highlighting the stronger

impact of AI-supported scaffolding. Similarly, the findings extend the conclusions of Chen et al. (2024), who reported that PBL improved self-regulated learning: in our data, the discrepancy between student self-assessments and instructor ratings was only 0.11 points in the PBL-AI group, while it reached 0.43 in PBL and 0.79 in lecture-based learning, indicating that AI feedback enhanced students' metacognitive accuracy. Nevertheless, not all skill domains improved equally; for example, time use, self-regulated learning, and academic communication showed smaller gains (around +0.4 to +0.6 points), which may be explained by the fact that these skills are more ingrained in students' long-term habits and communication styles and therefore require longer interventions or reinforcement across courses to show substantial progress. This pattern mirrors findings from Tam (2021) and Thi (2023), who also reported only modest short-term improvements in communication and time management through PBL. Furthermore, participation metrics confirmed the added value of AI: the PBL-AI groups had a full-member participation rate of 92.4% compared to 75.8% in traditional PBL groups and held more frequent meetings (2.7 vs. 1.9 per week), thereby addressing the challenge of uneven engagement and delayed feedback highlighted by Schmidt et al. (2011). Taken together, these results not only reinforce the established benefits of PBL but also provide concrete evidence that AI integration can nearly double the observed improvements in several soft skill domains, while at the same time enhancing fairness in assessment and equity in participation. However, it is important to acknowledge that the intervention was limited to a single institution and an 8-week course, which may restrict the generalizability and long-term conclusions; moreover, system logs, although useful, cannot fully capture the quality of individual contributions. Future research should therefore extend the duration of interventions, test the model across multiple institutions and disciplines, and incorporate qualitative measures of communication and teamwork quality to validate the sustainability and transferability of AI-supported PBL.

Although this study yielded encouraging evidence of the benefits of integrating AI Agents into PBL for soft skills development, certain limitations remain that should be acknowledged when interpreting the findings. First, the intervention was limited to a single institution, a single course, and a single topic (time management skills), which may restrict the generalizability of the results to other educational contexts and domains of soft skills. Second, the duration of the experiment was relatively short (8 weeks), making it difficult to capture long-term effects or the sustainability of skill improvements. Third, the novelty of AI integration may have created a temporary motivational boost (novelty bias), which could diminish once the technology becomes more familiar. Fourth, while system logs provided valuable indicators of student participation, they could not fully capture the quality of individual contributions or the nuances of team communication. Finally, part of the dataset relied on self-reported surveys, which may be affected by social desirability bias. Future research should therefore extend the intervention to multiple institutions and courses, explore a wider range of soft skills domains, and adopt longer-term and mixed-method designs—including qualitative assessments of communication and teamwork quality—to validate and extend the present findings.

## 5 CONCLUSION

The application of the AI-enhanced PBL model in this study has demonstrated significant effectiveness in developing students' soft skills, particularly within a blended learning environment. The results indicate that this model not only

substantially improves competencies such as planning, teamwork, and reflection, but also provides students with access to learning scenarios closely aligned with real-world professional contexts. This fosters interdisciplinary thinking and collaborative capacity—both critical in modern workplaces. Simultaneously, the AI Agent is crucial in tailoring the learning experience, assisting students according to their real-time performance, promoting equitable evaluation, and fostering independent learning habits. These results highlight the promise of incorporating advanced technologies into active learning frameworks, opening new pathways for innovative higher education strategies in the era of digital transformation. Looking ahead, further research into other active learning models combined with educational technologies will contribute to optimizing multi-platform learning experiences and guaranteeing that students remain the focus of all educational and ongoing skill-building initiatives.

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## 7 REFERENCES

- [1] M. Poláková, J. H. Suleimanová, P. Madzík, L. Copuš, I. Molnárová, and J. Polednová, “Soft skills and their importance in the labour market under the conditions of Industry 5.0,” *Heliyon*, vol. 9, no. 8, p. e19003, 2023. <https://doi.org/10.1016/j.heliyon.2023.e18670>
- [2] World Economic Forum, “The Future of Jobs Report 2023,” Geneva, Switzerland: World Economic Forum, 2023. [Online]. Available: <https://www.weforum.org/publications/the-future-of-jobs-report-2023>. [Accessed: Apr. 30, 2023].
- [3] L. Vargas-Mendoza and K. Gallardo, “Influence of self-regulated learning on the academic performance of engineering students in a blended-learning environment,” *International Journal of Engineering Pedagogy*, vol. 13, no. 8, pp. 4–18, 2023. <https://doi.org/10.3991/ijep.v13i8.38481>
- [4] P. Angulo, J. Galindo-Melero, S. De-Diego-Poncela, and Ó. Martín, “Promoting soft skills in higher engineering education: Assessment of the impact of a teaching methodology based on flipped learning, cooperative work and gamification,” *Education and Information Technologies*, vol. 30, no. 10, pp. 13463–13506, 2025. <https://doi.org/10.1007/s10639-025-13322-0>
- [5] T. V. Dang, T. G. B. Phung, D. M. Vu, and T. T. T. Nguyen, “The application of problem-based learning in soft skills courses: An experiment in classes with multidisciplinary students in Vietnam,” *International Journal of Engineering Pedagogy (IJEP)*, vol. 15, no. 5, pp. 20–41, 2025. <https://doi.org/10.3991/ijep.v15i5.53663>
- [6] H. S. Barrows, “A taxonomy of problem-based learning methods,” *Medical Education*, vol. 20, no. 6, pp. 481–486, 1986. <https://doi.org/10.1111/j.1365-2923.1986.tb01386.x>
- [7] P. B. Learning, “Problem-based learning,” in *The International Handbook of Collaborative Learning*, 2013, p. 370.
- [8] M. Alarfaj, S. Raja Mohamed, S. Chtourou, H. Enshasy, A. Aboulnaga, and M. Hassan, “Experience of project-based learning: Challenges, assessment, and analysis,” *International Journal of Engineering Pedagogy (IJEP)*, vol. 14, no. 3, pp. 123–139, 2024. <https://doi.org/10.3991/ijep.v14i3.43849>
- [9] M. Savin-Baden, *Problem-Based Learning in Higher Education: Untold Stories*. Maidenhead, UK: McGraw-Hill Education, 2000.

- [10] H. G. Schmidt, J. I. Rotgans, and E. H. Yew, "The process of problem-based learning: What works and why," *Medical Education*, vol. 45, no. 8, pp. 792–806, 2011. <https://doi.org/10.1111/j.1365-2923.2011.04035.x>
- [11] J. R. Savery, "Overview of problem-based learning: Definitions and distinctions," *Essential Readings in Problem-Based Learning: Exploring and Extending the Legacy of Howard S. Barrows*, vol. 9, no. 2, pp. 5–15, 2015. <https://doi.org/10.7771/1541-5015.1002>
- [12] S. Deep, B. M. Salleh, and H. Othman, "Exploring the role of problem-based learning in developing conflict resolving and other soft skills—a quasi-experimental study," *International Review of Management and Marketing*, vol. 6, no. 4, pp. 738–748, 2016.
- [13] N. Tam, "Using problem-based tasks to promote higher-order thinking skills for TESOL MA students in Vietnam," *Interdisciplinary Journal of Problem-Based Learning*, vol. 15, no. 1, 2021. <https://doi.org/10.14434/ijpbl.v15i1.28772>
- [14] N. L. P. Thi, "Investigation into the effectiveness of using problem-based learning in teaching communication skills in English to engineering students," *Interdisciplinary Journal of Problem-Based Learning*, vol. 17, no. 1, 2023. <https://doi.org/10.14434/ijpbl.v17i1.33869>
- [15] T. Chen *et al.*, "The effect of problem-based learning on improving problem-solving, self-directed learning, and critical thinking ability for pharmacy students: A randomized controlled trial and meta-analysis," *PLoS ONE*, vol. 19, no. 12, p. e0314017, 2024. <https://doi.org/10.1101/2023.10.26.564146>
- [16] L. Wijnia, G. Noordzij, L. R. Arends, R. M. Rikers, and S. M. Loyens, "The effects of problem-based, project-based, and case-based learning on students' motivation: A meta-analysis," *Educational Psychology Review*, vol. 36, no. 1, p. 29, 2024. <https://doi.org/10.1007/s10648-024-09864-3>
- [17] N. A. Ahmad, N. F. Elias, and N. Sahari, "The motivational factors in learning management system," in *Proc. Int. Conf. Electrical Engineering and Informatics (ICEEI)*, 2021, pp. 1–6. <https://doi.org/10.1109/ICEEI52609.2021.9611140>
- [18] Q. Wang, "Design and evaluation of a collaborative learning environment," *Computers & Education*, vol. 53, no. 4, pp. 1138–1146, 2009. <https://doi.org/10.1016/j.compedu.2009.05.023>
- [19] A. Ansori, N. Tarihoran, and E. Nugraha, "The influence of learning management systems (LMS) and the value of Istiqamah attitude on the quality of education," *International Journal of Education, Teaching, and Social Sciences*, vol. 4, no. 1, pp. 46–61, 2024. <https://doi.org/10.47747/ijets.v4i1.1828>
- [20] B. Ortega-Ruipérez and J. M. Correa-Gorospe, "Peer assessment to promote self-regulated learning with technology in higher education: Systematic review for improving course design," *Frontiers in Education*, vol. 9, p. 1376505, 2024. <https://doi.org/10.3389/educ.2024.1376505>
- [21] F. Mendez Gijon, V. Aguirre Hidalgo, and A. I. Arellano Vega, "The role of open-source software as a technological alternative for blended learning in LMS systems," *International Journal of Engineering Pedagogy (iJEP)*, vol. 15, no. 2, pp. 4–14, 2025. <https://doi.org/10.3991/ijep.v15i2.50169>
- [22] A. Horvat, M. Dobrota, M. Krsmanovic, and M. Cudanov, "Student perception of Moodle learning management system: A satisfaction and significance analysis," *Interactive Learning Environments*, vol. 23, no. 4, pp. 515–527, 2015. <https://doi.org/10.1080/10494820.2013.788033>
- [23] J. W. Gikandi, D. Morrow, and N. E. Davis, "Online formative assessment in higher education: A review of the literature," *Computers & Education*, vol. 57, no. 4, pp. 2333–2351, 2011. <https://doi.org/10.1016/j.compedu.2011.06.004>
- [24] Y. Xia, Y. Hu, C. Wu, L. Yang, and M. Lei, "Challenges of online learning amid the COVID-19: College students' perspective," *Frontiers in Psychology*, vol. 13, p. 1037311, 2022. <https://doi.org/10.3389/fpsyg.2022.1037311>

- [25] B. P. Woolf, *Building Intelligent Interactive Tutors: Student-Centered Strategies for Revolutionizing E-Learning*. Burlington, MA: Morgan Kaufmann, 2010. <https://doi.org/10.1016/B978-0-12-373594-2.X0001-9>
- [26] R. Luckin and W. Holmes, *Intelligence Unleashed: An Argument for AI in Education*. London, UK: Pearson, 2016.
- [27] S. K. Banihashem, O. Noroozi, H. Khosravi, C. D. Schunn, and H. Drachsler, “Pedagogical framework for hybrid intelligent feedback,” *Innovations in Education and Teaching International*, pp. 1–17, 2025. <https://doi.org/10.1080/14703297.2025.2499174>
- [28] S. Guo, E. Latif, Y. Zhou, X. Huang, and X. Zhai, “Using generative AI and multi-agents to provide automatic feedback,” *arXiv preprint arXiv:2411.07407*, 2024. <https://doi.org/10.48550/arXiv.2411.07407>
- [29] O. Chamorro-Atalaya et al., “Application of the chatbot in university education: A bibliometric analysis of indexed scientific production in SCOPUS, 2013–2023,” *International Journal of Learning, Teaching and Educational Research*, vol. 22, no. 7, pp. 281–304, 2023. <https://doi.org/10.26803/ijlter.22.7.15>
- [30] L. Labadze, M. Grigolia, and L. Machaidze, “Role of AI chatbots in education: Systematic literature review,” *International Journal of Educational Technology in Higher Education*, vol. 20, no. 1, p. 56, 2023. <https://doi.org/10.1186/s41239-024-00461-6>
- [31] K. VanLehn, “The relative effectiveness of human tutoring, intelligent tutoring systems, and other tutoring systems,” *Educational Psychologist*, vol. 46, no. 4, pp. 197–221, 2011. <https://doi.org/10.1080/00461520.2011.611369>
- [32] W. Ma, O. O. Adesope, J. C. Nesbit, and Q. Liu, “Intelligent tutoring systems and learning outcomes: A meta-analysis,” *Journal of Educational Psychology*, vol. 106, no. 4, pp. 901–918, 2014. <https://doi.org/10.1037/a0037123>
- [33] F. L. da Silva, B. K. Slodkowski, K. K. A. da Silva, and S. C. Cazella, “A systematic literature review on educational recommender systems for teaching and learning: Research trends, limitations and opportunities,” *Education and Information Technologies*, vol. 28, no. 3, pp. 3289–3328, 2023. <https://doi.org/10.1007/s10639-022-11341-9>
- [34] P. Chatwattana, P. Yangthisarn, and A. Tabubpha, “The educational recommendation system with artificial intelligence chatbot: A case study in Thailand,” *International Journal of Engineering Pedagogy (iJEP)*, vol. 14, no. 5, pp. 51–64, 2024. <https://doi.org/10.3991/ijep.v14i5.48491>
- [35] Shi and V. Aryadoust, “A systematic review of AI-based automated written feedback research,” *ReCALL*, vol. 36, no. 2, pp. 187–209, 2024. <https://doi.org/10.1017/S0958344023000265>
- [36] W. Holmes, M. Bialik, and C. Fadel, *Artificial Intelligence in Education: Promises and Implications for Teaching and Learning*. Boston, MA: Center for Curriculum Redesign, 2019.
- [37] R. S. Baker, T. Martin, and L. M. Rossi, “Educational data mining and learning analytics,” in *The Wiley Handbook of Cognition and Assessment: Frameworks, Methodologies, and Applications*, A. A. Rupp and J. P. Leighton, Eds., Hoboken, NJ: Wiley, 2016, pp. 379–396. <https://doi.org/10.1017/CBO9781139519526.016>
- [38] H. El Kamouchi, M. Kissi, and O. El Beggar, “Low-code/No-code development: A systematic literature review,” in *Proc. 14th Int. Conf. Intelligent Systems: Theories and Applications (SITA)*, 2023, pp. 1–8. <https://doi.org/10.1109/SITA60746.2023.10373712>
- [39] W. Van Der Aalst, *Data Science in Action*. Berlin, Germany: Springer, 2016, pp. 3–23. [https://doi.org/10.1007/978-3-662-49851-4\\_1](https://doi.org/10.1007/978-3-662-49851-4_1)
- [40] B. R. Belland, A. E. Walker, and N. J. Kim, “A Bayesian network meta-analysis to synthesize the influence of contexts of scaffolding use on cognitive outcomes in STEM education,” *Review of Educational Research*, vol. 87, no. 6, pp. 1042–1081, 2017. <https://doi.org/10.3102/0034654317723009>

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