Contemporary Educational Technology, 2025, **17**(4), ep603
ISSN: 1309-517X (Online)

OPEN ACCESS

Research Article

AI robots as learning companions in PBL: Effects on cognitive and self-regulatory outcomes

Jaitip Nasongkhla [1*]
0000-0001-5306-7688

Chich-Jen Shieh [1]
0000-0001-5889-4682

[1] Excellent Center of Disruptive Innovative Technology for Education, Chulalongkorn University, Bangkok, THAILAND
[*] Corresponding author: jaitip.n@chula.ac.th

Citation: Nasongkhla, J., & Shieh, C.-J. (2025). AI robots as learning companions in PBL: Effects on cognitive and self-regulatory outcomes. *Contemporary Educational Technology, 17*(4), ep603. https://doi.org/10.30935/cedtech/17417

ARTICLE INFO

Received: 24 Jul 2025

Accepted: 13 Oct 2025

ABSTRACT

This study examines the effect of robot-assisted problem-based learning (PBL) on learning outcomes in higher education. A quasi-experimental design was adopted, and the application was carried out over 16 weeks (48 hours) with two parallel branches. In the experimental group, a question-and-answer-focused educational robot was integrated into the project-based learning process, while in the control group, the same content was applied without robots. Measurements encompassed self-directed learning (including self-management), problem-solving, and comprehension/discovery dimensions. Bayesian comparisons showed that the level of evidence in favor of the experiment was in the medium-strong range for most variables; a significant increase was observed particularly in self-management. Problem-solving and comprehension/discovery scores were also higher in the experimental condition. Figures and tables report posterior effect sizes and 95% confidence intervals. The results indicate that robot-assisted PBL, which offers timely and elucidative feedback, improves the metacognitive processes associated with PBL and aids students in adhering to their study goals more consistently. In conclusion, robot-assisted PBL can significantly improve self-management, problem-solving, and comprehension outcomes, provided that appropriate feedback design and application fidelity are maintained. Future research should examine its effects across various fields by integrating long-term follow-up periods and behavioral performance assessments. The study enhances the reproducibility of results by evaluating the strength of evidence through open Bayesian reporting. This method makes design choices more transparent and establishes clear guidelines on how educational technologies should be used responsibly.

Keywords: problem-based learning, AI robots, blended learning, learning outcomes, self-directed learning

INTRODUCTION

Problem-based learning (PBL) is a student-centered methodology wherein learners assume responsibility for a tangible problem, seek information, formulate solutions, and engage in reflection (Albanese & Mitchell, 1993). Recent syntheses indicate that PBL can enhance cognitive outcomes and motivation, especially in higher education. The magnitude of the effect can differ based on the context of application and design specifics. So, it’s important to be clear about when PBL works best (Su et al., 2025).

AI-powered feedback systems and teaching robots can enhance student learning by providing personalized and timely feedback. Multi-level meta-analyses indicate that educational robots can improve success and conceptual understanding in science, technology, engineering, and mathematics (STEM) disciplines; however, their effectiveness depends on factors such as role, quality of interaction, and duration of intervention. Automated feedback can also slightly improve writing performance. These results suggest that robot/AI-powered feedback can be a valuable resource in project-based learning (PjBL) contexts (Fleckenstein et al., 2023; Ouyang & Xu, 2024; Trapero-González et al., 2024).

This study is positioned at the intersection of PjBL and robotics/artificial intelligence (AI) assistance. Planning, management, and supervision are important components of PjBL derived from self-regulated learning (SRL)/self-directed learning (SDL). Meta-analyses focusing on online and blended learning indicate that SRL interventions can significantly impact students' academic performance. Nonetheless, there is a deficiency of controlled studies examining the impact of robot-assisted PjBL on problem-solving and understanding in relation to the sub-dimensions of SRL and SDL (Guntur & Purnomo, 2024).

The research gap is concentrated in three areas. First, few studies report the gains observed in robot-assisted PBL by disaggregating them at the level of SRL/SDL sub-dimensions (such as self-regulation). Second, comprehensive evaluations of such interventions alongside problem-solving and comprehension/discovery outcomes are rare. Third, examples of findings being reported transparently and reproducibly using Bayesian principles are limited, even though reporting guidelines recommend presenting parameter estimates alongside Bayesian factors. These gaps necessitate strengthening the practically usable evidence on how and to what extent robot-assisted PBL is effective (Kruschke, 2021).

The aim of this study is to examine the effect of robot-assisted PBL on SDL, problem-solving, and comprehension outcomes in a higher education context; to evaluate changes in the self-management dimension in particular; and to present the findings using transparent Bayesian reporting principles. The research questions are as follows: Does robot-assisted PBL increase levels of SDL compared to teaching without robot support; is this increase more pronounced in the self-management dimension; does robot-assisted PBL provide superiority in problem-solving and comprehension/discovery outcomes; are the observed effects meaningful in terms of Bayesian evidence level. The answers to these questions are expected to generate applicable principles for how the feedback architecture and the role of robots should be structured in PBL designs (Ouyang & Xu, 2024; Su et al., 2025).

LITERATURE REVIEW

Problem-Based Learning

Albanese and Mitchell (1993) describe PBL as a teaching method in which students are initially presented with meaningful problem scenarios and encouraged to construct knowledge through group discussions and independent work, while also developing clinical reasoning and self-assessment skills. Servant and Schmidt (2016) view PBL as a problem scenario-centered method where repeated questioning and hypothesis testing guide self-monitoring and knowledge construction.

Leary et al. (2019) emphasize that at its core, PBL helps teach students how to learn, think, and reason within problem-focused social interactions. Furthermore, Leary et al. (2019) define PBL as an educational model that places real-world problems at the center of learning and promotes the integration of knowledge and the development of problem-solving skills through a combination of individual and group inquiry with appropriate teacher interaction. Abildinova et al. (2024) consider PBL as a student-led, problem-centered educational method that values contextual situations and reflective processes.

Current research further details the definition and applications of PBL. According to Jaganathan et al. (2024), the main goal of PBL is to help students understand how to solve problems, work together, study on their own, communicate, learn deeply, keep their knowledge longer, and learn for the rest of their lives. The goal of this method is to better prepare students for their jobs.

Zhang and Ma (2023) found in their meta-analysis that PBL has a moderate positive effect on student learning outcomes compared to traditional teaching models (standard deviation [SD] = 0.441, $p < 0.001$). These findings show that PBL (Su et al., 2025) develops not only academic achievement but also students' emotional attitudes, values, creative thinking skills, computational thinking skills, and other higher-order thinking skills.

Su et al. (2025) emphasize in their systematic review and meta-analysis that PBL has emerged as a transformative educational strategy for developing critical thinking skills in medical education. According to their studies, PBL students show significant improvement in critical thinking skills compared to traditional teaching methods. This improvement is explained by mechanisms such as PBL encouraging knowledge integration through contextual learning, facilitation supporting metacognitive development, and peer collaboration developing reflective dialogue.

Zakaria et al. (2025) investigated the effect of the combination of mobile learning and PBL (M-PBL) on student motivation and academic performance. The results show that the M-PBL method made a big difference in how motivated students were and how well they could solve problems compared to traditional methods. This study shows that PBL can make students more interested in learning by focusing on working together, communicating well in groups, analyzing problems, and gaining knowledge.

This model is based on constructivism theory and the assumption that students construct knowledge by doing things and participating in real-world production processes. The model creates collaborative, active learning opportunities that encourage students to find solutions and share them through inquiry-based activities involving tangible products (Jaganathan et al., 2024; Su et al., 2025).

The literature also emphasizes the connection between PBL and authentic assessment. Authentic assessments prioritize the learning experience as the ultimate outcome, unlike traditional assessment approaches that emphasize grades. This method of teaching recognizes that the reflective process can yield new insights and facilitate transformative learning for students (Duda et al., 2024). In PBL settings, it is essential that students are enabled to engage in the process of exhibiting real-world tasks, selecting methods to convey knowledge, and creating assessment instruments for that knowledge.

Blended Learning

Megahed and Ghoneim (2022) characterize blended learning as a purposeful integration of online and off-line resources in instructional design, intended to optimize cognitive and social learning processes. Hrastinski (2019) defines blended learning as a cohesive methodology that combines online SDL with synchronous, real-time interaction, offering students individualized pacing and contextual assistance.

Current research is expanding the definition and applications of blended learning. According to Platonova et al. (2022), blended learning has become popular since it is an excellent technique to handle a student body that is becoming more diverse. It mixes online and in-person learning to make the learning environment better. This strategy encourages both individual and group learning, and it allows students and teachers to use more methods to talk to each other. Niyomves et al. (2024) define blended learning as a combination of traditional classroom education, where students and teachers interact directly in a physical space, and online learning. This hybrid approach combines the flexibility of online education with the personal interaction of classroom education to meet various learning needs and schedules. According to their work, blended learning increases student participation, provides a more personalized learning experience, and leverages technological advances to improve educational outcomes.

Li et al. (2024b) examined the effect of active learning instructions in blended learning environments. The findings show that blended learning refers to the systematic integration of online and off-line elements within the same course and supports the development of students' comprehension skills. This systematic integration has positive effects on students' anxiety levels and academic performance. Singh et al. (2021) comprehensively addressed blended and hybrid learning in the context of the COVID-19 pandemic. According to their work, blended learning is a teaching method that combines the efficiency of student-centered teaching and the socialization opportunities of traditional face-to-face classes with the digitally enriched learning possibilities of the online delivery mode. This approach includes student-centered teaching, which requires each student to actively participate in the content; increased opportunities for interaction between teacher-student, student-student, content-student, and student-supplementary learning materials; and opportunities to collect formative and summative assessments to improve lessons. Sharma et al. (2022) have comprehensively examined online, off-line, and blended learning methods. They emphasize that the education sector is witnessing a paradigm shift with rapid technological developments and that online, off-line, and blended learning modes continue to evolve over time. Their research highlights the advantages, challenges, and requirements of each of these learning methods.

AI Robot-Assisted Instruction

AI-powered robot-assisted instruction is a way of teaching that uses robotic hardware and smart computers to make teaching more interactive and adaptable (Mubin et al., 2013). Interest in the application of social robots in education has surged markedly in recent years, with 2023-2024 emerging as pivotal years in this domain (Lampropoulos, 2025). Social robots can serve as educators, peer learners, or facilitators in educational settings and have demonstrated efficacy in improving cognitive and emotional results (Belpaeme et al., 2018).

Studies indicate that the tangible presence of social robots enhances learning results in contrast to virtual representations or contexts lacking educational support (Donnermann et al., 2022). This approach aims to provide personalized teaching and emotional engagement by combining sensor technology, machine intelligence, and a human-like appearance. Adaptive robotic teaching systems can shape interaction based on student performance, provide encouragement, and empathize based on student responses (Donnermann et al., 2022). The roles of social robots in education have diversified and expanded in recent years. Robots can do more than only teach; they can also let students join in on class by behaving like "skilled ignorant peers" (Nasir et al., 2024). This strategy helps the robot aid with learning even if it doesn't know much about the subject, and it makes it easier for the robot to adapt to different places where people study.

Multi-modal robots that use different types of interaction, like animation, song, dance, gestures, and touch, make students far more likely to learn, be interested, and interact with each other (Fung et al., 2024). It has been shown to be effective in developing inclusive learning systems, especially for students with specific learning difficulties such as dyslexia. Comprehensive reviews in the field of robot-assisted language learning show that, with the development of speech and language technologies, social robots are gaining increasing academic and commercial interest (Huang & Moore, 2023). The creation of a stable and reliable learning partnership through social interaction and personalized responses increases children's learning participation and self-efficacy perception (Lin et al., 2022).

Research examining human-robot interactive communication shows that robots can provide long-term, dynamic instructional support for specific learning goals through their verbal and nonverbal communication abilities (Mavridis, 2015). In long-term child-robot interactions, it has been found that robots act as social catalysts, enhancing the quality of family interactions and enriching learning experiences (Chen et al., 2025).

Collaborative problem-solving studies between children and robots reveal that children interact with robots in different ways depending on their developmental stages and individual characteristics (Charisi et al., 2020). Individual differences such as children's age groups, temperament characteristics, and social anxiety levels influence their behavioral, emotional, and verbal interactions with robots (Barry et al., 2025). These findings emphasize the importance of child-centered approaches in the use of social robots in educational settings.

The integration of AI-based generative models into robotic systems has increased the potential for personalized language teaching and offered new opportunities to overcome barriers created by limited resources and staffing constraints (Verhelst et al., 2024). However, caution is needed regarding the effects of long-term interactions between social robots and children on socio-emotional development, and ethical considerations must be considered (Langer et al., 2023).

Bibliometric evaluations indicate that the efficacy of social robots as educators and learning companions has been thoroughly investigated in recent years and has become a fundamental component of educational technology (Pai et al., 2024). During the years 2023-2024, AI made a lot of progress, which led to a big increase in the use of social robots in education (Lampropoulos, 2025).

The Impact of AI Robot-Assisted Instruction Using Problem-Based Learning on Self-Directed Learning

AI-supported robot teaching and PBL integration offer an innovative approach to developing students' SDL skills. In PBL environments, robots not only provide subject knowledge but also facilitate students' discovery and inquiry processes by offering social and emotional support (Nasir et al., 2024). Robots take on the role of "skilled ignorant peers," supporting students' productive participation and enriching learning processes without requiring subject knowledge. Comprehensive systematic reviews examining the effects of AI-based education systems on SRL show that AI-supported tools strengthen student autonomy by providing personalized, adaptive, and real-time support (Younas et al., 2025). Generative AI tools have been found to develop students' self-regulation skills and conceptual understanding by providing dynamic content and feedback.

Scaffolding strategies play a critical role in AI-supported learning environments. AI systems can change how they guide students based on how well they do, and they can also get students to think about their reasoning repeatedly by asking questions like "why do you think that?" or "could there be another possibility?" (Kim et al., 2025). This guided discussion method is the main part of PBL and helps with the self-monitoring that is needed for SDL.

The emotional aspect of educational AI systems is becoming a significant field of study. When students face challenges or setbacks, empathic answers from AI systems can mitigate their disappointment and maintain their enthusiasm to explore. The tone and quality of AI-based feedback significantly influence students' motivation and confidence. Additionally, emotional responses are crucial in elucidating the link between feedback quality and learning engagement (Rong et al., 2025; Zong & Yang, 2025).

In PBL environments, AI robots can maintain enhanced group dynamics while respecting individual learning autonomy (Yang et al., 2023). Experimental studies show that gamified AI-assisted educational robot systems significantly boost student motivation and effectiveness in learning. Students exhibit a pronounced inclination to engage in continuous study when afforded the autonomy to determine the methods by which they monitor their academic progress and solicit pertinent information from robotic systems. AI-enhanced individualized learning trajectories can tailor each learner's educational journey according to their pre-existing knowledge and their aspirations for further learning. AI instructors who provide prompt feedback facilitate students' comprehension of their errors, allowing for immediate rectification and learning (Guo et al., 2024; Venter et al., 2024). These frameworks ensure that students are not exposed to material that is either excessively complex or overly simplistic, thereby optimizing their educational experience.

A comprehensive examination of the implications of generative AI on SDL reveals that models such as ChatGPT, Claude, and Gemini are transforming educational paradigms by offering personalized, interactive learning environments (Li et al., 2024a; Wu et al., 2024). Nevertheless, it is crucial to acknowledge that educators must place greater emphasis on technology-supported SDL, as students may lack proficiency in the utilization of contemporary technological tools.

Impact of AI Robot-Assisted Instruction Using Problem-Based Learning on Problem-Solving Ability

Educational robotics applications, particularly AI-powered robots, offer significant opportunities for developing students' problem-solving skills. Ouyang and Xu (2024) conducted a multi-level meta-analysis demonstrating that educational robotics enhance learning performance in STEM education, stimulate student interest, and develop cognitive thinking skills. The research results revealed that robot-assisted learning environments outperformed traditional classroom environments in terms of students' performance on problem-solving tests and group project outcomes. Bellas et al. (2024) examined how long-term classroom technologies based on intelligent robotics transform education in the age of AI. The study noted that robots dramatically shorten students' data organization time and enable groups to focus more on problem analysis and decision-making processes. This increases both the efficiency and quality of problem-solving.

Bertacchini et al. (2022) found that students showed significant improvements in computational thinking skills in an educational robotics lab using the PjBL approach and the NAO robot. Students demonstrated improvements in systematic thinking and decision-making strategies while interacting with the robot to tackle complex problems. Yang et al. (2023) demonstrated that a gamified AI-supported educational robot system significantly increased students' learning success, improved their learning motivation, flow experiences, and problem-solving tendencies. The study emphasizes that the robots' provision of instant feedback enabled students to take a more active role in the problem-solving process and made them more willing to seek alternative solutions.

Fung et al. (2025) conducted a comparative study examining the effect of learning interaction with multimodal robots on student participation. The findings show that robot interaction increases students' emotional, behavioral, and cognitive participation and provides inclusive learning environments for students with different learning needs, including those with dyslexia. Huang et al. (2025) found that an AI-supported personalized two-tiered PBL approach improved students' reading performance and problem-solving skills. In this study, conducted using generative AI, it was determined that receiving personalized feedback and guidance according to students' cognitive levels positively affected learning outcomes. Long-term follow-up studies show that students have made significant progress in the speed and accuracy of their responses to new problem scenarios. Interviews reveal that students generally find this approach "challenging but rewarding" and that this motivates them to discover the fundamental principles or methods behind each problem.

Impact of AI Robot-Assisted Instruction Using Problem-Based Learning on Learning Outcomes

Students who learn in surroundings of robots that use AI show big increases on tests of their knowledge and grasp of concepts. Bertacchini et al. (2022) noted that students in the experimental group achieved superior scores compared to those in the control group during an educational robotics laboratory utilizing the project-based methodology. Interviews with students showed that they were more likely to ask the robot for help and more interested in exploring physical phenomena on their own. Kong et al. (2024) executed a 14-hour course utilizing the PjBL methodology to enhance AI literacy.

The study's findings indicated that students exhibited considerable enhancements in their AI problem-solving abilities and levels of empowerment, as well as a notable increase in their ethical comprehension. It was found that PjBL improved students' problem-solving skills and helped them evaluate the ethical use of AI.

Zhou et al. (2025) conducted a systematic bibliometric review on online PjBL. The study emphasized that the use of AI and virtual reality technologies is critical in developing collaboration, critical thinking, and problem-solving skills. It was noted that multi-channel digital teaching methods can improve the quality of distance education.

Yang et al. (2023) demonstrated that a gamified AI-supported educational robot system significantly increased student learning success in laboratory safety courses. The system significantly increased learning efficiency and the sense of achievement by providing students with real-time feedback. Students reported that "real-time assessment" significantly improved their learning processes. (Fung et al., 2025) conducted a comparative study examining the effect of multimodal robots on student engagement. Findings showed that robot interaction encouraged students' participation in classroom interactions and yielded satisfactory results for both students and educators.

Ouyang and Xu (2024) conducted a multi-level meta-analysis showing that educational robotics improved students' learning performance, motivation, and computational thinking skills in STEM education. The research revealed that robot-assisted learning had a moderate but statistically significant positive effect compared to traditional learning methods ($g = 0.57$).

Nannim et al. (2025) demonstrated that PjBL with Arduino robots has a significant impact on undergraduate students' success in robotic programming and task persistence. The platform provided equal learning opportunities to all students, actively engaging them in the learning process. The study showed that hands-on interaction and engaging activities increased student success.

In complex and interdisciplinary projects, it was observed that students were less likely to lose direction with the help of real-time cues from the robot. Groups maintained a high level of collaboration, and the overall integration and completion of projects were significantly better than in the control group.

METHODOLOGY

This study adopts a quasi-experimental design with a treatment and a control group to examine the effect of an AI-supported learning intervention when random assignment is not feasible (Cook et al., 2002). We

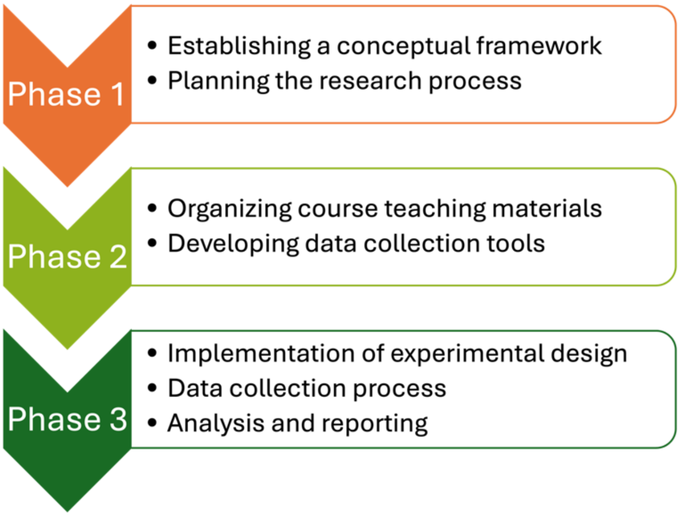

Figure 1. Research process (Original diagram by authors)

describe participants, procedures, instruments, and analytic decisions with emphasis on transparency and reproducibility. Measurement quality is evaluated using confirmatory factor analysis (CFA) and reliability indices consistent with current recommendations (Brown, 2015; McNeish, 2018).

Figure 1 summarizes the study in three sequential phases. Phase 1 establishes the conceptual framework and maps the research plan. Phase 2 prepares the instructional materials and develops the data-collection instruments. Phase 3 executes the quasi-experimental design, conducts data collection, and completes analysis and reporting–closing the loop from design to dissemination.

Data Collection Tools

This section describes the instruments used to capture the study's key constructs. Tools align with the conceptual framework and target three areas: SDL, problem-solving, and learning outcomes. Each scale was adapted from established measures and reviewed by domain experts for content relevance. Items use a Likert-type response format, with higher scores indicating stronger levels of the construct. We refined wording through small pilot checks and clarity edits. At the end of the intervention period, participants completed the full battery along with brief demographic items. Scale scoring, reliability, and validity evidence (e.g., CFA and internal consistency) are reported before the group comparisons.

Self-directed learning

SDL was assessed with a three-factor, nine-item scale adapted to the course context (Fooladvand & Nadi, 2019; Kar et al., 2019; Kumar et al., 2021). The subscales are *self-management*, *desire for learning*, and *self-control* (three items each). Items used a Likert-type response format, with higher values indicating stronger SDL. Subscale scores are the mean of their items; the overall SDL index is the mean of all nine items.

Self-management: Refers to an individual's ability to manage time, utilize resources, and plan learning progress. Sample questionnaire items include: "When I encounter new knowledge, I actively consult usage guidelines or relevant literature to ensure accuracy"; "Before starting a new learning session, I develop a detailed study plan"; "I regularly review my learning progress and adjust my study strategies as needed."

Desire for learning: Indicates the continuous pursuit of professional knowledge and an intrinsic interest in maintaining high-quality learning. Sample questionnaire items include: "I actively seek opportunities to learn the latest academic knowledge and skills"; "I have a strong passion for enhancing my knowledge and abilities"; "Even outside of class, I attend relevant seminars or additional courses to further develop my professional capabilities."

Self-control: Involves the ability to persevere toward goals and not give up when facing pressures or uncertainties during the learning process. Sample questionnaire items include: "When I encounter difficulties in my studies, I remain calm and continuously look for solutions"; "Even under time pressure, I persist in completing my scheduled learning tasks"; "When faced with uncertainties during learning, I actively reflect and adjust my strategies instead of giving up easily."

Construct validity was supported by a three-factor CFA, which showed good fit, $\chi^2/df = 1.88$, CFI = .987, TLI = .981, SRMR = .026, RMSEA = .051 (90% confidence interval [CI] [.027, .074]. Internal consistency was acceptable to high across subscales: *self-management* α = .892, ω = .892; *desire for learning* α = .854, ω = .855; *self-control* α = .850, ω = .855. These metrics indicate that the scale captures distinct yet related facets of SDL suitable for group comparisons in the present design.

Problem-solving ability

Problem-solving ability (PSA) was measured with a three-factor scale capturing *exploration and understanding*, *strategy selection*, and *monitoring and adjustment* (four items per subscale; 12 items total). Items were adapted from established problem-solving measures and tailored to the course context (Hesse et al., 2015; OECD, 2017). Responses used a 5-point Likert format (1 = strongly disagree to 5 = strongly agree). Subscale scores are computed as the mean of their items; a total PSA score is the mean of all 12 items, with higher values indicating stronger PSA.

Exploring and understanding: The ability to accurately define the scope and key points of a problem. Sample questionnaire items include: "When I face a challenging academic task, I can quickly identify the key elements of the problem"; "I am able to clearly describe the components of a complex problem and their interrelationships"; "I can break down a complex problem into parts that are easier to understand"; "When confronted with a new problem, I swiftly grasp its overall structure and main content."

Strategy selection: The capability to choose the most appropriate solution among several alternatives based on the context. Sample questionnaire items include: "When dealing with a complex problem, I proactively list multiple potential solutions and evaluate their feasibility"; "I can select the most suitable strategy based on the nature of the problem rather than relying on just one method"; "I am good at comparing different solutions and choosing the most effective one"; "When solving a problem, I consider the risks and benefits of each option."

Monitoring and adjustment: The practice of continually checking one's progress and modifying strategies based on feedback during problem-solving. Sample questionnaire items include: "I frequently reflect on whether my problem-solving strategy is effective and make adjustments as needed"; "When my solution doesn't work, I quickly adopt a new strategy to overcome the challenge"; "During the problem-solving process, I am able to promptly detect my mistakes and correct them"; "I regularly check if I have deviated from my original plan and, if necessary, re-plan my approach."

A three-factor CFA supported the intended structure, $\chi^2/df = 3.11$, CFI = .958, TLI = .945, SRMR = .035, RMSEA = .080 (90% CI [.066, .094]. Internal consistency was acceptable to high across subscales: *exploring and understanding* α = .894 ; ω = .895, *strategy selection* α = .886 ω = .887; *monitoring and adjustment* α = .886, ω = .887. These metrics indicate that reliable measurement suitable for group comparisons within the quasi-experimental design.

Learning outcomes

Learning outcomes were assessed with a two-factor scale comprising *process outcomes* (six items; learning process quality) and *learning outcomes* (six items; perceived performance and goal attainment). Items used a 5-point Likert format (1 = strongly disagree, 5 = strongly agree). Subscale scores are the mean of their items; a total *learning outcomes* score is the mean of all 12 items. Higher values indicate stronger outcomes. The measurement of learning outcomes in this study is based on the dimensions and items proposed by research (Erikson & Erikson, 2018; Li et al., 2023).

Learning process: Encompasses student participation, reflection, and the adjustment of strategies during the learning process. Sample questionnaire items include: "I actively participate in class discussions and frequently share my viewpoints"; "I take the initiative to interact with teachers and classmates to better understand the course content"; "I regularly reflect on my learning methods and evaluate whether I have achieved my goals"; "I keep a record of my learning progress and use it to assess my performance"; "After receiving feedback from my teacher, I proactively adjust my study strategies to improve my outcomes"; "If I

Table 1. Distribution of gender based on the groups

Group		N
Experimental	Male	68
	Female	36
	Total	104
Control	Male	54
	Female	48
	Total	102

find that my understanding of a particular section is insufficient, I seek additional learning resources to supplement it."

Learning outcomes: Refers to the final changes in knowledge, skills, and attitudes. Sample questionnaire items include: "I can clearly explain the main concepts and theories covered in this course"; "I can apply the knowledge I've learned to new situations and solve related problems"; "I am able to effectively utilize the skills I have acquired in practical tasks or projects"; "I believe that the skills taught in this course are highly beneficial for my professional development"; "I am satisfied with my learning experience in this course and feel it has enhanced my professional capabilities"; "Through this course, I have gained confidence and motivation for future learning."

A two-factor CFA supported the intended structure, $\chi^2/df = 1.14$, CFI = .998, TLI = .997, SRMR = .028, RMSEA = .020 (90% CI [.000, .042]; estimator = [ML/MLR/WLSMV, specify]). Internal consistency was excellent: Process α/ω = .938 and outcomes α/ω = .931, indicating precise and stable measurement suitable for group comparisons within the quasi-experimental design.

Sample

The study included two intact course sections assigned to control (n = 102; 54 male, 48 female) and treatment (n = 104; 68 male, 36 female) conditions (**Table 1**). Participants were undergraduate students enrolled in public administration department in Taiwan. Inclusion criteria were enrolled in the target course and consent to data use. Students with incomplete post-intervention surveys were excluded listwise from scale-level analyses.

Course Material Content

This study uses a procurement robot board game as the course content. The board game is inspired by the image recognition technology used in the Amazon Go unmanned store's shopping cart and incorporates game elements. In the experimental group, learners must apply IoT principles to control the procurement robot and utilize image recognition technology to "purchase" materials–strategically collecting the items required by the game's shopping list. In contrast, the control group receives instruction through traditional teacher-led lectures. For the blended learning component, the study employs the Google Classroom platform to support learning. Through this platform, learners can access all necessary course resources, including instructional videos and presentation slides. Course assignments are distributed via the assignment submission area, and an online discussion board is provided to enhance interaction throughout the course.

Experimental Design

Control group course design

The control group utilizes a traditional lecture-based approach. In this setup, key course content, supplemental information, and practical reviews are delivered through teacher-led verbal explanations within a PBL framework. As students complete their learning records, they are encouraged to ask questions at any time to the teacher or teaching assistant. For the practical component, learners engage with instructional videos and other resources available on the online platform, which include a series of sequential tasks.

Experimental group course design

The experimental group integrates the PBL process through a Q&A robot. Students follow the PBL steps to answer questions, with course content and duration identical to that of the control group. Here, key points, additional content, and practical reviews are still communicated via teacher lectures; however, each module also includes a set of questions posed by the Q&A robot. Learners must search for answers in the instructional videos or online resources and respond accordingly. After responding, the robot provides reference answers, allowing students to reflect on their responses. Finally, the teacher consolidates the various questions and conducts a class-wide review and course summary. This Q&A robot is designed to guide learners in focusing on critical content within each module, encouraging them to seek answers independently from the videos or online and thereby deepening their understanding. The emphasis is on fostering student autonomy and active participation, with the teacher playing a supporting role by guiding learners to complete specific tasks at designated times, which helps minimize disparities in group progress.

Comparison between control and experimental groups

In the control group, the traditional lecture method is used within a PBL framework, where teachers deliver content verbally and students ask questions as needed. In the experimental group, however, the PBL process is implemented with students following the established PBL steps–namely, clarifying the problem (I), gathering data (G), generating solutions (G), implementing solutions (I), and assessing/improving (A)–with the Q&A robot replacing the role of the teacher during the Q&A segment. Both groups use the same online instructional platform with access to videos and presentation slides, but the experimental group benefits from the additional guidance of the Q&A robot. In both groups, a Q&A session is conducted at the end of each module: in the control group, students are responsible for asking questions, while in the experimental group, the Q&A robot presents multiple questions. Learners then search for the answers in the instructional materials or online, respond to the robot's questions, and finally, check their responses against the provided reference answers.

The intervention consists of AI robot-assisted instruction using a PBL approach, implemented over 16 weeks (3 hours per week, totaling 48 hours).

Data Analysis

We followed a transparent, stepwise plan. First, we screened data for completeness and plausibility. There is no missing data. Primary group comparisons used Bayesian independent-samples t-tests for each subscale and total score. We report BF_{10} (evidence for the alternative over the null), the posterior median of the mean difference, and its 95% CIs. Unless otherwise noted, we used the default Cauchy prior on standardized effect size (r = 0.707), which is appropriate for psychology and education applications (Rouder et al., 2009; Wagenmakers et al., 2018). For interpretation, we use conventional labels as rough guides: $BF_{10} \approx 1$ (anecdotal), ≈ 3 (moderate), ≥ 10 (strong) (Kass & Raftery, 1995).

Because our inference is Bayesian and focused on evidence quantification rather than null-hypothesis rejection, we did not apply null-hypothesis multiple-comparison corrections. Still, we present the full pattern of Bayes factors and effect sizes across outcomes to support cautious, construct-level interpretation (Wagenmakers et al., 2018). All analyses were conducted in JASP 0.19.3, which provides validated implementations for CFA (via lavaan) and Bayesian t-tests, along with reproducible output (JASPTeam, 2025). Visualizations use raincloud plots to display raw data, distribution shape, and summary statistics in a single figure (Allen et al., 2019).

FINDINGS

Self-Directed Learning

The experimental group shows a clear rightward shift, with many scores clustered near 4.5-5.0 and a higher mean marker than the control group (**Figure 2**). The control group centers near 4.0-4.2 and has a thicker lower tail around 3.2-3.8. The box and whiskers suggest slightly lower dispersion for the experimental group, consistent with its smaller SD. A few low outliers appear in both groups, but high scores are more frequent in the experimental group. Overall, the distribution indicates better and more consistently strong self-management under the Q&A-robot conditions, while some overlap remains between groups. A Bayesian t-test was performed to determine whether the experimental and control groups differed according to the dimensions of SDL.

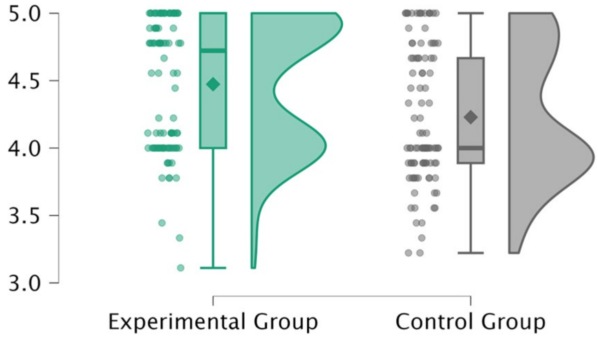

Figure 2. Rainclouds plot of SDL scale based on group (Original diagram by authors)

Table 2. Bayesian t-test result related to SDL based on group

	Group	N	Mean	SD	BF_{10}	W	Rhat
Self-management	Experimental	104	4.542	0.61	14.011	6,787.500	1.001
	Control	102	4.229	0.689			
Desire for learning	Experimental	104	4.474	0.539	4.000	6,428.000	1.001
	Control	102	4.219	0.677			
Self-control	Experimental	104	4.404	0.517	1.122	6,152.000	1.000
	Control	102	4.239	0.610			

For the three SDL facets (SMa, SMb, and SMc), the experimental group scored higher than the control group on every comparison (**Table 2**). For SMa, the experimental mean was 4.542 (SD = 0.61) versus 4.229 (SD = 0.689) in the control group, with BF_{10} = 14.011. This is strong evidence for a group difference and points to a clear gain in planning and resource use under the Q&A-robot condition. For SMb, the experimental mean was 4.474 (SD = 0.539) versus 4.219 (SD = 0.677), with BF_{10} = 4.000. This is moderate evidence and suggests a meaningful, though smaller, advantage for the experimental group. For SMc, the experimental mean was 4.404 (SD = 0.517) versus 4.239 (SD = 0.610), with BF_{10} = 1.122. This provides only anecdotal evidence, so the difference is uncertain.

Taken together, the pattern favors the experimental design. The largest and most reliable gain appears on SMa, which fits the mechanism of the Q&A robot: prompt-driven searching, immediate reference answers, and frequent checks likely reinforced planning and time management. SMb also benefits, consistent with more active engagement in tasks. SMc shows a small mean advantage but weak evidence, which suggests persistence and control may be more stable or may need a longer exposure to change. Overall, robots seem to strengthen day-to-day self-management processes while effects on sustained self-control are less certain.

Problem-Solving Ability

The PS chart shows a clear shift in favor of the experimental group (**Figure 3**). The experimental scores cluster around 4.3-4.8 with many points near 5.0. The mean marker is higher than the control group. The control group centers closer to 4.0 and has a longer lower tail down to about 3.0. The experimental box is higher and slightly tighter, which matches the smaller SD. There are a few low outliers in both groups, but they are more frequent in the control group. This pattern supports **Table 3**: the robot condition improves problem-solving, with the strongest lift at the upper end of performance. A Bayesian t-test assessed differences in problem-solving subskills between the experimental and control groups.

For problem-solving, the experimental group scored higher than the control group on all three facets (**Table 3**). For Psa (Exploring and understanding), the experimental mean was 4.349 (SD = 0.538) versus 4.115 (SD = 0.617), with BF_{10} = 3.886. This is moderate evidence for a real difference. It suggests the Q&A robot helped students define problems and extract key elements more clearly. For PSb (strategy selection), the experimental mean was 4.349 (SD = 0.497) versus 4.115 (SD = 0.769), with BF_{10} = 1.813. This is weak-to-moderate evidence. It points to a likely, but less certain, advantage in choosing and comparing solution methods. For PSc (monitoring and adjustment), the experimental mean was 4.389 (SD = 0.524) versus 4.174 (SD = 0.754), with BF_{10} = 1.145. This is only anecdotal evidence, so the difference is uncertain.

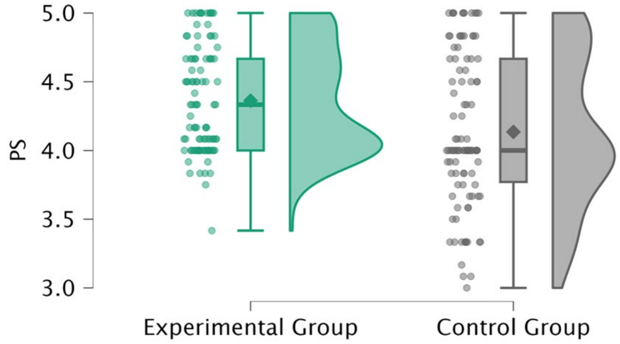

Figure 3. Rainclouds plot of PSA scale based on group (Original diagram by authors)

Table 3. Bayesian t-test result related to PSA based on group

	Group	N	Mean	SD	BF_{10}	W	Rhat
Exploring and understanding	Experimental	104	4.349	0.538	3.886	6,410.500	1.000
	Control	102	4.115	0.617			
Strategy selection	Experimental	104	4.349	0.497	1.813	6,150.500	1.000
	Control	102	4.115	0.769			
Monitoring and adjustment	Experimental	104	4.389	0.524	1.145	6,108.500	1.000
	Control	104	4.349	0.538			

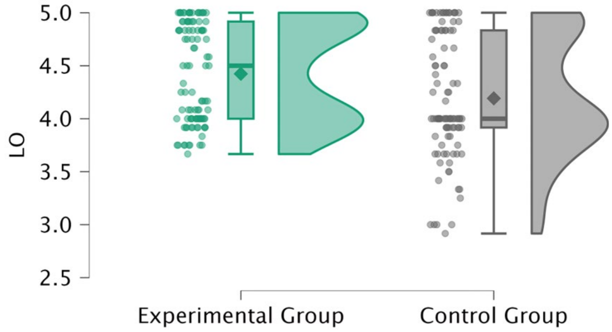

Figure 4. Rainclouds plot of learning outcomes scale based on group (Original diagram by authors)

Overall, the pattern fits the course design. The robot's prompts and reference answers likely supported early steps of the PBL cycle, especially clarifying and structuring problems. Gains in strategy selection and self-monitoring appear smaller and less certain, which may require more time-on-task or stronger scaffolds to solidify. The W statistics are consistent with the direction of effects, and Rhat ≈ 1.00 indicates stable Bayesian estimation. In short, the Q&A-supported PBL shows its clearest benefit in how students frame problems, with tentative advantages in choosing and revising strategies.

Learning Outcome

The LO chart mirrors the table pattern (**Figure 4**). The experimental group sits higher overall, with many scores between 4.3 and 5.0 and a mean marker above the control group. The control group centers closer to ~4.0 and shows a longer lower tail, with several points near 3.0. The box for the experimental group is higher and slightly tighter, suggesting better outcomes and a bit less spread. The chart supports moderate gains in learning process and a modest advantage in final outcomes under the Q&A-robot condition. Overlap remains, but the density peak for the experimental group is clearly shifted upward. A Bayesian t-test was used to examine whether there were differences in specific learning outcomes between the experimental group and the control group.

For learning outcomes, the experimental group scored higher on both facets (**Table 4**). For Loa (learning process), the experimental mean was 4.409 (SD = 0.551) versus 4.186 (SD = 0.664), with BF_{10} = 3.194. This is moderate evidence for a real difference. It suggests the Q&A robot supported participation, reflection, and strategy adjustment during study. For lob (final learning outcomes), the experimental mean was 4.439 (SD =

Table 4. Bayesian t-test result related to learning outcomes based on group

	Group	N	Mean	SD	BF_{10}	W	Rhat
Learning process	Experimental	104	4.409	0.551	3.194	6,312.500	1.001
	Control	102	4.186	0.664			
Learning outcomes	Experimental	104	4.439	0.629	1.482	6,247.500	1.000
	Control	104	4.198	0.779			

0.629) versus 4.198 (SD = 0.779), with BF_{10} = 1.482. This is anecdotal to weak evidence. The mean gap favors the experimental group, but the strength of evidence is modest.

Taken with the earlier results, the pattern is consistent. The robot shows its clearest effects on process-oriented skills and behaviors. Students plan better, frame problems more clearly, and stay engaged with the tasks. Gains on final outcomes are present but less certain. A longer duration, more transfer tasks, or tighter alignment between robot prompts and assessments may help translate process gains into stronger performance effects. The W and Rhat values indicate stable estimation and do not conflict with these conclusions.

DISCUSSION

This study showed that using robots in PBL has a favorable and important effect on student outcomes. The most significant improvement occurred in the "self-management" aspect of SDL. This outcome aligns with existing data indicating that PBL initiates cycles of planning and self-regulation by assigning responsibility to students (Ge et al., 2025; Su et al., 2025). The demonstrated superiority in problem-solving and comprehension/discovery skills aligns with the structure of PBL, which fosters critical thinking and knowledge transfer. Recent reviews covering higher education samples show that PBL leads to meaningful increases in cognitive outcomes (Su et al., 2025). Educational robot support may have amplified this effect through feedback quality and personalization. Multilevel meta-analyses show that robot-assisted instruction produces positive effects on achievement, attitudes, and computational thinking, particularly in STEM contexts; the effect may vary depending on the robot's role and type of interaction (Ouyang & Xu, 2024; Trapero-González et al., 2024). The findings indicate that AI/robot feedback produces more effective learning outcomes when it is prompt and comprehensive. Recent studies of intelligent tutoring systems and AI feedback highlight that customized and clarifying feedback substantially improves learning, although the effect is dependent on context (Fleckenstein et al., 2023; Kaliisa et al., 2025).

Our results concerning SDL align with meta-analyses indicating moderate effects of self-regulation tools on academic outcomes in online and mixed learning contexts. This parallel theoretically elucidates the self-management improvements observed in our study (Guntur & Purnomo, 2024; Yu et al., 2025). Nonetheless, the literature indicates that impact estimates for AI interventions are inconsistent. The effect might change depending on the type of feedback, how well the content fits, the teacher's role, and how well the plan was carried out. In applications employing extensive language models such as ChatGPT, effects have been noted to fluctuate based on context (Kaliisa et al., 2025; Wang & Fan, 2025). So, when we talk about our positive results in general, we need to focus on the conditions in which they happened.

This study has some limitations. Quasi-experimental assignment carries the risk of selection bias. Self-report-based measures might result in social desirability and recall bias. The particulars of the robot's intervention (feedback content, delay, accuracy check) may have influenced the outcomes. The literature indicates that the functionality of the robot/AI and the organization of the feedback are pivotal elements affecting the outcome (Letourneau et al., 2025; Ouyang & Xu, 2024). Three recommendations emerge for application and research. First, feedback design should be aligned with PBL stages and be explanatory (Kaliisa et al., 2025). Second, the robot's role as "instructor/peer/facilitator" should be clearly defined and selected to match the task (Xu & Ouyang, 2025). Third, behavioral and product-based indicators should be added to SDL measurements (Guntur & Purnomo, 2024).

Overall, the findings indicate that robot-assisted PBL can produce meaningful and practically valuable effects on self-regulation, problem-solving, and comprehension. This effect is enhanced by appropriate feedback design and a clarified robot role; however, contextual elements must be closely managed.

CONCLUSION

This study demonstrates that robot-assisted PBL can produce meaningful gains in SDL, problem-solving, and comprehension levels. The most significant increase was observed in the self-management dimension. Students demonstrated more consistent behaviors in planning the work process, completing tasks on time, and effectively using learning resources. The rise in problem-solving and comprehension/discovery skills is strengthened when PBL's metacognitive flow is combined with the robot's timely and explanatory feedback. The findings show that well-designed robot support can increase learning outcomes through the functions of guidance, prompting, and error conversion in the PBL cycle.

The study's contribution to the literature stands out in three dimensions. First, by systematically testing robotic support in a PBL context, it provides detailed evidence on the sub-dimensions of SDL; specifically, the increase in self-management concretizes the general findings in the field at the discipline and context levels. Second, by focusing not only on success but also on process indicators, it reveals the relationship between the quality of feedback and learning outcomes. Third, by using a Bayesian reporting approach, it transparently discloses the degree of evidence strength, thereby increasing the interpretability and reproducibility of the findings.

Recommendations have been developed based on the study results. The role of robots in learning environments should be clearly defined and aligned with the course objectives; a structure that provides facilitative and explanatory feedback should be preferred. Feedback should be timely, detailed, and directly related to the task; explanations that go beyond right-wrong information support student self-management and lasting learning. Application fidelity should be monitored regularly; checklists, sample interaction scenarios, and deviation logs should be kept for each session. Measurement strategies should be enriched with performance tasks, product quality, and behavioral traces alongside self-report scales; thus, the transfer of acquired gains to real tasks can be assessed more reliably. To increase the generalizability of the design, multiple studies should be planned across different disciplines, different institutions, and with longer follow-up intervals. In Bayesian reporting, effect size estimates and CIs should be provided regularly, clearly presenting the levels of evidence. Finally, regulatory variables such as student diversity, teacher support, and content difficulty should be defined in advance; these variables should be modeled systematically to determine under which conditions the effect is highest.

Overall, the findings indicate that robot-assisted PBL is a pedagogically robust and scalable approach. The sustainability of the effect depends on the quality of feedback design, the clarity of role definitions, and the multidimensional design of assessment processes. When these principles are observed, robot-assisted PBL has the potential to produce lasting learning outcomes across different disciplines and student profiles.

Author contributions: JN: co-conceptualization, advise analysis, original draft; **C-JS:** conceptualization, data curation, formal analysis, visualization, supervision, writing – review & editing. Both authors approved the final version of the article.

Funding: This research is funded by Thailand Science Research and Innovation Fund Chulalongkorn University (SOC_FF_68_338_2700_006).

Ethics declaration: The authors declared that this study did not require ethical approval. Neither the institute nor the funder required ethical approval for this type of research. This is because this study was conducted as a classroom course, with the instructor dividing students into experimental and control groups for case studies; Dr. Chich-Jen Shieh was a part-time instructor at Tung Fang Design University, Taiwan. This study also adheres to the ethical principles of the Declaration of Helsinki.

Declaration of interest: The authors declared no competing interest.

Data availability: Data generated or analyzed during this study are available from the authors on request.

REFERENCES

Abildinova, G., Abdykerimova, E., Assainova, A., Mukhtarkyzy, K., & Abykenova, D. (2024). Preparing educators for the digital age: Teacher perceptions of active teaching methods and digital integration. *Frontiers in Education, 9*. https://doi.org/10.3389/feduc.2024.1473766

Albanese, M. A., & Mitchell, S. (1993). Problem-based learning: A review of literature on its outcomes and implementation issues. *Academic Medicine, 68*(1), 52–81.

Allen, M., Poggiali, D., Whitaker, K., Marshall, T. R., van Langen, J., & Kievit, R. A. (2019). Raincloud plots: A multi-platform tool for robust data visualization. *Wellcome Open Research, 4*, Article 63. https://doi.org/10.12688/wellcomeopenres.15191.2

Barry, R.-J., Neumann, M. M., & Neumann, D. L. (2025). Individual differences and young children's engagement with a social robot. *Computers in Human Behavior: Artificial Humans, 4*, Article 100139. https://doi.org/10.1016/j.chbah.2025.100139

Bellas, F., Naya-Varela, M., Mallo, A., & Paz-Lopez, A. (2024). Education in the AI era: A long-term classroom technology based on intelligent robotics. *Humanities and Social Sciences Communications, 11*, Article 1425. https://doi.org/10.1057/s41599-024-03953-y

Belpaeme, T., Kennedy, J., Ramachandran, A., Scassellati, B., & Tanaka, F. (2018). Social robots for education: A review. *Science Robotics, 3*(21), Article eaat5954. https://doi.org/10.1126/scirobotics.aat5954

Bertacchini, F., Scuro, C., Pantano, P., & Bilotta, E. (2022). A project based learning approach for improving students' computational thinking skills. *Frontiers in Robotics and AI, 9*. https://doi.org/10.3389/frobt.2022.720448

Brown, T. A. (2015). *Confirmatory factor analysis for applied research*. Guilford Publications.

Charisi, V., Gomez, E., Mier, G., Merino, L., & Gomez, R. (2020). Child-robot collaborative problem-solving and the importance of child's voluntary interaction: A developmental perspective. *Frontiers in Robotics and AI, 7*. https://doi.org/10.3389/frobt.2020.00015

Chen, H., Kim, Y., Patterson, K., Breazeal, C., & Park, H. W. (2025). Social robots as conversational catalysts: Enhancing long-term human-human interaction at home. *Science Robotics, 10*(100), Article eadk3307. https://doi.org/10.1126/scirobotics.adk3307

Cook, T. D., Campbell, D. T., & Shadish, W. (2002). *Experimental and quasi-experimental designs for generalized causal inference*. Houghton Mifflin.

Donnermann, M., Schaper, P., & Lugrin, B. (2022). Social robots in applied settings: A long-term study on adaptive robotic tutors in higher education. *Frontiers in Robotics and AI, 9*. https://doi.org/10.3389/frobt.2022.831633

Duda, H. J., Wibowo, D. C., Suryani, N. Y., Thoharudin, M., & Budiman, J. (2024). Problem-based learning through authentic assessment: Students' cognitive and creative thinking abilities. *Pedagogika, 156*(4), 52–73. https://doi.org/10.15823/p.2024.156.3

Erikson, M. G., & Erikson, M. (2018). Learning outcomes and critical thinking–Good intentions in conflict. *Studies in Higher Education, 44*(12), 2293–2303. https://doi.org/10.1080/03075079.2018.1486813

Fleckenstein, J., Liebenow, L. W., & Meyer, J. (2023). Automated feedback and writing: A multi-level meta-analysis of effects on students' performance. *Frontiers in Artificial Intelligence, 6*. https://doi.org/10.3389/frai.2023.1162454

Fooladvand, M., & Nadi, M. A. (2019). Validation of revisited self-directed learning readiness scale for nursing education among Iranian nursing and midwifery students. *Journal of Education and Health Promotion, 8*, Article 266. https://doi.org/10.4103/jehp.jehp_82_19

Fung, K. Y., Fung, K. C., Lui, T. L. R., Sin, K. F., Lee, L. H., Qu, H., & Song, S. (2025). Exploring the impact of robot interaction on learning engagement: A comparative study of two multi-modal robots. *Smart Learning Environments, 12*, Article 12. https://doi.org/10.1186/s40561-024-00362-1

Fung, K. Y., Lee, L. H., Sin, K. F., Song, S., & Qu, H. (2024). Humanoid robot-empowered language learning based on self-determination theory. *Education and Information Technologies, 29*(14), 18927–18957. https://doi.org/10.1007/s10639-024-12570-w

Ge, W.-L., Zhu, X.-Y., Lin, J. B., Jiang, J.-J., Li, T., Lu, Y.-F., Mi, Y.-F., & Tung, T.-H. (2025). Critical thinking and clinical skills by problem-based learning educational methods: An umbrella systematic review. *BMC Medical Education, 25*, Article 455. https://doi.org/10.1186/s12909-025-06951-z

Guntur, M., & Purnomo, Y. W. (2024). A meta-analysis of self-regulated learning interventions studies on learning outcomes in online and blended environments. *Online Learning, 28*(3), 563–584. https://doi.org/10.24059/olj.v28i3.4025

Guo, K., Zhang, E. D., Li, D., & Yu, S. (2024). Using AI-supported peer review to enhance feedback literacy: An investigation of students' revision of feedback on peers' essays. *British Journal of Educational Technology, 56*(4), 1612–1639. https://doi.org/10.1111/bjet.13540

Hesse, F., Care, E., Buder, J., Sassenberg, K., & Griffin, P. (2015). A framework for teachable collaborative problem solving skills. In P. Griffin, & E. Care (Eds.), *Assessment and teaching of 21st century skills. Educational assessment in an information age* (pp. 37–56). Springer. https://doi.org/10.1007/978-94-017-9395-7_2

Hrastinski, S. (2019). What do we mean by blended learning? *TechTrends, 63*(5), 564–569. https://doi.org/10.1007/s11528-019-00375-5

Huang, C., Zhong, Y., Li, Y., Wang, X., Han, Z., Zhang, D., & Liu, M. (2025). Enhancing student reading performance through a personalized two-tier problem-based learning approach with generative artificial intelligence. *Humanities and Social Sciences Communications, 12*, Article 645. https://doi.org/10.1057/s41599-025-04919-4

Huang, G., & Moore, R. K. (2023). Using social robots for language learning: Are we there yet? *Journal of China Computer-Assisted Language Learning, 3*(1), 208–230. https://doi.org/10.1515/jccall-2023-0013

Jaganathan, S., Bhuminathan, S., & Ramesh, M. (2024). Problem-based learning–An overview. *Journal of Pharmacy and Bioallied Sciences, 16*(Suppl 2), S1435–S1437. https://doi.org/10.4103/jpbs.jpbs_820_23

JASPTeam. (2025). JASP (version 0.19). *JASP*. https://jasp-stats.org/download/

Kaliisa, R., Misiejuk, K., López-Pernas, S., & Saqr, M. (2025). How does artificial intelligence compare to human feedback? A meta-analysis of performance, feedback perception, and learning dispositions. *Educational Psychology*. https://doi.org/10.1080/01443410.2025.2553639

Kar, S., Akkilagunta, S., Premarajan, K. C., Lakshminarayanan, S., Ramalingam, A., Chacko, T., & Bhandary, S. (2019). Assessment of reliability and adaptation of fisher's 52-item self-directed learning readiness scale among medical students in Southern India. *International Journal of Advanced Medical and Health Research, 6*(1), 7–11. https://doi.org/10.4103/ijamr.Ijamr_39_18

Kass, R. E., & Raftery, A. E. (1995). Bayes factors. *Journal of the American Statistical Association, 90*(430), 773–795. https://doi.org/10.1080/01621459.1995.10476572

Kim, H., Hwang, J., Kim, T., Choi, M., Lee, D., & Ko, J. (2025). Impact of generative artificial intelligence on learning: Scaffolding strategies and self-directed learning perspectives. *International Journal of Human-Computer Interaction*. https://doi.org/10.1080/10447318.2025.2531267

Kong, S.-C., Cheung, M.-Y. W., & Tsang, O. (2024). Developing an artificial intelligence literacy framework: Evaluation of a literacy course for senior secondary students using a project-based learning approach. *Computers and Education: Artificial Intelligence, 6*, Article 100214. https://doi.org/10.1016/j.caeai.2024.100214

Kruschke, J. K. (2021). Bayesian analysis reporting guidelines. *Nature Human Behaviour, 5*, 1282–1291. https://doi.org/10.1038/s41562-021-01177-7

Kumar, A. P., Omprakash, A., Mani, P. K. C., Swaminathan, N., Maheshkumar, K., Maruthy, K. N., Sathiyasekaran, B. W. C., Vijayaraghavan, P. V., & Padmavathi, R. (2021). Validation of internal structure of self-directed learning readiness scale among Indian medical students using factor analysis and the structural equation modelling approach. *BMC Medical Education, 21*, Article 614. https://doi.org/10.1186/s12909-021-03035-6

Lampropoulos, G. (2025). Social robots in education: Current trends and future perspectives. *Information, 16*(1), Article 29. https://doi.org/10.3390/info16010029

Langer, A., Marshall, P. J., & Levy-Tzedek, S. (2023). Ethical considerations in child-robot interactions. *Neuroscience & Biobehavioral Reviews, 151*, Article 105230. https://doi.org/10.1016/j.neubiorev.2023.105230

Leary, H., Walker, A., Lefler, M., & Kuo, Y.-C. (2019). Self-directed learning in problem-based learning. In M. Moallem, W. Hung, & N. Dabbagh (Eds.), *The Wiley handbook of problem-based learning* (pp. 181–198). Wiley. https://doi.org/10.1002/9781119173243.ch8

Letourneau, A., Deslandes Martineau, M., Charland, P., Karran, J. A., Boasen, J., & Leger, P. M. (2025). A systematic review of AI-driven intelligent tutoring systems (ITS) in K-12 education. *npj Science of Learning, 10*, Article 29. https://doi.org/10.1038/s41539-025-00320-7

Li, B., Bonk, C. J., Wang, C., & Kou, X. (2024a). Reconceptualizing self-directed learning in the era of generative AI: An exploratory analysis of language learning. *IEEE Transactions on Learning Technologies, 17*, 1489–1503. https://doi.org/10.1109/tlt.2024.3386098

Li, B., Yu, J., Sun, L., & Yang, H. (2024b). Impact of active learning instruction in blended learning on students' anxiety levels and performance. *Frontiers in Education, 9*. https://doi.org/10.3389/feduc.2024.1332778

Li, S., Kwok, S. W. H., Siu, S. C. N., Chung, J. Y. S., Lam, H. C. Y., Tsang, E. Y. M., Li, K. C., Yeung, J. W. Y., & Lam, S. C. (2023). Development of generic student engagement scale in higher education: An application on healthcare students. *Nursing Open, 10*(3), 1545–1555. https://doi.org/10.1002/nop2.1405

Lin, V., Yeh, H.-C., & Chen, N.-S. (2022). A systematic review on oral interactions in robot-assisted language learning. *Electronics, 11*(2), Article 290. https://doi.org/10.3390/electronics11020290

Mavridis, N. (2015). A review of verbal and non-verbal human-robot interactive communication. *Robotics and Autonomous Systems, 63*(P1), 22–35. https://doi.org/10.1016/j.robot.2014.09.031

McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. *Psychological Methods, 23*(3), 412–433. https://doi.org/10.1037/met0000144

Megahed, N., & Ghoneim, E. (2022). Blended learning: The new normal for post-COVID-19 pedagogy. *International Journal of Mobile and Blended Learning, 14*(1), 1–16. https://doi.org/10.4018/IJMBL.291980

Mubin, S., Stevens, C. J., Shahid, S., Al Mahmud, A., & Dong, J.-J. (2013). A review of the applicability of robots in education. *Technology in Education and Learning, 1*. https://doi.org/10.2316/Journal.209.2013.1.209-0015

Nannim, F. A., Ibezim, N. E., Mosia, M., & Oguguo, B. C. E. (2025). Project-based learning with Arduino robots: Impact on undergraduate students' achievement and task persistence in robotics programming. *Frontiers in Robotics and AI, 12*. https://doi.org/10.3389/frobt.2025.1615427

Nasir, J., Bruno, B., & Dillenbourg, P. (2024). Social robots as skilled ignorant peers for supporting learning. *Frontiers in Robotics and AI, 11*. https://doi.org/10.3389/frobt.2024.1385780

Niyomves, B., Kunacheva, N., & Sutadarat, S. (2024). Hybrid learning: A combination of face-to-face and online learning. *Journal of Education and Learning Reviews, 1*(3), 11–20. https://doi.org/10.60027/jelr.2024.673

OECD. (2017). *PISA 2015 results (volume V)*. OECD Publishing. https://doi.org/10.1787/9789264285521-en

Ouyang, F., & Xu, W. (2024). The effects of educational robotics in STEM education: A multilevel meta-analysis. *International Journal of STEM Education, 11*, Article 7. https://doi.org/10.1186/s40594-024-00469-4

Pai, R. Y., Shetty, A., Dinesh, T. K., Shetty, A. D., & Pillai, N. (2024). Effectiveness of social robots as a tutoring and learning companion: A bibliometric analysis. *Cogent Business & Management, 11*(1), Article 2299075. https://doi.org/10.1080/23311975.2023.2299075

Platonova, R. I., Orekhovskaya, N. A., Dautova, S. B., Martynenko, E. V., Kryukova, N. I., & Demir, S. (2022). Blended learning in higher education: Diversifying models and practical recommendations for researchers. *Frontiers in Education, 7*. https://doi.org/10.3389/feduc.2022.957199

Rong, M., Yao, Y., Li, Q., & Chen, X. (2025). Exploring student engagement with artificial intelligence-guided chatbot feedback in EFL writing: Interactions and revisions. *Computer Assisted Language Learning*. https://doi.org/10.1080/09588221.2025.2539979

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian *t* tests for accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*, 225–237. https://doi.org/10.3758/PBR.16.2.225

Servant, V. F. C., & Schmidt, H. G. (2016). Revisiting foundations of problem-based learning: Some explanatory notes. *Medical Education, 50*(7), 698–701. https://doi.org/10.1111/medu.12803

Sharma, D., Sood, A. K., Darius, P. S. H., Gundabattini, E., Darius Gnanaraj, S., & Joseph Jeyapaul, A. (2022). A study on the online-offline and blended learning methods. *Journal of the Institution of Engineers (India): Series B, 103*(4), 1373–1382. https://doi.org/10.1007/s40031-022-00766-y

Singh, J., Steele, K., & Singh, L. (2021). Combining the best of online and face-to-face learning: Hybrid and blended learning approach for COVID-19, post vaccine, & post-pandemic world. *Journal of Educational Technology Systems, 50*(2), 140–171. https://doi.org/10.1177/00472395211047865

Su, T., Liu, J., Meng, L., Luo, Y., Ke, Q., & Xie, L. (2025). The effectiveness of problem-based learning (PBL) in enhancing critical thinking skills in medical education: A systematic review and meta-analysis. *Frontiers in Education, 10*. https://doi.org/10.3389/feduc.2025.1565556

Trapero-González, I., Hinojo-Lucena, F. J., Romero-Rodríguez, J.-M., & Martínez-Menéndez, A. (2024). Didactic impact of educational robotics on the development of STEM competence in primary education: A systematic review and meta-analysis. *Frontiers in Education, 9*. https://doi.org/10.3389/feduc.2024.1480908

Venter, J., Coetzee, S. A., & Schmulian, A. (2024). Exploring the use of artificial intelligence (AI) in the delivery of effective feedback. *Assessment & Evaluation in Higher Education, 50*(4), 516–536. https://doi.org/10.1080/02602938.2024.2415649

Verhelst, E., Janssens, R., Demeester, T., & Belpaeme, T. (2024). Adaptive second language tutoring using generative AI and a social robot. In *Proceedings of the Companion of the 2024 ACM/IEEE International Conference on Human-Robot Interaction* (pp. 1080–1084). ACM. https://doi.org/10.1145/3610978.3640559

Wagenmakers, E. J., Love, J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Selker, R., Gronau, Q. F., Dropmann, D., Boutin, B., Meerhoff, F., Knight, P., Raj, A., van Kesteren, E. J., van Doorn, J., Smira, M., Epskamp, S., Etz, A., Matzke, D., … Morey, R. D. (2018). Bayesian inference for psychology. Part II: Example applications with JASP. *Psychonomic Bulletin & Review, 25*, 58–76. https://doi.org/10.3758/s13423-017-1323-7

Wang, J., & Fan, W. (2025). The effect of ChatGPT on students' learning performance, learning perception, and higher-order thinking: Insights from a meta-analysis. *Humanities and Social Sciences Communications, 12*, Article 621. https://doi.org/10.1057/s41599-025-04787-y

Wu, D., Zhang, S., Ma, Z., Yue, X.-G., & Dong, R. K. (2024). Unlocking potential: Key factors shaping undergraduate self-directed learning in AI-enhanced educational environments. *Systems, 12*(9), Article 332. https://doi.org/10.3390/systems12090332

Xu, W., & Ouyang, F. (2025). Robotic roles in education: A systematic review based on a proposed framework of the learner-robot relationships. *Educational Research Review, 47*, Article 100685. https://doi.org/10.1016/j.edurev.2025.100685

Yang, Q.-F., Lian, L.-W., & Zhao, J.-H. (2023). Developing a gamified artificial intelligence educational robot to promote learning effectiveness and behavior in laboratory safety courses for undergraduate students. *International Journal of Educational Technology in Higher Education, 20*, Article 18. https://doi.org/10.1186/s41239-023-00391-9

Younas, M., Abdel Salam El-Dakhs, D., & Jiang, Y. (2025). A comprehensive systematic review of AI-driven approaches to self-directed learning. *IEEE Access, 13*, 38387–38403. https://doi.org/10.1109/access.2025.3546319

Yu, Q., Yu, K., & Wang, J. (2025). Unraveling the impact of blended learning vs. online learning on learners' performance: Perspective of self-determination theory. *Behavioral Science, 15*(9), Article 1263. https://doi.org/10.3390/bs15091263

Zakaria, M. I., Abdullah, A. H., Alhassora, N. S. A., Osman, S., & Ismail, N. (2025). The impact of M-learning and problem-based learning teaching method on students motivation and academic performance. *International Journal of Instruction, 18*(1), 503–518. https://doi.org/10.29333/iji.2025.18127a

Zhang, L., & Ma, Y. (2023). A study of the impact of project-based learning on student learning effects: A meta-analysis study. *Frontiers in Psychology, 14*. https://doi.org/10.3389/fpsyg.2023.1202728

Zhou, G., Liu, W., Guo, S., & Lin, Y. (2025). Where are we in online project-based learning? Evidence from a visualized bibliometric review (2013–2023). *Computer Applications in Engineering Education, 33*(3), Article e70044. https://doi.org/10.1002/cae.70044

Zong, Y., & Yang, L. (2025). How AI-enhanced social-emotional learning framework transforms EFL students' engagement and emotional well-being. *European Journal of Education, 60*(1), Article e12925. https://doi.org/10.1111/ejed.12925