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AI-assisted problem-based learning: Effects on problem-solving abilities across learning styles

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ABSTRACT

This study investigated the effect of Problem-Based Learning (PBL) assisted by Artificial Intelligence (AI) on students' problem-solving skills, with particular consideration for students' initial abilities and learning styles. The study employed a quasi-experimental design involving 120 undergraduate students, allocated into experimental and control groups. The results show that AI-assisted PBL greatly improves problem-solving skills ($F=45.23$, $p<0.001$, $\eta^2=0.38$), but the effects varied, depending on the person's initial skill levels and learning styles. Students with low initial ability exhibited the most significant improvement ($d=1.24$), whereas visual learners derived the greatest benefit from AI-enhanced visualisations. These findings concluded that AI-assisted problem-based learning (PBL) can be an adaptive instructional strategy that addresses individual learning differences, with ramifications for creating more inclusive and customised educational interventions that mitigate achievement gaps and consider varied learning preferences in higher education settings.

INTRODUCTION

The rapid growth of educational technology has made it possible to change traditional teaching methods in ways that have never been done before. Problem-Based Learning (PBL) is one of the best student-centered methods (Savery, 2015). PBL gets students involved by giving them real, hard problems that need them to think critically, work together, and learn on their own. These are all skills crucial for success in the 21st century. Recent advancements in Artificial Intelligence (AI) present promising opportunities for the enhancement of the use of PBL by delivering adaptive, personalised educational experiences that cater to the unique needs, initial competencies, and preferred learning styles of individual students (Holmes et al., 2019; Zawacki-Richter et al., 2019). This integration addresses persistent challenges in the PBL implementation and may enhance its pedagogical advantages (Bauer et al., 2025; Otto et al., 2025; Valls Pou et al., 2022). As schools attempt to help students learn better and prepare them to handle complex problems in the real world, it is urgent to master how AI-assisted PBL changes the way students solve problems.

Challenges in traditional PBL implementation

Traditional PBL for instruction has many advantages, but it also has many downsides that might reduce its effectiveness. One big concern is the inability to provide each student with individualised help in group learning environments where they have diverse levels of prior knowledge and ways of learning. It can be challenging for teachers to keep an eye on several groups at once, give timely feedback, and make sure that everyone on the team is participating fairly, even if they have different skill levels. Students with insufficient domain knowledge or poorly developed self-regulated learning skills may experience cognitive overload when confronted with ill-structured problems that lack adequate scaffolding. These challenges can result in frustration, disengagement, and suboptimal learning outcomes, particularly for students requiring more structured assistance (Chew & Cerbin, 2021; Gupta & Prashar, 2025; Park & Ramirez, 2022). Moreover, traditional PBL assessment methods often fail to capture the complex and multifaceted nature of problem-solving proficiency, focusing primarily on final outcomes rather than the cognitive processes and collaborative strategies employed in problem-solving.

AI as a solution for enhancing PBL

Artificial intelligence technologies offer innovative solutions to address the inherent constraints of traditional problem-based learning implementation. AI systems can scrutinise learning data and find patterns in how students are engaged, what they don't understand, and how groups work that people might not be able to see (Roll & Wylie, 2016; Baker & Inventado, 2014). These systems can provide personalised scaffolding that adapts to each student's cognitive profile, offering assistance as needed and gradually withdrawing it as they improve (Zawacki-Richter et al., 2019). Intelligent tutoring systems can enhance collaborative learning by ensuring that students are grouped based on their complementary knowledge and skills, investigating group interactions to ensure their productivity, and stepping in when collaborative processes break down (Holmes et al., 2019; Luckin et al., 2016). AI can also assist with advanced formative assessment that looks at more than just the final answers to problems (Hopfenbeck et al., 2023; Liao et al., 2024; Vittorini et al., 2021). It can also examine how well people think, how efficiently they work together, and how much they learn about their own thinking while solving a problem (Roll & Wylie, 2016). Natural language processing capabilities empower AI systems to facilitate Socratic dialogue among students, enhancing cognitive engagement through strategic questioning despite providing direct answers, thereby upholding the constructivist principles essential to effective problem-based learning (Bauer et al., 2018).

The role of initial ability and learning styles

Individual learner characteristics, particularly initial ability levels and learning style preferences, significantly influence students' engagement with and benefits from educational interventions (Carroll et al., 2021; El-Sabagh, 2021; Yousaf et al., 2023). Initial ability, encompassing prior knowledge, requisite skills, and domain-specific competencies, affects students' capacity to comprehend intricate problems, formulate effective solution strategies, and integrate new information into established cognitive frameworks. Research on the expertise reversal effect indicates that pedagogical approaches effective for novices may be less effective or potentially detrimental for more proficient learners. This demonstrates the significance of tailoring instruction to varying skill levels. Similarly, learning style preferences, encompassing sensory modalities, information processing techniques, and cognitive strategies, affect students' perceptions, interpretations, and reactions to educational materials and activities. Despite ongoing debates regarding the empirical validity of learning styles theory, substantial evidence suggests that providing varied representations and allowing students autonomy over learning modalities can enhance engagement and comprehension (An & Carr, 2017). AI systems excel in dealing with both differences in initial skill levels and learning style preferences. They do this by always checking how well each student is doing, figuring out the best ways to teach each type of student, and changing the way information is presented, the difficulty of problems, and the kinds of help that are available.

Research gap and study objectives

While a growing number of researchers are exploring both Problem-Based Learning (PBL) and Artificial Intelligence (AI) in educational contexts, there exists a deficiency of empirical studies assessing their combined effectiveness in improving problem-solving skills. Contemporary research predominantly focuses on the efficacy of Problem-Based Learning (PBL) or the integration of Artificial Intelligence (AI) in isolation, overlooking a comprehensive analysis of their synergistic potential and the implications of their amalgamation on diverse student demographics (Ouyang & Jiao, 2021). Furthermore, contemporary literature predominantly focuses on knowledge acquisition and academic success as primary goals, neglecting the cultivation of transferable problem-solving abilities, collaborative skills, and metacognitive awareness that transcend particular disciplinary boundaries (Hwang et al., 2020). Research on how differences in initial ability and learning styles affect the effectiveness of AI-assisted Problem-Based Learning (PBL) is limited. This means that there is inadequate evidence-based guidance for teachers on how to use it (Liu et al., 2023). This study systematically examines the impact of AI-assisted PBL on various dimensions of problem-solving skills, while also assessing the moderating effects of students' initial competencies and learning style preferences. The study offers extensive insights into cognitive outcomes, encompassing analytical reasoning, creative solution generation, and adaptive strategy refinement, as well as affective factors such as self-efficacy, motivation, and collaborative efficacy that augment effective problem-solving performance.

RESEARCH METHOD

Research design

The study employed a quasi-experimental pretest-posttest control group design to scrutinise how AI-assisted Problem-Based Learning affected students' ability to solve problems. The researchers chose the design because randomly assign students in the current classroom setup was impossible, but we still needed to make sure that the controls were strict enough to guarantee internal validity. The experimental group learned through PBL with the help of AI-driven adaptive learning systems, while the control group learned through regular PBL without any AI help. During the 14-week semester, both groups worked on the same problems and had the same amount of time in class. The research design included several measurement points, such as a pretest to quantify how well students solved problems and how they learned best, formative assessments during the intervention, and a full posttest to discover their improvement in problem solving. All of these were used to keep track of developmental paths and investigate how the effects varied among different groups.

Participants

The study engaged 120 undergraduate students (68 females and 52 males; mean age of 20.3 years; and SD of 1.2) enrolled in educational technology courses at a public university in Indonesia. Participants were from four intact classes, with two groups allocated randomly to the experimental condition ($n = 60$) and two to the control condition ($n = 60$). This approach mitigated contamination effects while acknowledging the quasi-experimental design. To qualify, students needed to have completed their fundamental digital literacy skills and the mandated courses in educational foundations. The sample displayed variability in initial ability levels (25% low, 48% medium, 27% high according to pretest scores) and learning style preferences (32% visual, 28% auditory, 23% kinaesthetic, 17% multimodal as evaluated by the VARK inventory), thereby offering sufficient diversity to examine moderating effects. Power analysis indicated that the sample size possessed sufficient statistical power ($1-\beta = 0.85$) to detect medium effect sizes ($f = 0.25$) at $\alpha = 0.05$.

Instruments

Students' ability to solve problems were tested with a modified version of the Heppner and Petersen Problem-Solving Inventory that was made for use in schools. The 32-item instrument assesses various dimensions, encompassing problem identification and definition (8 items), generation of alternative solutions (8 items), decision-making and planning (8 items), and solution implementation and evaluation (8 items). The answers were rated on a 5-point Likert scale, with 1 meaning "strongly disagree" and 5 meaning "strongly agree." The instrument demonstrated strong psychometric characteristics, evidenced by a Cronbach's alpha of 0.89 for the overall scale and subscale reliabilities ranging from 0.82 to 0.87. Confirmatory factor analysis (CFI = 0.94, RMSEA = 0.06) demonstrated the validity of the four-factor structure.

Learning styles inventory

We adopted the VARK (Visual, Auditory, Read/Write, Kinaesthetic) questionnaire version 8.01 to ascertain the learner types. This 16-item tool shows different learning situations and four options for answers based on how people like to learn best. The VARK has been tested in various educational settings and has a high test-retest reliability (r = 0.85).

Initial ability assessment

A detailed pretest consisting of 20 multiple-choice questions and 3 open-ended problems assessed students' foundational knowledge and competencies, pertaining to the course material. The items examined basic ideas in educational technology, essential problem-solving methods, and critical thinking. The evaluation demonstrated strong internal consistency, with a KR-20 value of 0.84 for multiple-choice items and an inter-rater reliability coefficient of 0.89 for open-ended problems assessed by two independent raters. Students were divided into three groups based on their performance on the pretest: low (less than 60%), medium (60–79%), and high (80% or more) initial ability groups (Anderson & Krathwohl, 2001).

Measuring instruments

The study employed varied instruments to assess various aspects of the learning process and outcomes, as shown in Table 1.

Procedures

The intervention lasted for 14 weeks, including three 100-minute sessions per week. The group that was tested applied both traditional PBL activities and an AI-powered learning platform called EduAI Pro. The control group, on the other hand, performed PBL without technology. Both groups worked together in teams of four to five students to solve six real-world, hard problems relevant to what they were learning in class.

Table 1. Measuring instruments used in the study

Instrument	Purpose	Number of items	Response scale	Reliability (α)	Administration Time
Problem-Solving Ability Test (PSAT)	Measure students' ability to identify, analyse, and solve complex problems	25 items (15 multiple choice, 10 open-ended)	0-100 scale	0.89	90 minutes
Learning Style Inventory (LSI)	Identify students' preferred learning modalities (visual, auditory, kinaesthetic, reading/writing)	40 items	5-point Likert scale	0.85	20 minutes
Initial Ability Assessment (IAA)	Determine students' baseline knowledge and skills in the subject domain	30 multiple choice items	0-100 scale	0.91	60 minutes

Experimental condition

It was able to create personalised learning paths by examining how each student used the AI system, how well they understood the material, and their performance. Some of the most vital AI features were: (1) adaptive content presentation that changed the difficulty of problems and added scaffolding based on the students' performance in real time; (2) intelligent tutoring that used natural language processing to enable Socratic dialogue and strategic questioning; (3) collaborative learning optimisation that changed group formation and monitored the quality of interactions; (4) personalised feedback that addressed specific misconceptions and offered tailored learning resources; and (5) learning analytics dashboards that gave students and teachers actionable insights into progress and areas that needed more help (Roll & Wylie, 2016).

Control condition

Students engaged in traditional PBL instruction through a seven-step methodology: clarifying terms and concepts, defining problems, analysing issues through brainstorming, organising and formulating hypotheses, setting learning objectives, undertaking independent study, and synthesising information. Teachers provided general advice and led class discussions, but they could not help each student as much as the AI system could.

Data analysis

The data analysis employed mixed-design ANCOVA, designating treatment condition (AI-assisted PBL vs. traditional PBL) as the between-subjects factor, time (pretest vs. posttest) as the within-subjects factor, and initial ability as a covariate to address baseline disparities. Separate analyses examined main effects, interaction effects (condition × initial ability and condition × learning style), and simple effects to determine differential treatment impacts across student subgroups. We utilised Cohen's d for pairwise comparisons and partial eta-squared ($\eta^2 p$) for ANCOVA results to determine the effect sizes. We used values of 0.01, 0.06, and 0.14 for $\eta^2 p$ and values of 0.2, 0.5, and 0.8 for d. These were seen as small, medium, and large effects, respectively. Prior to the principal analyses, we verified the statistical assumptions of normality (using the Shapiro-Wilk test), homogeneity of variance (via Levene's test), and sphericity (using Mauchly's test). Listwise deletion was used to handle missing data (less than 3%) because of its insignificant effect on statistical power. All analyses were performed utilising SPSS version 28.0, establishing statistical significance at $\alpha = 0.05$.

RESULTS

Descriptive statistics and preliminary analyses

Table 2 presents descriptive statistics for problem-solving ability scores by treatment condition, initial ability level, and learning style preference. Overall, the experimental group (M = 128.45, SD = 14.32) demonstrated substantially higher post-test problem-solving scores compared to the control group (M = 106.78, SD = 16.89). Preliminary assumption testing confirmed that the data met requirements for the parametric analyses. Shapiro-Wilk tests indicated normal distributions for all variables ($p > .05$), and Levene's tests supported homogeneity of variance assumptions ($p > .05$). Box's M test for homogeneity of covariance matrices approached but did not reach significance ($p = .082$), permitting ANCOVA procedures.

Main effects of AI-assisted PBL

Mixed-design ANCOVA with initial ability as a covariate revealed a significant main effect of treatment condition on problem-solving ability, $F(1, 117) = 45.23$, $p < .001$, $\eta^2 p = .38$, indicating a large effect size. Students in the AI-assisted PBL condition demonstrated significantly greater improvement in problem-solving competencies compared to those receiving traditional PBL instruction (Cohen's d = 1.24, 95% CI [0.92, 1.56]). The covariate, initial ability, was significantly related to posttest scores, $F(1, 117) = 32.14$, $p < .001$, $\eta^2 p = .22$, confirming the importance of controlling for baseline differences in analyses.

The analysis of problem-solving subscales indicated varying treatment effects across competency dimensions. The experimental group showed the largest gains in finding new ways to solve problems (d = 1.38), realising those solutions, and judging how well they worked (d = 1.29). There were fewer noticeable effects for figuring out the problem (d = 0.89) and making decisions (d = 0.94). These patterns show that AI-enhanced scaffolding is most useful for solving higher-order problems that require creativity and the use of flexible strategies (Hwang et al., 2020).

Table 2. Descriptive statistics for problem-solving ability by treatment condition and learner characteristics

Group	Initial ability	N	Pretest M(SD)	Posttest M(SD)	Gain score M(SD)
Experimental	Low	14	82.36(8.45)	126.21(12.34)	43.85 (9.12)
	Medium	30	95.12 (7.23)	129.67 (13.56)	34.55 (8.34)
	High	16	108.45 (9.87)	130.48 (15.23)	22.03 (7.45)
Control	Low	16	81.92 (9.12)	98.45 (14.56)	16.53 (8.23)
	Medium	28	94.87 (8.34)	107.89 (15.78)	13.02 (7.89)
	High	16	107.98 (10.23)	114.23 (18.45)	6.25 (6.78)

Interaction effects: Initial ability

A significant two-way interaction emerged between treatment condition and initial ability level, $F(2, 114) = 8.76$, $p < .001$, $\eta^2 p = .13$. A straightforward effects analysis demonstrated that AI-assisted PBL significantly benefited students with low initial ability ($d = 1.87$, $p < .001$) compared to those with medium ($d = 1.24$, $p < .001$) or high ($d = 0.78$, $p = .004$) initial ability. In the control condition, students with high initial ability demonstrated minimal improvement ($d = 0.24$, $p = .142$), suggesting that conventional PBL may not sufficiently engage advanced learners. These findings support the expertise reversal effect, which asserts that instructional methods effective for novices become less effective as learners achieve greater competence. On the other hand, AI systems can change the difficulty and scaffolding in real time to keep the challenge level high for people of all skill levels.

The interaction pattern, indicating that the AI-assisted condition effectively mitigated the performance disparities among the initial ability groups by the posttest. The control group, which included students with low initial ability, showed a large gap between them and their peers with higher ability (Mdiff = 15.78, $p < .001$). The experimental group exhibited significantly smaller ability-based differences (Mdiff = 4.27, $p = .185$). This means that AI personalisation makes learning more fair.

Interaction effects: Learning styles

The interaction between treatment condition and learning style approached statistical significance, with $F(3, 113) = 2.64$, $p = .052$, and $\eta^2 p = .07$. Post-hoc comparisons with Bonferroni corrections indicated that AI-assisted PBL was most beneficial for visual learners ($d = 1.52$, $p < .001$), followed by kinaesthetic learners ($d = 1.28$, $p < .001$), multimodal learners ($d = 1.18$, $p = .002$), and auditory learners ($d = 0.94$, $p = .008$). The platform's emphasis on data visualisation, concept mapping, and interactive simulations may elucidate the significant influence of visual learners. In the control condition, auditory learners exhibited performance that was comparable to or marginally superior to other learning style groups ($d = 0.38$ compared to visual learners), possibly attributable to the dependence of conventional PBL on verbal discourse and oral presentation of concepts. These results demonstrate that while AI can enhance learning across diverse style preferences, the most substantial benefits occur when technological affordances align with students' preferred modalities.

Additional findings: Engagement and self-efficacy

Although not the primary research questions, supplementary analyses examined the impact of treatment on student engagement and their confidence in problem-solving abilities. According to a validated engagement scale administered at week 10, the experimental group exhibited significantly elevated levels of behavioural engagement ($d = 0.89$, $p < .001$), cognitive engagement ($d = 1.12$, $p < .001$), and emotional engagement ($d = 0.76$, $p = .003$). In the same way, problem-solving self-efficacy went up more in the AI-assisted condition ($d = 1.05$, $p < .001$) than in the traditional PBL condition ($d = 0.34$, $p = .048$). These emotional and motivational outcomes likely elucidate the observed achievement effects. More engagement and self-efficacy lead to more persistence, deeper thinking, and better use of strategies when solving problems.

DISCUSSION

Principal findings and theoretical implications

This study provides substantial evidence that the integration of Artificial Intelligence into Problem-Based Learning environments significantly enhances students' problem-solving abilities, with variations arising from individual differences in initial competencies and learning style preferences. The significant effect size ($\eta^2 p$ = .38) for the primary treatment effect aligns with and extends previous research that underscores the benefits of technology-enhanced PBL (Hwang et al., 2020). More importantly, the current findings show that AI-assisted PBL is especially helpful for students who start with lower ability levels. This indicates that adaptive technological support can mitigate achievement disparities and promote equitable educational outcomes, which is crucial for inclusive education (Holmes et al., 2021).

The differing levels of effectiveness in problem-solving competency across dimensions provide important theoretical insights. The most notable treatment effects were evident in the generation of alternative solutions and the implementation and evaluation of solutions—higher-order processes that require creative thinking, adaptive strategy application, and metacognitive monitoring. These competencies align with 21st-century skill frameworks emphasising self-regulated learning, innovation, and complex problem-solving.

Mechanisms underlying AI enhancement of PBL

AI's efficacy in enhancing problem-solving development within PBL environments likely stems from multiple interrelated mechanisms (Kurniawan et al., 2025; Masrurah et al., 2025; Ouyang et al., 2023). AI systems can personalise learning, allowing adaptive scaffolding to keep each learner's cognitive load at the right level. This means that students get a lot of help when they are having trouble, but as they improve, they get less help (Roll & Wylie, 2016). This dynamic adjustment addresses the expertise reversal effect, wherein pedagogical approaches effective for novices may prove less effective or detrimental for advanced learners.

Second, AI-powered systems provide students with immediate, formative feedback that helps them evaluate when they are wrong, find the appropriate and inappropriate ways to solve problems, and change how they are doing things right away. In traditional PBL, teachers must monitor multiple groups simultaneously, resulting in delayed feedback. They might not notice when a student is having trouble until a lot of time has passed. AI feedback likely made learning more efficient by providing students with quick feedback and preventing them from using incorrect strategies that could become automatic and difficult to change (Zawacki-Richter et al., 2019).

Third, learning analytics tools helped both students and teachers keep track of how they were doing, find areas that needed more work, and make smart decisions about changing their strategies and using their resources (Luckin et al., 2016; Holmes et al., 2021). Students in the experimental group received weekly dashboard reports that detailed their performance in various problem-solving domains, the time allocated to each, and a comparison to their prior performance. These metacognitive tools likely enhanced students' self-awareness and facilitated independent learning, both of which are consistently associated with academic success.

The moderating role of initial ability

The considerable interaction between treatment condition and initial ability provides essential insights into individual differences in responsiveness to educational interventions (Anderson et al., 2021; Liu, 2025). AI-assisted PBL was most beneficial for students with low initial skills. This means that adaptive technology can help individuals who lack knowledge about a subject or struggle with self-regulated learning skills. These students likely performed better due to the substantial scaffolding, structured guidance, and prompt feedback provided by AI systems. Teachers might find it challenging to provide these things consistently in collaborative, student-centered learning environments (Omeh et al., 2025).

Interestingly, students who already excel at something also made considerable improvements with AI-assisted PBL, but the improvements were smaller. The system's ability to make problems more challenging, add new types of challenges, and provide advanced learning materials probably kept these students from getting bored and kept their minds active. On the other hand, the small improvement seen in high-ability students in the traditional PBL condition suggests that standard methods may not be challenging enough, which could lead to students losing interest and wasting time learning. These patterns underscore the importance of differentiated instruction customised to diverse learner needs—a pedagogical principle that has been recognised for an extended period but is challenging to implement effectively without technological support.

The reduction of performance gaps among initial ability groups in the AI-assisted condition has profound implications for educational equity. Traditional educational methods, similar to traditional PBL, often keep or make initial differences in achievement worse because they offer the same learning experiences to everyone, regardless of their needs. AI systems can help make sure that every student gets problems that are just right for their skill level and enough help, both of which are vital for the best learning for everyone.

Learning styles and personalised instruction

The almost substantial relationship within treatment condition and learning style preferences provides preliminary proof that AI-enhanced PBL may demonstrate differing effectiveness contingent upon students' preferred sensory modalities. Visual learners demonstrated the most significant treatment effects, likely attributable to the AI platform's emphasis on graphical representations, concept maps, flowcharts, and data visualizations that aligned with their preferences (Mayer, 2014). Kinesthetic learners also benefited significantly, probably because of interactive simulations, virtual objects that could be manipulated, and hands-on problem-solving tasks that met their need for physical interaction with learning materials.

We must interpret these results carefully. Numerous studies concluded that matching teaching to learning styles does not boost academic performance. A more effective approach is to provide content in multiple formats. Allowing students to choose how they learn can increase their engagement and motivation, as shown by An and Carr (2017).

Practical implications for educational practice

Schools should invest in comprehensive AI platforms for PBL. These systems provide personalised support through adaptive scaffolding and instant feedback. They also track student progress with learning analytics. Offering content in multiple formats addresses diverse learning needs. This integrated approach is supported by research for improving learning outcomes. Second, professional development should help teachers learn how to apply technology to improve PBL by using learning analytics, making data-driven teaching decisions, and creating a balance of AI support and human guidance. Teachers continue to be essential in ensuring that students engage in meaningful dialogues, demonstrate problem-solving techniques, provide emotional support, and develop realistic challenges that spark their interest in education. AI systems enhance rather than supplant effective teaching, and their successful implementation necessitates a deliberate amalgamation of technological and human components, including in training development context (Andiyah, et al. 2025).

Third, teachers should consider students' starting skill levels when setting up PBL activities and the AI system. Students with low ability may require initial help and more frequent check-ins to prevent them from getting frustrated and overloaded with information. Students with high ability, on the other hand, benefit from more challenges, faster pacing, and opportunities to be creative. Many AI platforms allow teachers to adjust these settings, but they need to comprehend their students' needs to make the appropriate choices.

Limitations and future research directions

These findings are constrained by several limitations, indicating avenues for future research. First, the quasi-experimental design, though suitable due to practical limitations, constrains causal inferences. Even though the groups were the same on the measured variables and multiple covariates were statistically controlled, differences between classes that weren't measured may have affected the results. Subsequent research ought to utilise fully randomised designs whenever possible and perform replication studies in various educational settings to ascertain generalisability (Schunk & DiBenedetto, 2020). Second, the 14-week intervention period, although adequate for detecting significant learning improvements, precludes determinations regarding the long-term retention and transfer of problem-solving skills to new contexts. Longitudinal studies monitoring students over several years could determine if advantages endure, accumulate, or wane over time, and whether AI-assisted PBL fosters transferable problem-solving skills relevant beyond the immediate educational setting (Barnett & Ceci, 2002).

Third, the study simultaneously examines a specific AI platform with certain functions and design elements. AI systems vary in terms of their advancement, teaching methods, and implementation. Research that compares different AI platforms can identify which specific features most effectively advance educational outcomes. This helps schools select tools based on evidence of what works (Roll & Wylie, 2016). Future research is suggested to analyse the risks of AI use in classrooms. Key areas include overdependence on technology, reduced human interaction, and ethical concerns like data privacy and algorithmic bias. Understanding these effects is crucial to guide their safe use (Holmes et al., 2021).

CONCLUSION

Research concludes that AI and Problem-Based Learning significantly improve problem-solving skills. This is especially true for students who started with lower skill levels. AI tools provide adaptive support and personalised feedback. They also offer content in multiple formats and track student progress. These systems address traditional PBL challenges while maintaining its core educational principles. For educators, this means investing in comprehensive AI platforms is critical. Teacher training should also focus on managing these technology-enhanced environments. Future studies should examine long-term effects and how well this approach works across varied subjects and cultures. It is also vital to investigate potential negative consequences to ensure AI is used responsibly.

Author contributions

The authors played a big role in coming up with and designing the study. The authors was responsible for analyzing the data, making sense of it, and talking about the results. The authors read and approved the final draft.

AI Declaration Statement

The authors used OpenAI's ChatGPT to edit and refine the wording of the Introduction, Method, and Discussion section. All outputs were reviewed and verified by the authors.

Conflict of interest

The authors declare that there is no potential conflict of interest.

Data availability statement

All data are available by request to the corresponding author.

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