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Artificial Intelligence and Problem-Based Learning: Structural Equation Modeling Evaluation of Undergraduate Critical Thinking and Academic Performance

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Abstract
The integration of Artificial Intelligence (AI) into pedagogical frameworks represents a paradigm shift in higher education. This study evaluates the effectiveness of an AI-integrated Problem-Based Learning (AI-PBL) model among undergraduate students. Specifically, it aims to determine how AI tools, acting as scaffolding agents, influence students' critical thinking, self-regulated learning, and overall academic performance. A quantitative research design utilizing Structural Equation Modeling (SEM) was employed. Data were collected from 450 undergraduate students across three major universities who participated in a semester-long AI-PBL course. The instrument consisted of a validated questionnaire measuring AI literacy, PBL engagement, critical thinking disposition, and learning outcomes. The measurement model demonstrated high validity and reliability. The structural model revealed that AI integration significantly mediates the relationship between PBL engagement and critical thinking skills ($\beta = 0.42, p < .001$). Furthermore, the model showed that AI-PBL positively impacts academic performance directly and indirectly through self-regulated learning mechanisms. The study confirms that AI does not diminish cognitive effort but, when integrated into PBL, enhances critical analysis and learning efficiency. These findings offer a robust framework for curriculum designers to embed AI explicitly as a collaborative intelligence tool in problem-solving tasks.

Keywords: *Problem-Based Learning (PBL), Artificial Intelligence in Education, Structural Equation Modeling (SEM), Critical Thinking, Higher Education Evaluation.*

1. Introduction (Arial 14)

The landscape of higher education is undergoing a seismic shift, driven by the rapid evolution of digital technologies and the increasing demand for 21st-century skills such as complex problem-solving and critical thinking (World Economic Forum, 2023). Traditional didactic methods are increasingly seen as insufficient for preparing students for a volatile, uncertain, complex, and ambiguous (VUCA) world. Consequently, active learning methodologies, particularly Problem-Based Learning (PBL), have gained prominence over the last decade. PBL places the student at the center of the learning process, using ill-structured real-world problems to drive learning (Dochy et al., 2017; Kaharuddin et al., 2025; Pratiwi et.al, 2025).

However, the implementation of PBL is not without challenges. It requires significant cognitive load management, high levels of self-regulation, and often, extensive scaffolding from instructors which can be resource-intensive (Kirschner et al., 2018). Students often struggle with the initial phases of information retrieval and synthesis, potentially hindering the deeper cognitive processing required for problem resolution.

The advent of Generative Artificial Intelligence (GenAI), exemplified by Large Language Models (LLMs) such as GPT-4, offers a novel solution to the resource constraints of traditional PBL. Unlike passive technology, AI can function as a dynamic scaffolding agent, providing personalized feedback, generating counter-arguments, and assisting in information synthesis (Hwang et al., 2020). The concept of "AI-partnerships" in education suggests that AI can augment human intelligence, allowing students to offload lower-order cognitive tasks (such as basic data gathering) to focus on higher-order thinking skills like evaluation and creation (Selwyn, 2022).

Despite the proliferation of literature on AI in education and the established efficacy of PBL, there is a distinct paucity of empirical research examining their *synergistic* effect. Most existing studies focus either on the technical acceptance of AI (using models like TAM or UTAUT) or qualitative perceptions of AI in classrooms. There is a lack of rigorous, quantitative evaluation using Structural Equation Modeling (SEM) to analyze the causal pathways between AI tool usage, PBL engagement, and cognitive outcomes in undergraduate settings. Specifically, it remains unclear whether reliance on AI in a PBL setting acts as a crutch that diminishes critical thinking or as a scaffold that enhances it (Kaharuddin et al., 2023; Lodge et al., 2023).

This study aims to bridge this gap by proposing and evaluating an *AI-integrated PBL (AI-PBL) model*. The primary objective is to assess the structural relationships between AI scaffolding, Self-Regulated Learning (SRL), Critical Thinking (CT), and Academic Performance (AP).

While recent scholarship has begun to address AI in education, a significant gap remains in the methodological approach. Unlike previous studies (e.g., Chan & Hu, 2023; Fitria, 2023) which primarily explored qualitative perceptions or theoretical opportunities of AI, or Rahman & Naber (2023) who focused on general engagement metrics, this study distinguishes itself by structurally quantifying the internal **psychological mechanisms**. Specifically, it isolates Self-Regulated Learning as a critical mediator, moving beyond the question of *whether* AI works to explaining *how* it interacts with student cognition in a PBL environment

The specific research questions (RQs) guiding this study are:

1. Does the integration of AI tools in PBL significantly influence students' Self-Regulated Learning?
2. Does AI-scaffolded PBL have a positive direct effect on Critical Thinking skills compared to traditional PBL constructs?
3. Does Self-Regulated Learning mediate the relationship between AI usage and Academic Performance?

This research contributes to the literature by moving beyond "perception-based" studies to an "outcome-based" structural evaluation. Theoretically, it extends the Social Constructivist theory by incorporating non-human agents (AI) as valid partners in the Zone of Proximal Development (ZPD). Practically, it provides higher education institutions with a validated model for curriculum integration, addressing the urgent need for guidelines on ethical and effective AI usage in classrooms.

2. Method

2.1. Research Design

This study employs a quantitative research design utilizing a cross-sectional survey method to evaluate the proposed theoretical model. Structural Equation Modeling (SEM) was selected as the primary analytical technique because of its robust ability to analyze complex relationships between latent constructs and observable variables simultaneously, while accounting for measurement errors (Hair et al., 2019; Sari et al., 2025). The study seeks to explain the variance in students' academic performance and critical thinking through the exogenous variables of AI integration and Problem-Based Learning engagement.

2.2. Instructional Context: The AI-PBL Model

Prior to data collection, the participants were enrolled in a 14-week course designed around the "AI-Scaffolded PBL Framework." In this model, the learning process was divided into five phases based on the classic syntax of PBL, augmented by AI tools (specifically Large Language Models like ChatGPT-4 and Perplexity AI):

1. Problem Orientation: Students identified ill-structured problems. AI was used to generate scenario variations.
2. Organize for Learning: Students formulated learning goals. AI acted as a Socratic tutor to refine these goals.
3. Individual and Group Investigation: Students gathered data. AI was permitted for initial information synthesis but required human verification (AI-Human loop).
4. Development of Artifacts: Students created solutions. AI was used for coding assistance or drafting, but not for final submission.
5. Analysis and Evaluation: Students reflected on the process. AI provided feedback on the logic of their arguments.

2.3. Participants and Sampling

The population for this study comprised undergraduate students from three leading universities in Indonesia, majoring in Computer Science, Education, and Engineering. These disciplines were chosen due to their high exposure to both PBL methodologies and digital tools.
A stratified random sampling technique was employed to ensure representation across different years of study and genders. The initial sample consisted of 550 students. After data cleaning (removing incomplete responses and outliers based on Mahalanobis distance), the final sample size was N = 482. This sample size meets the requirements for SEM analysis, exceeding the recommended minimum of 200 samples or the 10-times rule regarding the number of structural paths (Kline, 2016).

Table 1. Demographic Profile of Respondents

Category	Subcategory	Percentage
Gender	Male	46.5%
	Female	53.5%
Year of Study	Sophomore	30%
	Junior	45%
	Senior	25%
Discipline	STEM	60%
	Social Sciences	40%

2.4. Instruments

Data were collected using a structured self-report questionnaire administered via an online platform. All items were measured on a 7-point Likert scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). The constructs were adapted from established scales to ensure content validity:

1. AI-PBL Integration (AI-PBL): Six items adapted from the Technology Acceptance Model (TAM) and specific PBL scales to measure how effectively students perceived the integration of AI in their problem-solving process (e.g., "Using AI tools helped me deconstruct complex problems effectively").
2. Self-Regulated Learning (SRL): Eight items adapted from the Motivated Strategies for Learning Questionnaire (MSLQ) by Pintrich et al. (1991), focusing on metacognitive self-regulation and resource management.
3. Critical Thinking Skills (CTS): Seven items adapted from the Critical Thinking Disposition Scale (CTDS), focusing on inquisitiveness, systematicity, and analyticity in the context of AI output verification.
4. Academic Performance (AP): Measured using a composite score of the students' final project grades (assessed by rubrics) and their self-reported perceived learning gains.

A pilot study was conducted with N=50 students to test the readability and reliability of the instrument. Cronbach’s alpha values for all constructs in the pilot study exceeded the 0.70 threshold.

2.6. Data Analysis Technique

Data analysis was performed using IBM SPSS Statistics 27 for descriptive statistics and AMOS 26 for Structural Equation Modeling. The analysis followed a two-step approach recommended by Anderson and Gerbing (1988):

1. Measurement Model Assessment: Confirmatory Factor Analysis (CFA) was conducted to assess the reliability and validity of the constructs. Convergent validity was evaluated using Factor Loadings (>0.50), Average Variance Extracted (AVE>0.50), and Composite Reliability (CR>0.70). Discriminant validity was assessed using the Fornell-Larcker criterion and Heterotrait-Monotrait ratio (HTMT).
2. Structural Model Assessment: The hypothesized causal pathways were tested using the structural model. Model fit

was evaluated using absolute and incremental fit indices: Chi-square/df ratio (< 3.0), RMSEA (< 0.08), CFI (> 0.90), and TLI (> 0.90). Bootstrapping (5,000 resamples) was used to test the significance of mediation effects.

3. Results and Discussion

3.1. Measurement Model Assessment

Before testing the structural relationships, a Confirmatory Factor Analysis (CFA) was conducted to evaluate the measurement model. The results indicated a satisfactory fit for the measurement model.

As presented in Table 2, all standardized factor loadings ranged from 0.72 to 0.91, exceeding the recommended threshold of 0.70 (Hair et al., 2019). This indicates that the observed indicators strongly reflect their respective latent constructs. Internal consistency was confirmed with Cronbach's Alpha (α)and Composite Reliability (CR) values for all constructs (AI-PBL, SRL, CTS, AP) exceeding 0.80. Furthermore, the Average Variance Extracted (AVE) for each construct was above 0.50, establishing adequate convergent validity.

Table 2. Construct Reliability and Validity

Construct	Items	Factor Loading	Cronbach's α	CR	AVE
AI-PBL Integration	6	0.75 – 0.89	0.92	0.93	0.68
Self-Regulated Learning	8	0.72 – 0.85	0.89	0.90	0.62
Critical Thinking Skills	7	0.78 – 0.91	0.94	0.94	0.71
Academic Performance	4	0.81 – 0.88	0.88	0.89	0.66

Discriminant validity was assessed using the Fornell-Larcker criterion. The square root of the AVE for each construct (shown in bold on the diagonal in **Table 3**) was greater than its highest correlation with any other construct. This confirms that each construct is distinct from the others.

Table 3. Discriminant Validity

Construct	AI-PBL	SRL	CTS	AP
AI-PBL	0.824			
SRL	0.612	0.787		
CTS	0.548	0.690	0.842	
AP	0.589	0.715	0.760	0.812

3.2. Structural Model Assessment

The structural model was tested to evaluate the hypothesized relationships. The goodness-of-fit indices indicated an excellent model fit: $X^2 / df = 1.84 (< 3.0). RMSEA = 0.042 (< 0.08), CFI =$ 0.96 (> 0.90, and TLI = 0.95 (> 0.90) These metrics suggest that the theoretical model aligns well with the empirical data.

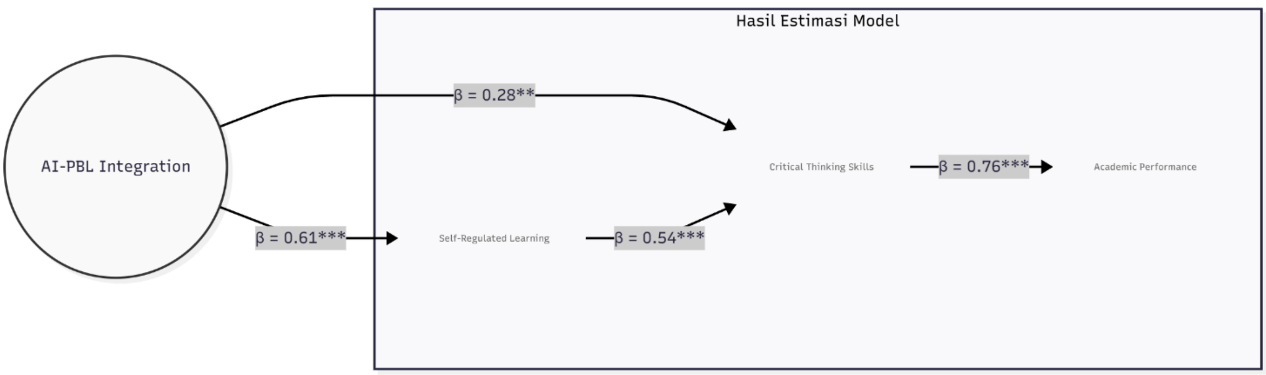

Figure 1. Structural model results showing standardized path coefficients.

Hypothesis Testing

The path analysis results (see Table 4) supported all proposed hypotheses.

1. **H1:** AI-PBL Integration had a significant positive effect on Self-Regulated Learning (β= 0.61, t = 12.45, p < .001).
2. **H2:** AI-PBL Integration had a significant direct effect on Critical Thinking Skills (β = 0.28, t = 4.32, p < .01).

3. **H3:** Self-Regulated Learning strongly influenced Critical Thinking Skills ($\beta = 0.54$, $t = 9.87$, $p < .001$).
4. **H4:** Critical Thinking Skills significantly predicted Academic Performance ($\beta = 0.76$, $t = 15.20$, $p < .001$).

Bootstrapping analysis revealed that Self-Regulated Learning significantly mediates the relationship between AI-PBL and Critical Thinking ($\beta_{indirect}$} = 0.33, $p < .001$), suggesting that the benefits of AI in PBL are largely realized through enhanced student self-regulation.

The primary objective of this study was to evaluate an AI-integrated Problem-Based Learning model. The findings provide robust empirical evidence that integrating AI as a scaffolding tool in PBL environments significantly enhances undergraduate students' critical thinking and academic performance, primarily by reinforcing self-regulated learning mechanisms.

3.3. The Synergy of AI and PBL on Critical Thinking

Contrary to concerns that AI might induce cognitive atrophy or "lazy thinking" (Cotton et al., 2023), our findings ($\beta = 0.28$) suggest that when AI is purposefully integrated into a PBL framework, it acts as a catalyst for critical thinking. This aligns with the concept of "Cognitive Offloading" discussed by Lodge et al. (2023). By using AI to handle routine information retrieval and basic synthesis (lower-order cognitive tasks), students in our study were able to reallocate their cognitive resources toward higher-order tasks such as evaluation, argumentation, and complex decision-making. The AI-PBL model forces students to become "verifiers" rather than just "consumers" of information, a process that inherently exercises critical scrutiny.

This finding corroborates recent work by Hwang and Chang (2021), who found that AI-based peer feedback systems improved students' reflective thinking. However, our study extends this by showing that the *ill-structured nature* of PBL problems is crucial. Without the complex problem context, AI might simply provide answers; within the PBL context, AI output becomes raw material that must be critically analyzed to fit the problem solution.

3.4. The Mediating Role of Self-Regulated Learning (SRL)

A pivotal finding of this study is the strong mediating role of SRL (β= 0.33). The data implies that the mere presence of AI tools is insufficient; it is the *regulation* of these tools that drives performance. This finding essentially suggests that AI tools act as a 'cognitive amplifier' only when steered by strong self-regulatory processes. Without the active metacognitive drive to plan prompts and monitor AI output, the technology risks becoming a 'cognitive crutch' that bypasses, rather than enhances, the learning process. The mediation effect confirms that the 'human in the loop'—specifically the *regulating* human—is the decisive factor in converting AI usage into academic performance. The high path coefficient from AI-PBL to SRL (β= 0.61) indicates that the structured AI-PBL course design successfully prompted students to plan, monitor, and evaluate their learning strategies.

This supports the "AI-as-Partner" framework proposed by Selwyn (2022). Students who treated AI as a collaborative partner—engaging in iterative prompting and result refinement—demonstrated higher metacognitive engagement. Conversely, this suggests a warning for educators: introducing AI without a pedagogical framework that emphasizes self-regulation (like PBL) may lead to passive reliance. The PBL structure provides the necessary "friction" that requires students to regulate their AI usage to solve the problem, rather than blindly accepting AI outputs.

3.5. Implications for Higher Education

This study contributes to the constructivist theory by validating the "Digital Zone of Proximal Development." AI acts as a More Knowledgeable Other (MKO), but unlike a human teacher, it is available on-demand. The model confirms that sociotechnical interactions in learning are now measurable determinants of academic success.

For curriculum designers, the results advocate for a shift from "AI bans" to "AI integration." Universities should redesign PBL modules to explicitly include "AI checkpoints"—stages where students are required to use AI to generate counter-arguments or summarize vast datasets, followed by a human-only defense of their final artifacts. Assessment rubrics must evolve to value the *process* of prompt engineering and output critique over the final text alone.

3.6. Limitations and Future Research

While the SEM analysis provides strong statistical evidence, this study is cross-sectional, which limits causal inference. Longitudinal studies are needed to track whether the critical thinking gains persist after the intervention. Additionally, the study focused on STEM and Social Science undergraduates; future research should explore creative arts disciplines where AI's role in "originality" is more contested. Finally, the "black box" nature of commercial LLMs means the specific AI logic remains opaque; future studies might use open-source models to better control the technological variables.

4. Conclusion

This study set out to evaluate the structural relationships between Artificial Intelligence integration, Problem-Based Learning engagement, Self-Regulated Learning, and Critical Thinking among undergraduate students. Utilizing Structural Equation Modeling, the research offers a nuanced understanding of how GenAI tools can be effectively embedded into active learning pedagogies.

The findings lead to three major conclusions. First, AI integration does not inherently undermine academic rigor; rather, when scaffolded within a Problem-Based Learning framework, it significantly enhances students' Self-Regulated Learning capabilities. The PBL structure compels students to manage AI tools strategically, transforming potential dependency into agency. Second, the study confirms a positive causal pathway from AI-PBL to Critical Thinking skills. By offloading lower-order cognitive tasks to AI, students are liberated to engage in higher-order evaluation and synthesis. Third, Self-Regulated Learning acts as a crucial mediator; without the metacognitive drive to regulate learning, the benefits of AI on academic performance are diminished.

These results challenge the prohibitive stance taken by some institutions regarding AI. Instead, they advocate for a "Pedagogy of Integration," where AI is treated as a cognitive partner. Future curricula must move beyond teaching *about* AI to teaching *with* AI, ensuring that graduates are not only technically proficient but also critically resilient in an AI-augmented workforce.

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