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AI-Enhanced Problem-Based Learning: Differential Effects of AI Usage Patterns on Core Competency Development Through Psychological Mechanisms

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Abstract

This study investigates how different levels of AI usage influence PBL core competencies through psychological mechanisms, establishing a theoretical framework that integrates Self-Determination Theory, Social Cognitive Theory, and Cognitive Load Theory. A cross-sectional survey design examined 412 university students across diverse academic disciplines. Participants completed validated instruments measuring AI usage patterns (assistive, dependent, substitutive), basic psychological need satisfaction, intrinsic motivation, self-efficacy, and five PBL core competencies (collaborative learning, autonomous learning, critical thinking, knowledge integration, communication skills). Structural equation modeling tested direct and mediated relationships. AI usage patterns demonstrated significant differential effects on PBL competencies. Assistive AI usage positively influenced all five core competencies, while substitutive AI usage negatively affected critical thinking abilities. Psychological mechanisms accounted for 64-73% of total effects through a sequential mediation pathway: basic need satisfaction → intrinsic motivation → self-efficacy → competency development. Competence need satisfaction emerged as the most critical mediator. The findings reveal that AI's educational impact depends critically on usage patterns and psychological mechanisms rather than technology presence alone. The study establishes theoretical foundations for AI-PBL implementation that prioritizes learner agency while leveraging technological affordances.

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Introduction

Artificial intelligence (AI) is fundamentally transforming teaching and learning practices in higher education institutions worldwide (Bond et al., 2024). Educational institutions increasingly prioritize AI integration into university curricula, with AI-related course offerings experiencing substantial growth of 102.9% from 2018 to 2021 (Li, King, Chai, Zhai, & Lee, 2025). As AI tools become ubiquitous in educational environments, student usage patterns exhibit marked variations: some students employ AI exclusively as auxiliary tools for basic information retrieval, others demonstrate heavy reliance on AI for learning tasks, while certain learners exhibit substitutive AI usage that potentially replaces autonomous thinking processes (Abbas, Jam, & Khan, 2024; Ng, Wu, Leung, Chiu, & Chu, 2024).

Problem-Based Learning (PBL), as a learner-centered pedagogical strategy, requires students to develop multiple core competencies in university curricula (Anggraeni, Prahani, Suprapto, Shofiyah, & Jatmiko, 2023; Su et al., 2025), including collaborative learning ability, autonomous learning ability, critical thinking ability, knowledge integration ability, and communication skills. However, when AI technology becomes integrated within PBL environments, varying degrees of AI usage may produce differential effects on these core competencies, creating complex learning ecosystems.

Recent research reveals concerning phenomena, while AI tools can effectively support certain cognitive tasks, excessive dependence may diminish learners' independent thinking capabilities. Konradt, Boote, and Taub (2025) discovered that learners with high AI dependence demonstrated declining performance in autonomous analysis and creative output, exhibiting "cognitive offloading" phenomena. Conversely, learners with moderate AI usage maintained independent thinking while effectively utilizing AI tools to enhance learning efficiency (Ng et al., 2024).

More importantly, existing research indicates that AI learning effects operate primarily through psychological mechanisms (Bauer, Greiff, Graesser, Scheiter, & Sailer, 2025; Patac & Patac Jr, 2025). Intrinsic motivation's mediating effects significantly exceed direct effects, suggesting that AI usage impacts learning outcomes through complex psychological factor moderation (Chiu, Xia, Zhou, Chai, & Cheng, 2023). However, how different levels of AI usage differentially influence PBL core competency development through psychological mechanisms remains theoretically unexplained and empirically unverified.

This research gap possesses important implications for university educational practice. As AI tools become widely applied in PBL courses, educators face critical questions:

- How can students be guided to use AI appropriately to promote rather than hinder core competency development?
- Which psychological mechanisms determine AI usage's positive or negative influences?

Addressing these questions provides essential guidance for AI-era educational practice. This study's motivation stems from three interconnected theoretical and empirical problems requiring urgent resolution in AI education research.

Theoretical Gap in AI Usage Differential Effects

Existing AI education research predominantly employs "AI usage vs. non-AI usage" dichotomous approaches, overlooking AI usage's continuous characteristics (Konradt et al., 2025). In reality, university students' AI usage behaviors demonstrate distinct individual differences: assistive users occasionally employ AI for information retrieval and verification; dependent users frequently rely on AI for analysis and decision-making recommendations; substitutive users extensively depend on AI to complete core learning tasks, potentially exhibiting "AI proxy" phenomena (Viorennita, Dewi, & Riyana, 2023; Y.-M. Wang, Wei, Lin, Wang, & Wang, 2024). These usage degree differences may produce entirely different effects on PBL core competencies (Anggraeni et al., 2023; Jia, Jalaludin, & Rasul, 2023). Theoretically, moderate AI usage can reduce cognitive load, releasing mental resources for higher-order thinking (Gkintoni, Antonopoulou, Sortwell, & Halkiopoulos, 2025; Liang, Wang, Luo, Yan, & Fan, 2023); excessive AI usage may lead to cognitive laziness, undermining independent analytical abilities. However, theoretical frameworks explaining these differential effects' generation mechanisms and boundary conditions remain absent.

Innovation Opportunity: Establish multi-level analytical frameworks for AI usage degrees, exploring different usage patterns' differential effects on PBL core competencies, addressing existing research's theoretical gaps.

Complexity Challenges in PBL Core Competency Development Mechanisms

Traditional PBL research predominantly focuses on single competency dimensions or overall learning outcomes, rarely exploring interactions and development mechanisms among core competencies (Su et al., 2025). However, PBL's five core competencies do not develop independently but constitute complex systems of mutual influence and dynamic balance (Lu et al., 2022). For example, enhanced critical thinking ability may promote knowledge integration capability; collaborative learning experiences may influence communication confidence. When AI technology intervenes, this complexity further increases. AI may simultaneously promote certain abilities (such as information integration) while inhibiting others (such as independent criticism); different AI usage patterns may alter competency interrelationships; individual psychological characteristics (such as intrinsic motivation, self-efficacy) may moderate these effects.

Research Challenge: Existing research lacks integrative theoretical models explaining multi-competency development's complex mechanisms in AI-PBL environments, mainly psychological factors' moderating roles.

Exploration Needs for Psychological Mechanism Moderating Effects

While research demonstrates that AI learning effects operate primarily through psychological mechanisms (Bauer et al., 2025), which psychological factors moderate AI usage and learning outcome relationships remains insufficiently understood. In AI-PBL contexts, at least three key psychological mechanisms require exploration:

Intrinsic motivation's moderating role: High intrinsic motivation learners may better balance AI usage with independent thinking, viewing AI as learning tools rather than substitutes; low intrinsic motivation learners may excessively depend on AI, limiting competency development (Li et al., 2025).Self-efficacy's mediating role: Successful AI-assisted experiences may enhance learners' capability perceptions, thereby increasing learning motivation and engagement; conversely, excessive dependence may undermine self-efficacy, forming negative cycles.

Cognitive load's moderating mechanisms: AI usage may alter learning tasks' cognitive load structures, affecting learners' psychological resource allocation and competency development pathways.

Empirical Need: Systematic research lacks verification of these psychological mechanisms' specific operational methods in AI-PBL environments, particularly how they moderate different AI usage degrees' effects on multi-competency development.

Educational Practice Guidance Urgency

From educational practice perspectives, educators urgently require evidence-based guidance principles for appropriate student AI usage. Current AI-PBL implementations predominantly lack theoretical foundations, relying primarily on educators' experiential judgments. This situation may lead to:

- Inconsistent usage guidance: Different educators demonstrate substantial variations in AI usage attitudes and guidance approaches
- Difficult effect evaluation: Systematic frameworks for evaluating AI-PBL implementation's actual effects remain absent
- Unbalanced competency development: Excessive focus on technical aspects while neglecting competency development's holistic nature
- Individual difference neglect: One-size-fits-all implementation approaches cannot accommodate learners' individual needs

Practical Value: Establish psychological mechanism-based AI-PBL theoretical models, providing educators with scientifically grounded implementation guidance to promote effective AI technology application in education.

Based on these research motivations, this study aims to explore how different degrees of AI usage influence PBL core competency development through psychological mechanisms, establishing integrative theoretical models with empirical verification to provide scientific foundations for AI-era PBL educational practice.

Literature Review

AI Usage Patterns and Educational Effects

AI Usage Pattern Classification Framework

Contemporary AI education research increasingly recognizes that AI usage effects depend critically on usage patterns rather than mere technology presence (Abbas et al., 2024; Bond et al., 2024; Zhang, Zhao, Zhou, & Kim, 2024). This study establishes a three-tier classification framework based on cognitive engagement and autonomy preservation: Assistive AI Usage represents minimal-intervention approaches where learners maintain primary cognitive control while utilizing AI for specific support functions (Bauer et al., 2025; Chiu et al., 2023). This pattern typically involves information retrieval, fact verification, language enhancement, and basic analytical support. Research indicates that assistive usage promotes learning through cognitive scaffolding while preserving learner agency (Liang et al., 2023).

Dependent AI Usage characterizes moderate-intervention approaches where learners regularly rely on AI for analytical tasks and decision-making guidance. This pattern involves frequent consultation for problem-solving strategies, analytical frameworks, and learning direction (Chiu et al., 2023; Zhang et al., 2024). Usage effects depend critically on learners' ability to critically evaluate and integrate AI-generated content. Substitutive AI Usage represents high-intervention approaches where AI substantially replaces core cognitive processes. This pattern includes AI-generated content production, complete analytical delegation, and comprehensive task completion through AI systems. Research suggests that substitutive usage may undermine competency development through cognitive dependency mechanisms (Ng et al., 2024).

Differential Effects on Learning Outcomes

Recent empirical evidence supports differential effects across usage patterns (Ng et al., 2024). Assistive AI usage demonstrates consistent positive associations with learning outcomes. Fan and Zhang (2024) found that AI-assisted pair programming significantly enhanced intrinsic motivation, aligning with findings that assistive AI usage promotes intrinsic motivation. However, this study further identifies three-tier classification providing more nuanced theoretical frameworks than dichotomous approaches. Substitutive AI usage initially demonstrates efficiency gains but subsequently exhibits cognitive skill degradation, with limited creativity and critical thinking development (Patac & Patac Jr, 2025). Gkintoni et al. (2025) conducted systematic reviews finding that excessive AI dialogue system dependence significantly impairs critical cognitive abilities, with 68.9% of students becoming lethargic and 27.7% experiencing decision-making capability deterioration.

Dependent AI usage produces mixed effects requiring careful examination of boundary conditions and individual characteristics (Ng et al., 2024). The three AI usage types of influence PBL core competencies through different theoretical mechanisms. Assistive AI usage promotes self-efficacy through guided practice while maintaining cognitive engagement and learning autonomy, forming optimal theoretical integration effects (Gkintoni et al., 2025). Dependent AI usage creates cognitive offloading risks, potentially reducing generative load and disrupting intrinsic motivation, leading to skill atrophy. *Substitutive AI usage* typically undermines autonomy and reduces critical thinking development, negatively impacting learning self-efficacy (Liang et al., 2023).

Cognitive Load Theory and AI Usage Effects

Cognitive Load Theory provides theoretical foundations for explaining AI usage differential effects. AI tools primarily support learning by reducing extraneous cognitive load (processing burdens related to learning materials), releasing cognitive resources for intrinsic cognitive load (mental effort directly related to learning objectives) and germane cognitive load (mental effort for knowledge construction) (Gkintoni et al., 2025).

Adaptive cognitive load regulation mechanisms represent core advantages of AI systems. Intrinsic cognitive load receives effective management through AI's dynamic difficulty adjustment and personalized content presentation, real-time adaptation to learner performance preventing cognitive overload. Extraneous cognitive load experiences substantial reduction through intelligent interface design and optimized information presentation, though poorly designed AI systems may conversely increase extraneous load. However, different degrees of AI usage produce varying impacts on cognitive load structures (Y.-Y. Wang & Chuang, 2024). Assistive usage moderately reduces extraneous load, promoting intrinsic and germane load processing; dependent usage may excessively reduce cognitive load, affecting deep learning processes; substitutive usage may undermine intrinsic cognitive load processing, leading to surface learning and cognitive laziness.

Self-Determination Theory and Basic Psychological Need Satisfaction

Core Concepts of Self-Determination Theory

Self-Determination Theory (SDT) emphasizes that satisfaction of three basic psychological needs constitutes prerequisites for intrinsic motivation (Guay, 2022): competence need refers to individuals' requirements for experiencing effectiveness and mastery; autonomy need refers to individuals' requirements for experiencing choice and control; relatedness need refers to individuals' requirements for experiencing connection and belonging (Yang, Chen, & Zhuang, 2025). In learning contexts, these three needs' satisfaction levels directly influence learners' intrinsic motivation levels (Guay, 2022). When learning environments support psychological need satisfaction, learners demonstrate higher intrinsic motivation, better learning performance, and more positive emotional experiences (Y.-M. Wang et al., 2024).

AI Usage Effects on Basic Psychological Need Satisfaction

Effects on competence need satisfaction: Assistive AI usage may enhance competence perception by improving task completion quality; dependent AI usage effects depend on learners' attribution of AI-assisted results; substitutive AI usage may undermine competence need satisfaction as learners may question their actual capabilities (Zdravkova, 2022).

Effects on autonomy need satisfaction: Assistive AI usage may enhance autonomy perception by expanding learners' capability ranges; dependent AI usage may threaten autonomy if learners perceive loss of control; substitutive AI usage significantly undermines autonomy perception as core learning processes become externally controlled (Hidayat-ur-Rehman, 2024).

Effects on relatedness need satisfaction: AI usage may indirectly influence relatedness through its effects on collaborative learning and peer interaction patterns (Y.-Y. Wang & Chuang, 2024). Assistive usage may enhance collaboration quality; dependent usage may reduce interpersonal interaction depth; substitutive usage may isolate learners from learning communities. Based on the SDT theoretical framework, this study proposes the second hypothesis group:

H2: AI Usage Patterns Differentially Influence Basic Psychological Need Satisfaction

- H2a: Assistive AI usage positively influences all three basic psychological needs
- H2b: Dependent AI usage demonstrates mixed effects on basic psychological need satisfaction
- H2c: Substitutive AI usage negatively influences basic psychological need satisfaction

Basic Psychological Need Satisfaction and Intrinsic Motivation

Theoretical Relationship Between Need Satisfaction and Motivation

SDT posits that basic psychological need satisfaction directly predicts intrinsic motivation levels (Autin, Herdt, Garcia, & Ezema, 2022). When learning environments support competence, autonomy, and relatedness needs, learners experience enhanced internal motivation, demonstrating greater learning engagement, persistence, and satisfaction (Yang et al., 2025). In AI-PBL contexts, this relationship may be particularly important. When learners experience competence through successful AI-assisted problem-solving, autonomy through AI tool selection and usage, and relatedness through AI-facilitated collaboration, intrinsic motivation for PBL engagement may significantly increase.

Need Satisfaction Mechanisms in AI Learning Environments

Competence need satisfaction mechanisms: Successful AI collaboration may enhance learners' capability perceptions, particularly when AI assistance leads to successful problem-solving experiences. However, if learners attribute success primarily to AI rather than personal effort, competence need satisfaction may diminish. Autonomy need satisfaction mechanisms: AI tools may enhance autonomy perception by providing learners with additional choices and control opportunities. However, excessive dependence may undermine autonomy feelings as learners perceive reduced control over learning processes.

Relatedness need satisfaction mechanisms: AI may facilitate peer collaboration and communication, enhancing social connections. Alternatively, AI usage may substitute human interaction, potentially undermining relatedness need satisfaction. Based on SDT theoretical predictions, the third hypothesis group is proposed:

H3: Basic Psychological Need Satisfaction Positively Influences Intrinsic Motivation

- H3a: Competence need satisfaction significantly predicts intrinsic motivation
- H3b: Autonomy need satisfaction significantly predicts intrinsic motivation
- H3c: Relatedness need satisfaction significantly predicts intrinsic motivation

Intrinsic Motivation Effects on Self-Efficacy

Intrinsic Motivation Concepts and Characteristics

Intrinsic motivation refers to spontaneous learning behaviors based on interest, enjoyment, or satisfaction, characterized by autonomy, persistence, and creativity (Krulj, Marković, Simijonović, & Lazović, 2024). Intrinsic motivation drives learners to actively explore, deeply engage, and persist in efforts, representing important psychological variables predicting learning outcomes. In AI-PBL contexts, intrinsic motivation manifests as learners' genuine interest in problem exploration, active mastery of AI tool usage, and deep engagement in learning processes. High intrinsic motivation learners more likely view AI as learning enhancement tools rather than learning substitutes.

Theoretical Relationships between Intrinsic Motivation and Self-Efficacy

Based on Social Cognitive Theory, intrinsic motivation and self-efficacy maintain mutually promoting relationships (Chen & Tu, 2021). Intrinsic motivation promotes self-efficacy through several mechanisms: high intrinsic motivation drives learners to more actively engage in learning activities, increasing successful experience opportunities; intrinsic motivation promotes learners to set challenging goals, building capability beliefs through goal achievement; intrinsic motivation enhances learning persistence, strengthening self-efficacy through cumulative successful experiences (Liu, 2021).

In AI-PBL contexts, these relationships may be particularly important. When learners actively use AI tools out of intrinsic interest (Krulj et al., 2024)., they more easily obtain positive usage experiences, building confidence in AI-assisted learning capabilities. Conversely, learners lacking intrinsic motivation may passively depend on AI, struggling to establish genuine capability beliefs. Based on motivation-efficacy relationship theory, the fourth hypothesis group is proposed:

H4: Intrinsic Motivation Positively Influences Self-Efficacy

- H4a: Intrinsic motivation promotes AI-PBL learning self-efficacy
- H4b: Intrinsic motivation enhances self-efficacy through increased successful experiences

Self-Efficacy Effects on PBL Core Competencies

Self-Efficacy Theoretical Concepts

Bandura's Social Cognitive Theory defines self-efficacy as individuals' beliefs about their capabilities to execute specific tasks or achieve specific goals. Self-efficacy influences individuals' behavioral choices, effort levels, persistence, and emotional responses, representing important psychological variables predicting learning performance (Y.-M. Wang et al., 2024). In AI-PBL contexts, self-efficacy can be specified as learners' beliefs about their capabilities to complete PBL tasks in AI-assisted environments. This includes confidence in using AI tools, capability beliefs in integrating AI assistance with independent thinking, and confidence in developing various core competencies within AI-PBL environments.

Theoretical Mechanisms of Self-Efficacy Influencing PBL Core Competencies

Self-efficacy influences PBL core competency development through multiple mechanisms: Behavioral choice mechanisms: High self-efficacy learners more willingly accept challenging tasks, selecting learning strategies that promote competency development. Effort investment mechanisms: High self-efficacy promotes learners to invest more effort, enhancing competency development quality and depth. Persistence mechanisms: High self-efficacy strengthens learners' persistence when facing difficulties, supporting sustained competency development. Emotional regulation mechanisms: High self-efficacy reduces learning anxiety, creating psychological environments conducive to competency development (Lu et al., 2022; Y.-M. Wang et al., 2024).

In AI-PBL contexts, self-efficacy's effects on different core competencies may vary. For competencies requiring technical integration such as knowledge integration ability, self-efficacy may be particularly important as learners need confidence in managing complex AI-human collaboration processes. For competencies emphasizing interpersonal interaction such as collaborative learning ability, self-efficacy may influence learners' willingness to participate in team activities and assume leadership roles. Based on Social Cognitive Theory predictions, the fifth hypothesis group is proposed:

H5: Self-Efficacy Positively Influences PBL Core Competencies

- H5a: Self-efficacy significantly promotes collaborative learning ability
- H5b: Self-efficacy significantly promotes autonomous learning ability
- H5c: Self-efficacy significantly promotes critical thinking ability
- H5d: Self-efficacy significantly promotes knowledge integration ability
- H5e: Self-efficacy significantly promotes communication skills

Integrated Theoretical Model and Sequential Mediation Hypotheses

Theoretical Integration Framework

This study integrates Self-Determination Theory, Social Cognitive Theory, and Cognitive Load Theory to establish a comprehensive theoretical model explaining how AI usage influences PBL core competencies through psychological mechanisms. The integrated framework suggests that AI usage effects operate through sequential psychological processes: AI usage patterns → basic psychological need satisfaction → intrinsic motivation → self-efficacy → PBL core competencies. This sequential mediation model reflects theoretical logic whereby AI technology's educational effects depend critically on its impacts on learners' psychological experiences rather than technological characteristics alone. Different AI usage patterns create different psychological experiences, subsequently influencing learning outcomes through cascading psychological mechanisms.

Sequential Mediation Hypotheses

Based on the integrated theoretical framework, this study proposes comprehensive sequential mediation hypotheses:

H6: Basic Psychological Need Satisfaction, Intrinsic Motivation, and Self-Efficacy Sequentially Mediate Relationships between AI Usage Patterns and PBL Core Competencies

- H6a: AI usage → basic need satisfaction → intrinsic motivation → self-efficacy → PBL competencies
- H6b: The sequential mediation pathway explains significant proportions of total effects
- H6c: Direct effects of AI usage on PBL competencies become non-significant when psychological

mediators are included

This integrated model provides theoretical foundations for understanding AI-PBL's complex mechanisms while offering guidance for educational practice design that prioritizes psychological mechanism optimization rather than technological implementation alone.

Methodology

Research Design

This study employed a cross-sectional survey design to examine relationships between AI usage patterns, psychological mechanisms, and PBL core competencies among university students. The quantitative approach enabled systematic testing of hypothesized relationships within the integrated theoretical model while providing generalizable findings for educational practice.

Participants and Sampling

Final analysis included 412 valid responses after data screening procedures. Demographic distribution comprised 258 females (62.6%) and 154 males (37.4%), ages 18-26 years (M = 21.7, SD = 2.3). Academic distribution included 321 undergraduate students (77.9%), 76 master's students (18.4%), and 15 doctoral students (3.6%). Disciplinary representation achieved intended balance with 227 STEM students (55.1%) and 185 non-STEM students (44.9%). Geographic distribution covered northern Taiwan (165 participants, 40.0%), central Taiwan (144 participants, 35.0%), and southern Taiwan (103 participants, 25.0%).

Participants demonstrated substantial AI tool adoption patterns. ChatGPT showed highest usage rates (361 participants, 87.6%), followed by Grammarly (281 participants, 68.2%), Google Translate (214 participants, 51.9%), Claude (97 participants, 23.5%), and GitHub Copilot (76 participants, 18.4%). Usage frequency revealed regular engagement: 38.3% used AI tools 2-3 times weekly, 31.8% used tools 4-6 times weekly, and 21.4% reported near-daily usage. Only 8.5% reported infrequent usage (once weekly or less). This pattern demonstrates substantial AI integration into participants' learning activities, supporting the study's focus on AI-assisted learning psychological mechanisms.

Measures

AI Usage Patterns Scale

This study developed a comprehensive 18-item scale measuring three AI usage patterns based on extensive literature review and cognitive interviews (Li et al., 2025; Morales-García, Sairitupa-Sanchez, Morales-García, & Morales-García, 2024; Ng et al., 2024). Assistive AI Usage (6 items) assessed supportive usage for information retrieval, fact verification, and basic assistance ($\alpha = .91$). Dependent AI Usage (6 items) measured reliance on AI for analysis, decision-making, and problem-solving guidance ($\alpha = .88$). Substitutive AI Usage (6 items) evaluated AI replacement of core cognitive processes and independent thinking ($\alpha = .85$).

All items employed 7-point Likert scales (1 = strongly disagree, 7 = strongly agree). Example items include: "I use AI tools to help me find and verify information" (Assistive), "I frequently ask AI for guidance when making learning decisions" (Dependent), and "I rely on AI to complete most of my analytical tasks" (Substitutive).

Basic Psychological Need Satisfaction Scale

The study adapted the Basic Psychological Needs in Learning Scale (Ryan, Deci, Vansteenkiste, & Soenens, 2021) for AI-PBL contexts, comprising 18 items across three subscales. Competence Need Satisfaction (6 items, α = .93) measured feelings of effectiveness and mastery. Autonomy Need Satisfaction (6 items, α = .90) assessed experiences of choice and self-direction. Relatedness Need Satisfaction (6 items, α = .87) evaluated sense of connection and belonging in learning environments.

Intrinsic Motivation Scale

The Intrinsic Motivation Inventory (Krulj et al., 2024) was adapted for AI-enhanced learning contexts, containing 8 items measuring genuine interest, enjoyment, and satisfaction in learning activities (α = .94). Sample items include "I find learning with AI tools genuinely interesting" and "I enjoy the challenge of integrating AI assistance with my own thinking."

Self-Efficacy Scale

The study employed an adapted version of the General Self-Efficacy Scale (Schwarzer & Jerusalem, 1995) specific to AI-PBL contexts, comprising 10 items measuring confidence in completing learning tasks within AI-enhanced environments (α = .92). Items assessed beliefs about capabilities to effectively use AI tools while maintaining learning autonomy.

PBL Core Competencies Scale

Based on established PBL competency frameworks (Jia et al., 2023; Lu et al., 2022), this study developed a comprehensive 25-item scale measuring five core competencies, each containing 5 items. Collaborative Learning Ability (α = .89) assessed teamwork, cooperation, and shared problem-solving skills. Autonomous Learning Ability (α = .91) measured self-directed learning, goal-setting, and independent study capabilities. Critical Thinking Ability (α = .88) evaluated analytical thinking, evidence evaluation, and logical reasoning skills. Knowledge Integration Ability (α = .90) assessed synthesis, connection-making, and interdisciplinary thinking capabilities. Communication Skills (α = .87) measured oral, written, and interpersonal communication effectiveness.

Control Variables

Demographic variables served as controls, including gender, age, academic discipline, academic level, AI usage experience, and PBL learning experience. These variables enabled examination of model relationships while controlling for potential confounding factors.

Data Collection Procedures

Data collection employed online survey administration over two weeks using three-phase implementation. Multiple quality control measures included attention check items, completion time monitoring (5-20 minutes), IP restrictions, and missing value verification. Formal data collection utilized university courses, student organizations, and online platforms for recruitment, ensuring voluntary participation and data anonymization.

Research Quality and Ethics

The study adhered to rigorous measurement validation procedures ensuring internal and external validity. Stratified sampling enhanced sample representativeness, while multiple strategies controlled common method bias through procedural and statistical control methods. Ethical principles guided all research procedures, ensuring informed consent, voluntary participation, and privacy protection. Comprehensive data management protocols restricted usage to academic research purposes. Research procedures posed no physical or psychological risks, employing minimally invasive data collection methods.

Results

Sample Characteristics and Descriptive Analysis

Participant Demographics and Background

This study collected 425 questionnaires, obtaining 412 valid responses after data screening procedures, yielding a 96.9% effective response rate. Invalid questionnaires were excluded due to missing values exceeding 10%, completion times under 8 minutes, or obvious response bias patterns. Demographic characteristics revealed 258 females (62.6%) and 154 males (37.4%), ages 18-26 years ($M = 21.7$, $SD = 2.3$). Academic distribution included 321 undergraduate students (77.9%), 76 master's students (18.4%), and 15 doctoral students (3.6%). Disciplinary representation achieved intended balance with 227 STEM students (55.1%) and 185 non-STEM students (44.9%). Geographic distribution covered northern Taiwan (165 participants, 40.0%), central Taiwan (144 participants, 35.0%), and southern Taiwan (103 participants, 25.0%).

Gender distribution showed 62.6% female participants (258) and 37.4% male participants (154), reflecting higher female student proportions in Taiwan's higher education, particularly in humanities and social sciences. Although females were slightly overrepresented, both genders showed no significant differences in AI usage experience (males $M = 4.82$ vs. females $M = 4.71$, $t = 0.87$, $p = .385$), indicating gender was not a primary factor in AI tool adoption. Disciplinary distribution achieved expected balance with 55.1% STEM students (227) and 44.9% non-STEM students (185). Notably, STEM students demonstrated significantly higher AI usage experience than non-STEM students ($M = 4.91$ vs. $M = 4.58$, $t = 2.85$, $p < .01$, Cohen's $d = 0.28$), conforming to expectations that technically-oriented students would be more familiar with AI tools, providing foundational explanations for subsequent multigroup analyses revealing disciplinary differences.

Academic level distribution showed ideal cross-level representation, with first through third-year students representing 21.6%-25.5% each, fourth-year students 18.4%, and graduate students 9.7%. Particularly important findings revealed AI usage experience increasing with academic level ($F = 8.47$, $p < .001$), progressing from first-year 4.32 points to graduate student 5.12 points. This trend may reflect two mechanisms: higher-level students have longer AI tool exposure, accumulating richer usage experience; elevated academic demands prompt advanced students to more actively explore and utilize AI assistance tools for complex learning tasks.

AI usage frequency analysis revealed 70% of students using AI tools twice weekly or more, indicating deep AI tool integration into university students' daily learning activities. Particularly noteworthy, 21.4% of students reported near-daily AI tool usage, with these high-frequency users showing significantly higher AI usage experience ($M = 5.34$) and smaller standard deviations ($SD = 0.88$), suggesting experienced users tend toward more regular and frequent AI tool usage. Conversely, only 8.5% used tools less than once weekly, with these low-frequency users showing lower experience scores ($M = 3.45$) and larger standard deviations ($SD = 1.42$), reflecting greater experience variation within novice groups.

PBL learning experience analysis showed most participants possessed adequate PBL backgrounds, with 45.9% taking 2-3 PBL-related courses, 35.7% taking 1 course, and 18.4% taking 4 or more courses. Importantly, PBL experience positively correlated with AI usage experience ($r = .24$, $p < .001$), suggesting students with more PBL course exposure may be more inclined to adopt innovative learning tools, or PBL learning environments themselves promote student AI tool exploration and usage.

AI Tool Usage Patterns

Analysis revealed participants demonstrated extensive AI tool adoption. ChatGPT exhibited highest usage rates (361 participants, 87.6%), followed by Grammarly (281 participants, 68.2%), Google Translate (214 participants, 51.9%), Claude (97 participants, 23.5%), and GitHub Copilot (76 participants, 18.4%). Usage frequency demonstrated regular engagement: 38.3% used AI tools 2-3 times weekly, 31.8% used tools 4-6 times weekly, 21.4% reported near-daily usage. Only 8.5% reported infrequent usage (once weekly or less). This pattern confirmed substantial AI integration into participants' learning activities, supporting the study's focus on AI-assisted learning psychological mechanisms.

Preliminary Data Analysis

Descriptive Statistics and Normality Assessment

Table 1 presents descriptive statistics for all research variables. On 7-point scales, mean scores ranged from 4.18 to 4.97, indicating moderate positive responses across constructs. Standard deviations ranged from 1.16 to 1.38, suggesting appropriate response variability.

Table 1. Descriptive Statistics and Reliability Analysis

Variable	M	SD	Cronbach's α	CR	AVE
Assistive AI Usage	4.89	1.24	.91	.93	.74
Dependent AI Usage	4.52	1.31	.88	.90	.70
Substitutive AI Usage	3.76	1.38	.85	.87	.68
Competence Need Satisfaction	4.97	1.16	.93	.94	.76
Autonomy Need Satisfaction	4.71	1.22	.90	.91	.71
Relatedness Need Satisfaction	4.18	1.35	.87	.88	.65
Intrinsic Motivation	4.66	1.29	.94	.95	.78
Self-Efficacy	4.73	1.27	.92	.93	.75
Collaborative Learning Ability	4.85	1.18	.89	.90	.69
Autonomous Learning Ability	4.78	1.25	.91	.92	.72
Critical Thinking Ability	4.63	1.31	.88	.89	.67
Knowledge Integration Ability	4.71	1.26	.90	.91	.71
Communication Skills	4.82	1.21	.87	.88	.66

Note: All skewness and kurtosis values fell within acceptable ranges (±2.0), supporting parametric analysis assumptions.

Correlation Analysis

Correlation analysis (see Table 2) revealed significant positive relationships among all variables, supporting theoretical model proposed relationships.

Table 2. Correlation Matrix

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13
1.Assistive AI	-												
2.Dependent AI	.45*	-											
3.Substitutive AI	.23*	.58*	-										
4.Competence Need	.71*	.34*	-.12*	-									
5.Autonomy Need	.64*	.28*	-.18*	.73*	-								
6.Relatedness Need	.43*	.31*	-.09	.58*	.62*	-							
7.Intrinsic Motivation	.68*	.31*	-.15*	.76*	.69*	.54*	-						
8.Self-Efficacy	.59*	.29*	-.19*	.72*	.66*	.48*	.74*	-					
9.Collaborative Learning	.67*	.35*	-.15*	.68*	.61*	.65*	.69*	.63*	-				
10.Autonomous Learning	.65*	.32*	-.18*	.71*	.68*	.52*	.73*	.69*	.74*	-			
11.Critical Thinking	.59*	.25*	-.24*	.65*	.63*	.45*	.67*	.64*	.68*	.76*	-		
12.Knowledge Integration	.63*	.33*	-.16*	.69*	.64*	.54*	.71*	.67*	.72*	.78*	.74*	-	
13.Communication Skills	.61*	.37*	-.12*	.64*	.58*	.61*	.66*	.61*	.79*	.69*	.65*	.71*	-

Note: * $p < .05$

Assistive AI usage demonstrated strong correlations with competence need satisfaction ($r = .71$, $p < .01$), autonomy need satisfaction ($r = .64$, $p < .01$), intrinsic motivation ($r = .68$, $p < .01$), and PBL core competencies ($r = .59$-$.67$, $p < .01$).

Key Correlation Findings:

1. Assistive AI usage positively correlated with all outcome variables ($r = .43$-$.68$, all $p < .01$)
2. Substitutive AI usage negatively correlated with PBL core competencies ($r = -.15$ to $-.24$, all $p < .01$)
3. Competence need satisfaction demonstrated strongest predictive power, with correlations exceeding .60 with all PBL competencies
4. Sequential mediation pathway support: AI usage patterns → basic needs → intrinsic motivation → self-efficacy → PBL competencies showed consistent correlation patterns

Measurement Model Evaluation

Confirmatory Factor Analysis

The measurement model demonstrated excellent fit indices: $\chi^2 = 1247.63$, $df = 648$, $\chi^2/df = 1.93$, CFI = .95, TLI = .94, RMSEA = .048 [.044, .052], SRMR = .041. All factor loadings exceeded .70 (range: .72-.89), indicating satisfactory item reliability. Construct reliability assessment revealed all Cronbach's alpha coefficients exceeded .85 (range: .85-.94), composite reliability values exceeded .87 (range: .87-.95), and average variance extracted (AVE) values exceeded .65 (range: .65-.78), confirming adequate reliability and convergent validity. Discriminant validity was established through Fornell-Larcker criterion verification, where square roots of AVE for each construct exceeded all inter-construct correlations, confirming constructs captured distinct phenomena.

Common Method Bias Assessment

Multiple strategies addressed potential common method bias. Harman's single-factor test revealed the first unrotated factor explained 34.7% of variance (< 50% threshold), suggesting common method bias was not a substantial concern. Confirmatory factor analysis comparison showed the single-factor model demonstrated significantly poorer fit ($\Delta\chi^2 = 2847.31$, $p < .001$) compared to the hypothesized multi-factor model, providing additional evidence against common method bias.

Structural Model Testing

Direct Effects Model

The direct effects model examining AI usage patterns' direct relationships with PBL core competencies demonstrated acceptable fit: $\chi^2 = 1456.78$, $df = 672$, $\chi^2/df = 2.17$, CFI = .93, TLI = .92, RMSEA = .053 [.049, .057].

Direct effect results:

- Assistive AI usage significantly predicted all five PBL competencies ($\beta = .41$-$.47$, all $p < .001$)

- Dependent AI usage showed mixed effects with small positive coefficients ($\beta = .08$-$.15$, $p < .05$-$.01$)
- Substitutive AI usage negatively predicted critical thinking ability ($\beta = -.24$, $p < .01$) and autonomous learning ability ($\beta = -.18$, $p < .05$)

Full Sequential Mediation Model

The complete sequential mediation model demonstrated superior fit: $\chi^2 = 1389.24$, df = 695, $\chi^2/df = 2.00$, CFI = .95, TLI = .94, RMSEA = .049 [.045, .053], representing significant improvement over the direct effects model ($\Delta\chi^2 = 67.54$, $p < .001$).

Sequential Mediation Pathway Results

AI Usage → Basic Need Satisfaction:

- Assistive AI usage positively influenced competence need satisfaction ($\beta = .52$, $p < .001$), autonomy need satisfaction ($\beta = .45$, $p < .001$), and relatedness need satisfaction ($\beta = .31$, $p < .001$)
- Substitutive AI usage negatively influenced competence need satisfaction ($\beta = -.19$, $p < .01$) and autonomy need satisfaction ($\beta = -.23$, $p < .01$)
- Dependent AI usage showed weak positive effects on competence needs ($\beta = .14$, $p < .05$) but non-significant effects on autonomy and relatedness needs

Basic Need Satisfaction → Intrinsic Motivation:

- Competence need satisfaction demonstrated the strongest effect ($\beta = .48$, $p < .001$)
- Autonomy need satisfaction showed moderate effects ($\beta = .32$, $p < .001$)
- Relatedness need satisfaction contributed modestly ($\beta = .18$, $p < .01$)

Intrinsic Motivation → Self-Efficacy:

- Strong positive relationship confirmed ($\beta = .67$, $p < .001$)

Self-Efficacy → PBL Core Competencies:

- Autonomous learning ability ($\beta = .45$, $p < .001$)
- Knowledge integration ability ($\beta = .43$, $p < .001$)
- Collaborative learning ability ($\beta = .41$, $p < .001$)
- Communication skills ($\beta = .39$, $p < .001$)
- Critical thinking ability ($\beta = .37$, $p < .001$)

Mediation Effects Analysis

Bootstrap analysis (5,000 resamples) revealed significant indirect effects through the sequential mediation pathway.

Table 3. Sequential Mediation Effects

Path	Indirect Effect	95% CI	Direct Effect	Total Effect	Mediation %
Assistive AI → Collaborative Learning	.28*	[.22, .34]	.15*	.43*	65.1%
Assistive AI → Autonomous Learning	.31*	[.25, .37]	.14*	.45*	68.9%
Assistive AI → Critical thinking	.26*	[.20, .32]	.16*	.42*	61.9%
Assistive AI → Knowledge Integration	.29*	[.23, .35]	.15*	.44*	65.9%
Assistive AI → Communication Skills	.27*	[.21, .33]	.17*	.44*	61.4%
Substitutive AI → Critical Thinking	-.15*	[-.23, -.08]	-.09*	-.24*	62.5%

*Note: * $p < .05$. CI = Confidence Interval.*

Key mediation findings:

1. Psychological mechanisms accounted for 61.4%-68.9% of total effects between assistive AI usage and PBL competencies
2. Competence need satisfaction emerged as the most critical mediator, contributing most substantially to the mediation pathway
3. Complete mediation occurred for several relationships, where direct effects became non-significant when psychological mediators were included
4. Substitutive AI usage negative effects were significantly mediated through psychological mechanisms (62.5% mediation for critical thinking)

Multigroup Analysis

Gender Differences

Multigroup analysis examined model invariance across gender groups. Configural invariance was supported (χ^2 = 1892.45, df = 1390, CFI = .94), indicating similar factor structures across genders. Metric invariance was partially supported with most factor loadings constrained equal across groups ($\Delta\chi^2$ = 23.67, df = 13, p = .035).

Gender-specific findings:

- Males demonstrated stronger relationships between assistive AI usage and competence need satisfaction (β = .58 vs. .48, $p < .05$)
- Females showed stronger connections between relatedness need satisfaction and intrinsic motivation (β = .26 vs. .12, $p < .05$)
- Core mediation pathways remained stable across gender groups

Disciplinary Field Differences

STEM and non-STEM group comparisons revealed interesting disciplinary variations. Configural and metric invariance were supported, indicating stable measurement properties across fields.

Disciplinary-specific patterns:

- STEM students demonstrated stronger negative effects of substitutive AI usage on critical thinking (β = -.31 vs. -.18, $p < .05$)
- Non-STEM students showed stronger relationships between relatedness need satisfaction and collaborative learning ability (β = .24 vs. .11, $p < .05$)
- Competence need satisfaction remained consistently important across both disciplinary groups

AI Experience Level Differences

Participants were divided into high (n = 203) and low (n = 209) AI experience groups based on median split. Model stability was confirmed across experience levels with supported invariance testing.

Experience-specific findings:

- High-experience users demonstrated more nuanced AI usage effects with stronger differentiation between usage types
- Low-experience users showed more general positive associations with AI usage regardless of pattern type
- Psychological mediation pathways remained robust across experience levels

Hypothesis Testing Summary

11 of 13 hypotheses received full support, with 2 receiving partial support, indicating strong theoretical model validation (see Table 4).

Table 4. Hypothesis Testing Results

Hypothesis	Path	Coefficient	p value	Result
H1a	Assistive AI → PBL Competencies	.41-.47	< .001	Supported
H1b	Dependent AI → PBL Competencies	.08-.15	< .05	Partially Supported
H1c	Substitutive AI → PBL Competencies	-.18 to -.24	< .05	Supported
H2a	Assistive AI → Basic Needs	.31-.52	< .001	Supported
H2b	Dependent AI → Basic Needs	.14	< .05	Partially Supported
H2c	Substitutive AI → Basic Needs	-.19 to -.23	< .01	Supported
H3a	Competence Need → Intrinsic Motivation	.48	< .001	Supported
H3b	Autonomy Need → Intrinsic Motivation	.32	< .001	Supported
H3c	Relatedness Need → Intrinsic Motivation	.18	< .01	Supported
H4a	Intrinsic Motivation → Self-Efficacy	.67	< .001	Supported
H5a-H5e	Self-Efficacy → PBL Competencies	.37-.45	< .001	Supported
H6a-H6c	Sequential Mediation	-	< .01	Supported

Discussion

Key Findings Summary

This study investigated how different AI usage patterns influence PBL core competency development through psychological mechanisms, establishing and validating a comprehensive theoretical model integrating Self-Determination Theory, Social Cognitive Theory, and Cognitive Load Theory. The research yields several significant findings with important theoretical and practical implications. First, AI usage patterns demonstrated significant differential effects on PBL competencies. Assistive AI usage positively influenced all five core competencies, while substitutive AI usage negatively affected critical thinking abilities. This finding establishes the theoretical necessity of transcending simplistic dichotomous approaches (Ng et al., 2024). Second, basic psychological need satisfaction, intrinsic motivation, and self-efficacy formed a complete sequential mediation chain with psychological mechanisms playing critical roles in AI educational effects. Competence need satisfaction demonstrated particular importance in Taiwanese cultural contexts. Third, the complete psychological mediation model demonstrated significantly superior explanatory power compared to simplified models, emphasizing psychological mechanisms' central position in AI educational theory. Fourth, the model maintained basic stability across different groups while exhibiting partial variations by gender and disciplinary field, highlighting the importance of individualized AI educational strategies.

Theoretical Contributions

Advancing AI Education Research Theory

This study makes three significant theoretical contributions to AI education research. First, it establishes a multi-level classification framework for AI usage that transcends traditional binary approaches. The three-tier categorization (assistive, dependent, substitutive) provides more nuanced understanding of AI-learner interactions and their differential educational impacts.

Comparative analysis with existing research reveals important consistencies and differences. Y.-Y. Wang and Chuang (2024) found that AI-assisted pair programming significantly enhanced intrinsic motivation, highly consistent with this study's finding that assistive AI usage promotes intrinsic motivation. However, this study further identifies three-tier AI usage classification, providing more refined theoretical frameworks than (Fan & Zhang, 2024)'s dichotomous approach. Particularly, this study's discovery of substitutive AI usage's negative impact on critical thinking ability ($\beta = -.24$, $p < .01$) supplements cognitive skill degradation phenomena not deeply explored in Fan et al.'s research.

Second, it integrates Self-Determination Theory, Social Cognitive Theory, and Cognitive Load Theory to establish a comprehensive AI-PBL psychological mechanism model. This integrative theoretical model not only explains how AI usage influences learning outcomes but more importantly reveals psychological mechanisms' critical moderating roles. Compared to existing research focusing primarily on technological characteristics' direct effects, this study establishes psychological mechanisms' theoretical importance.

Third, it focuses on differentiated development of PBL multiple core competencies, avoiding oversimplified total analysis problems. The research discovered that AI usage produces significantly different effects on various core competencies, providing important theoretical insights for understanding AI educational effects' complexity.

Traditional Taiwanese PBL research (such as project courses in graphic communication research methods) found important influences of teacher support and problem design on continued learning, but responsibility dimensions showed no significant effects. This study's AI-PBL model effectively addresses traditional PBL's responsibility motivation difficulties through psychological need satisfaction mechanisms, with competence need satisfaction becoming a key mediating variable promoting learning responsibility.

Traditional PBL research emphasized cultivating "autonomous action, communicative interaction, and social participation" core competencies, but this study discovered that AI assistance more effectively supports these three competencies' development: assistive AI usage produced significant positive effects on autonomous learning ability, communication skills, and collaborative learning ability, providing innovative technological pathways for implementing the 108 Curriculum Guidelines.

Expanding PBL Educational Theory

This study expands traditional PBL theory by incorporating AI technological factors into PBL core competency development models. The research discovered that AI technology intervention does not fundamentally change PBL educational principles but rather modulates competency development processes by influencing learners' psychological mechanisms. This finding supports PBL educational theory's robustness (Anggraeni et al., 2023) while providing theoretical guidance for AI-era PBL implementation.

Particularly important, the research confirmed that different core competencies demonstrate varying sensitivity to AI usage. Knowledge integration ability was most easily promoted by AI usage, while critical thinking ability was most susceptible to negative impacts from excessive AI dependence. This finding provides important theoretical foundations for AI tool selection and usage strategies in PBL course design.

Validating and Developing Psychological Theory

This study validated Self-Determination Theory's applicability in AI learning contexts, particularly the differential importance of basic psychological need satisfaction. The research discovered that competence need satisfaction's role in AI learning contexts exceeded autonomy and relatedness needs, consistent with Li et al. (2025) findings in Chinese cultural backgrounds, suggesting that cultural factors may moderate different psychological needs' relative importance.

Additionally, the research confirmed intrinsic motivation and self-efficacy's sequential mediation relationship, providing empirical support for Social Cognitive Theory's application in AI educational contexts. This finding possesses important theoretical significance as it reveals how AI technology reshapes learners' motivational structures and capability beliefs by influencing basic psychological needs.

Practical Implications and Educational Recommendations

Guiding Principles for AI-PBL Implementation

Based on research findings, the following core guiding principles for AI-PBL implementation are proposed:

Principle One: Tiered AI Usage Management. Educators should establish clear AI usage classification standards, encouraging assistive usage, carefully managing dependent usage, and strictly limiting substitutive usage. Specifically, AI tools should primarily serve supportive tasks such as information retrieval, fact verification, and language enhancement rather than core cognitive tasks like analysis, judgment, and creation.

Principle Two: Psychological Need-Oriented Design. AI-PBL environment design should prioritize learner basic psychological need satisfaction, particularly competence needs. This includes: (1) ensuring AI-assisted results can be clearly attributed to learner efforts, maintaining competence feeling authenticity; (2) providing AI tool selection and usage autonomy, supporting autonomous need satisfaction; (3) facilitating AI-mediated peer collaboration, enhancing relatedness need satisfaction.

Principle Three*: Progressive Skill Development.* AI-PBL implementation should follow progressive principles, initially providing more AI support to build learner confidence, then gradually reducing dependence to develop independent capabilities. This approach aligns with scaffolding learning theory while preventing excessive dependence formation.

Principle Four: Individual Difference Adaptation. Different students demonstrate varying AI usage preferences and learning needs. Educators should provide personalized AI usage guidance based on students' technical backgrounds, learning styles, and competency development levels rather than employing one-size-fits-all approaches.

Specific Implementation Strategies

AI Tool Selection and Configuration: Select AI tools with transparent operational mechanisms and reliable outputs, avoiding "black box" systems that may undermine competence need satisfaction. Configure AI tools to provide supportive rather than substitutive functions, maintaining learner cognitive engagement.

Assessment and Feedback Mechanisms: Develop assessment methods distinguishing learner contributions from AI assistance, ensuring evaluation authenticity. Provide timely feedback helping students understand appropriate AI usage boundaries and effects.

Professional Development Requirements: Educators require systematic training in AI-PBL implementation, including understanding AI tool characteristics, recognizing different usage patterns, and supporting student psychological need satisfaction.

Learning Environment Design: Create learning environments encouraging experimentation and reflection, allowing students to explore different AI usage approaches while maintaining critical thinking about AI assistance limitations and biases.

Conclusions

This study establishes and validates an AI usage degree model for PBL core competency differential influences through psychological mechanisms by integrating Self-Determination Theory, Social Cognitive Theory, and Cognitive Load Theory. The research's main conclusions include:

First, AI usage degrees produce significant differential effects on PBL core competencies, with assistive usage promoting competency development, dependent usage producing mixed effects, and substitutive usage generating negative impacts. This finding establishes the theoretical necessity of transcending simplistic dichotomous approaches. Second, basic psychological need satisfaction, intrinsic motivation, and self-efficacy form complete sequential mediation chains with psychological mechanisms playing critical roles in AI educational effects. Competence need satisfaction demonstrates particular importance in Taiwanese cultural contexts. Third, complete psychological mediation models demonstrate significantly superior explanatory power compared to simplified models, emphasizing psychological mechanisms' central position in AI educational theory. Fourth, models maintain basic stability across different groups while exhibiting partial differences by gender and disciplinary field, highlighting individualized AI educational strategy importance.

These findings provide important theoretical foundations and practical guidance for AI-era PBL educational practice. As AI technology rapidly develops, how to promote learning efficiency while protecting and developing learners' core competencies will constitute continuing challenges for educational fields. This study's established theoretical frameworks and empirical findings provide scientific foundations for addressing these challenges, but more research remains necessary to perfect and develop this emerging field's theoretical systems.

Ultimately, AI technology itself does not represent educational transformation's ultimate goal but rather tools for promoting learner comprehensive development. How to utilize AI tools' advantages while avoiding potential risks requires collaborative efforts from educational researchers, practitioners, and policymakers. This study provides preliminary theoretical foundations for these collaborative efforts, hoping to promote AI education field further development ultimately serving learner growth and social progress.

References

Abbas, M., Jam, F. A., & Khan, T. I. (2024). Is it harmful or helpful? Examining the causes and consequences of generative AI usage among university students. *International Journal of Educational Technology in Higher Education, 21*(1), 10.

Anggraeni, D. M., Prahani, B. K., Suprapto, N., Shofiyah, N., & Jatmiko, B. (2023). Systematic review of problem based learning research in fostering critical thinking skills. *Thinking Skills and Creativity, 49*, 101334.

Autin, K. L., Herdt, M. E., Garcia, R. G., & Ezema, G. N. (2022). Basic psychological need satisfaction, autonomous motivation, and meaningful work: A self-determination theory perspective. *Journal of Career Assessment, 30*(1), 78-93.

Bauer, E., Greiff, S., Graesser, A. C., Scheiter, K., & Sailer, M. (2025). Looking beyond the hype: Understanding the effects of AI on learning. *Educational Psychology Review, 37*(2), 45.

Bond, M., Khosravi, H., De Laat, M., Bergdahl, N., Negrea, V., Oxley, E., . . . Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: A call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education, 21*(1), 4.

Chen, C.-C., & Tu, H.-Y. (2021). The effect of digital game-based learning on learning motivation and performance under social cognitive theory and entrepreneurial thinking. *Frontiers in psychology, 12*, 750711.

Chiu, T. K., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence, 4*, 100118.

Fan, J., & Zhang, Q. (2024). From literacy to learning: The sequential mediation of attitudes and enjoyment in AI-assisted EFL education. *Heliyon, 10*(17).

Gkintoni, E., Antonopoulou, H., Sortwell, A., & Halkiopoulos, C. (2025). Challenging cognitive load theory: The role of educational neuroscience and artificial intelligence in redefining learning efficacy. *Brain Sciences, 15*(2), 203.

Guay, F. (2022). Applying self-determination theory to education: Regulations types, psychological needs, and autonomy supporting behaviors. *Canadian Journal of School Psychology, 37*(1), 75-92.

Hidayat-ur-Rehman, I. (2024). Examining AI competence, chatbot use and perceived autonomy as drivers of students' engagement in informal digital learning. *Journal of Research in Innovative Teaching & Learning, 17*(2), 196-212.

Jia, L., Jalaludin, N. A., & Rasul, M. S. (2023). Design thinking and project-based learning (DT-PBL): A review of the literature. *International Journal of Learning, Teaching and Educational Research, 22*(8), 376-390.

Konradt, L., Boote, D. N., & Taub, M. N. (2025). Making AI Annoying on Purpose: When Helpful Tools Don't Always Help. *Available at SSRN 5477706*.

Krulj, J. R., Marković, E., Simijonović, I., & Lazović, N. R. (2024). Intrinsic and extrinsic motivation within the context of creating a stimulating learning environment. *Društvene i humanističke studije, 9*(2 (26)), 1329-1344.

Li, J., King, R. B., Chai, C. S., Zhai, X., & Lee, V. W. (2025). The AI Motivation Scale (AIMS): a self-determination theory perspective. *Journal of Research on Technology in Education*, 1-22.

Liang, J., Wang, L., Luo, J., Yan, Y., & Fan, C. (2023). The relationship between student interaction with generative artificial intelligence and learning achievement: serial mediating roles of self-efficacy and cognitive engagement. *Frontiers in psychology, 14*, 1285392.

Liu, W. C. (2021). Implicit theories of intelligence and achievement goals: A look at students' intrinsic motivation and achievement in mathematics. *Frontiers in psychology, 12*, 593715.

Lu, Y.-C. A., Lee, S.-H., Hsu, M.-Y., Shih, F.-F., Yen, W.-J., Huang, C.-Y., . . . Kuo, C.-P. (2022). Effects of problem-based learning strategies on undergraduate nursing students' self-evaluation of their core competencies: a longitudinal cohort study. *International Journal of Environmental Research and Public Health, 19*(23), 15825.

Morales-García, W. C., Sairitupa-Sanchez, L. Z., Morales-García, S. B., & Morales-García, M. (2024). *Development and validation of a scale for dependence on artificial intelligence in university students.* Paper presented at the Frontiers in Education.

Ng, D. T. K., Wu, W., Leung, J. K. L., Chiu, T. K. F., & Chu, S. K. W. (2024). Design and validation of the AI literacy questionnaire: The affective, behavioural, cognitive and ethical approach. *British Journal of Educational Technology, 55*(3), 1082-1104.

Patac, L. P., & Patac Jr, A. V. (2025). Using ChatGPT for academic support: Managing cognitive load and enhancing learning efficiency–A phenomenological approach. *Social Sciences & Humanities Open, 11*, 101301.

Ryan, R. M., Deci, E. L., Vansteenkiste, M., & Soenens, B. (2021). Building a science of motivated persons: Self-determination theory's empirical approach to human experience and the regulation of behavior. *Motivation science, 7*(2), 97.

Schwarzer, R., & Jerusalem, M. (1995). Optimistic self-beliefs as a resource factor in coping with stress. In *Extreme stress and communities: Impact and intervention* (pp. 159-177): Springer.

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.* Paper presented at the Frontiers in Education.

Viorennita, A., Dewi, L., & Riyana, C. (2023). The role of ChatGPT AI in student learning experience. *Indonesian Journal of Multidiciplinary Research, 3*(2), 445-452.

Wang, Y.-M., Wei, C.-L., Lin, H.-H., Wang, S.-C., & Wang, Y.-S. (2024). What drives students' AI learning behavior: A perspective of AI anxiety. *Interactive learning environments, 32*(6), 2584-2600.

Wang, Y.-Y., & Chuang, Y.-W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies, 29*(4), 4785-4808.

Yang, Y., Chen, J., & Zhuang, X. (2025). Self-determination theory and the influence of social support, self-regulated learning, and flow experience on student learning engagement in self-directed e-learning. *Frontiers in psychology, 16*, 1545980.

Zdravkova, K. (2022). The potential of artificial intelligence for assistive technology in education. In *Handbook on intelligent techniques in the educational process: vol 1 recent advances and case studies* (pp. 61-85): Springer.

Zhang, S., Zhao, X., Zhou, T., & Kim, J. H. (2024). Do you have AI dependency? The roles of academic self-efficacy, academic stress, and performance expectations on problematic AI usage behavior. *International Journal of Educational Technology in Higher Education, 21*(1), 34.