

How AI-Assisted Learning Satisfies Students' Psychological Needs: Evidence from Taiwan Universities

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ABSTRACT

Despite widespread AI adoption in universities globally, current implementations may inadvertently undermine learning engagement, with students reporting AI use primarily due to external pressures rather than genuine interest. This disconnect between technological sophistication and psychological understanding poses immediate challenges for educational institutions seeking to maximize AI benefits while supporting student wellbeing. This study examines how AI-assisted learning influences students' basic psychological needs satisfaction through Self-Determination Theory in Taiwanese university contexts, providing the first systematic investigation of all three psychological needs (competence, autonomy, relatedness) simultaneously within AI learning environments. A cross-sectional survey of 200 Taiwanese university students was conducted using structural equation modeling, with validated scales measuring AI-assisted learning usage and basic psychological needs satisfaction (competence, autonomy, relatedness). AI-assisted learning significantly influenced all three psychological needs, with competence showing the strongest effect, followed by autonomy and relatedness. Competence need satisfaction emerged as the primary factor in AI learning contexts, consistent with findings in Chinese educational settings. This research provides the first systematic application of Self-Determination Theory to AI education contexts, demonstrating that psychological need satisfaction determines AI learning effectiveness. Competence need primacy in AI contexts challenges traditional SDT applications where autonomy typically receives primary emphasis, suggesting that technological complexity and cultural factors moderate psychological need dynamics. The findings offer evidence-based guidance for designing culturally-informed AI educational systems that prioritize competence-centered features, integrate autonomy-supporting elements, and adopt hybrid implementation models combining AI's strengths with essential human instruction elements for emotional support and interpersonal connection.

Keywords: AI-assisted Learning, Educational Technology, Psychological Needs, Self-Determination Theory

INTRODUCTION

The integration of artificial intelligence (AI) into educational settings represents one of the most significant technological transformations in contemporary higher education (Wang et al., 2025). AI-assisted learning systems, featuring adaptive algorithms, personalized content recommendations, and intelligent feedback mechanisms, have rapidly proliferated across university campuses worldwide (Gibson et al., 2023; Li et al., 2025). However, despite substantial investments in AI educational technologies and their widespread adoption, a critical knowledge gap persists regarding the psychological mechanisms underlying their educational effectiveness (Zhang & Zhang, 2024). This disconnect between technological sophistication and psychological understanding poses immediate challenges for educational

institutions seeking to maximize the benefits of AI investments while supporting student wellbeing.

Research Urgency and Contemporary Significance

The urgency of understanding AI's psychological impact on learners has intensified due to three converging factors. First, recent evidence reveals a concerning paradox: while students increasingly utilize AI tools, many report doing so primarily due to external pressures rather than genuine interest or internal motivation (Li et al., 2025; Zhang et al., 2024). This suggests that current AI implementations may inadvertently undermine the very learning engagement they aim to enhance. Second, the rapid evolution of generative AI technologies such as ChatGPT, which 87.5% of students in preliminary surveys report using regularly, has outpaced educational research's capacity to understand their psychological implications (Patac & Patac Jr, 2025; Song & Song, 2023). Third, as AI becomes increasingly embedded in educational infrastructure, institutions urgently require evidence-based frameworks to guide implementation decisions that affect millions of students globally.

Despite AI's omnipresence in education, existing research exhibits a critical theoretical limitation: the predominant focus on technological capabilities while neglecting learners' fundamental psychological experiences (Gibson et al., 2023). Current studies typically evaluate AI systems through performance metrics, accuracy, efficiency, and technical functionality without examining whether these systems satisfy the basic psychological needs that drive human motivation and well-being. This technological determinism approach fails to address a fundamental question: regardless of how sophisticated AI systems become, will they be effective if they do not support learners' core psychological needs?

Theoretical Gap: The Absence of Comprehensive SDT Application in AI Learning Contexts

Self-Determination Theory (SDT), one of the most empirically validated motivational frameworks in psychology with thousands of supporting studies across diverse contexts, posits that human motivation and wellbeing depend fundamentally on satisfying three basic psychological needs: competence (feeling capable and effective), autonomy (experiencing choice and self-direction), and relatedness (feeling connected to others) (Ryan & Deci, 2000; Xia et al., 2022). Bureau et al. (2022) comprehensive meta-analysis of 144 studies involving over 79,000 students demonstrated SDT's robust predictive power in educational contexts, with competence need satisfaction showing particularly strong effects on academic outcomes. However, despite SDT's established theoretical power in traditional educational settings, its application to AI-assisted learning environments remains remarkably limited and fragmented.

Gap 1: Fragmented Investigation of Psychological Needs. While previous technology-enhanced learning research has examined SDT in contexts such as gamification (Luarn et al., 2023) and mobile learning, no prior research has comprehensively examined all three basic psychological needs simultaneously within AI-assisted learning systems. Existing studies typically focus on isolated needs (e.g., autonomy alone or competence alone) without investigating their interrelationships or relative importance in AI contexts. This fragmented approach prevents holistic understanding of how AI technologies influence the complete motivational profile required for optimal learning.

Gap 2: Absence of AI-Specific SDT Frameworks. Current research applies SDT principles developed for traditional educational settings directly to AI contexts without acknowledging fundamental technological differences. AI-assisted learning systems incorporating adaptive algorithms and intelligent feedback represent qualitatively different learning environments from earlier digital technologies like e-learning platforms or video-based instruction. These unique AI capabilities, particularly real-time adaptivity and personalized scaffolding, may fundamentally alter psychological need dynamics in ways that existing SDT applications fail to capture. For instance, while traditional SDT research emphasizes autonomy support as primary, AI's capability-enhancing features may shift relative need salience toward competence.

Gap 3: Limited Cultural Contextualization. Existing SDT research in educational technology contexts derives predominantly from Western cultural settings, with minimal investigation in Chinese educational contexts where achievement orientation and examination culture may moderate psychological need patterns differently (Li et al., 2025; Yang et al., 2025). This Western-centric bias limits understanding of whether psychological need satisfaction operates universally or exhibits cultural specificity when learners engage with AI technologies.

Research Novelty: Three Distinctive Contributions

Novelty 1: First Systematic Multi-Need Investigation in AI Learning Contexts. This research provides the first comprehensive examination of all three basic psychological needs (competence, autonomy, relatedness) simultaneously within AI-assisted learning environments, using validated SDT measurement instruments adapted specifically for AI contexts. Unlike previous studies examining needs in isolation, this integrated approach enables investigation of: (a) whether all three needs remain relevant in technologically complex learning environments, (b) the relative magnitude of effects across different need dimensions, and (c) whether certain needs demonstrate heightened salience in AI contexts compared to traditional educational settings. This comprehensive framework directly addresses Gap 1 by providing a complete motivational profile of AI learning experiences.

Novelty 2: AI-Specific Application of Self-Determination Theory. This study extends SDT into AI-assisted learning contexts that fundamentally differ from earlier educational technologies, investigating whether and how technological complexity (adaptive algorithms, intelligent feedback, personalized recommendations) moderates psychological need dynamics. Specifically, this research tests whether: (a) AI systems' capability-enhancement features amplify competence need satisfaction beyond levels observed in traditional educational settings, (b) AI-provided personalization genuinely supports autonomy or merely creates illusions of choice, and (c) AI-mediated learning environments can satisfy relatedness needs typically associated with direct human interaction. By examining whether established motivational principles maintain explanatory power in novel technological contexts, this research directly addresses Gap 2, contributing to the theoretical understanding of technology-motivation relationships.

Novelty 3: Culturally-Situated Investigation in Taiwanese University Context. By conducting this investigation in Taiwanese higher education, characterized by high AI adoption rates (87.5% ChatGPT usage), achievement-oriented culture, and collectivist values, this research examines whether psychological need patterns in AI learning exhibit cultural

specificity or universal consistency. This cultural contextualization is particularly important because: (a) Chinese educational culture emphasizes academic capability demonstration as central to social status and self-worth, potentially amplifying competence need salience (Li et al., 2025), (b) collectivist values may moderate relatedness need satisfaction patterns differently than individualist Western contexts, and (c) Taiwan's advanced technological infrastructure provides an ideal context for studying mature AI learning adoption. This culturally-situated approach directly addresses Gap 3, contributing evidence to the predominantly Western SDT literature while testing generalizability of motivational principles across cultural contexts.

Research Objectives

This study pursues three specific research objectives: Objective 1: To systematically investigate how AI-assisted learning influences students' satisfaction of three basic psychological needs (competence, autonomy, and relatedness) as conceptualized within Self-Determination Theory. Objective 2: To determine whether certain psychological needs demonstrate greater salience than others in AI learning contexts, particularly examining whether competence needs assume heightened importance given the achievement-oriented characteristics of Chinese educational culture and AI systems' capability-enhancement features. Objective 3: To provide evidence-based guidance for designing AI educational systems that effectively support learners' psychological needs, thereby enhancing both learning effectiveness and student wellbeing.

Research Question and Contributions

This study is guided by the following research question: How does AI-assisted learning influence learners' basic psychological needs satisfaction (competence, autonomy, and relatedness) according to Self-Determination Theory, and do these needs demonstrate differentiated patterns of influence that vary from traditional educational settings?

By addressing this question, this research makes significant theoretical and practical contributions. Theoretically, it extends SDT into emerging technological contexts, establishing whether this robust motivational framework maintains explanatory power when applied to complex AI-assisted learning environments that fundamentally differ from traditional settings where SDT was developed. It advances understanding of how technological complexity may moderate psychological need dynamics, challenging the assumption that all three needs contribute equally across contexts and demonstrating that competence satisfaction assumes primary importance in AI learning, a pattern contrasting with traditional SDT applications emphasizing autonomy primacy.

Practically, the findings offer evidence-based design principles for AI educational systems, enabling developers and educators to create technologies that support not only cognitive learning outcomes but also psychological well-being. For educational institutions investing heavily in AI technologies, this research provides crucial insights into maximizing return on investment by ensuring AI implementations align with fundamental human motivational principles, thereby enhancing both learning effectiveness and student satisfaction with AI-mediated learning experiences.

METHODS OF RESEARCH

Research Design

This study employed a cross-sectional survey design using a quantitative approach to investigate the relationships between AI-assisted learning usage and basic psychological needs satisfaction among Taiwanese university students. Cross-sectional design was selected as appropriate for this research because it enables efficient collection of data from a large sample at a single time point, allowing for examination of associations between variables while providing a snapshot of current AI learning experiences in higher education contexts (Qin et al., 2019; Zhang & Zhang, 2024). This design is particularly suitable for initial theory-testing research examining whether established psychological frameworks (Self-Determination Theory) apply to emerging technological contexts (AI-assisted learning), as recommended by Singleton and Straits (2018) for exploratory investigations of novel phenomena.

The study adopted a correlational research approach within the cross-sectional design, specifically utilizing structural equation modeling (SEM) to test hypothesized relationships between constructs. SEM was chosen as the primary analytical strategy because it allows simultaneous examination of multiple relationships between latent variables while accounting for measurement error, providing more robust estimates than traditional regression approaches (Hair et al., 2019). This methodological choice aligns with contemporary best practices in educational technology research examining psychological constructs (Teo, 2022).

Participants and Sampling Procedures

Sampling Method and Rationale: Participants were recruited through convenience sampling with stratified geographical distribution from universities across Taiwan during the fall semester of 2024 (September-December). While convenience sampling presents limitations regarding generalizability, this approach was deemed appropriate for several reasons. First, as an initial exploratory study applying SDT to AI-assisted learning contexts, theoretical generalization (testing whether psychological theory applies in a new domain) takes precedence over statistical generalization (representing a specific population) (Xia et al., 2022). Second, convenience sampling enabled efficient access to university students with substantial AI tool experience, which was essential for ensuring participants could meaningfully evaluate their psychological experiences with AI learning systems. Third, this sampling approach has been widely employed in similar educational technology research examining new phenomena where population parameters are unknown (Li et al., 2025; Song & Song, 2023).

Geographical Stratification: To enhance sample representativeness within the constraints of convenience sampling, recruitment employed a stratified approach targeting universities across three geographical regions: northern Taiwan (including Taipei and New Taipei City), central Taiwan (Taichung area), and southern Taiwan (Kaohsiung and Tainan areas). This geographical stratification helps ensure the sample captures potential regional variations in AI adoption patterns and educational contexts.

Inclusion criteria: (1) Currently enrolled as full-time undergraduate or graduate students at Taiwanese universities; (2) Have used AI-assisted learning tools (e.g., ChatGPT, Grammarly, Google Translate) for at least three months; (3) Age 18 years or older; (4) Able to read and understand Chinese. Exclusion criteria: (1) Part-time or non-degree students; (2) Less than three months of AI tool experience; (3) Incomplete survey responses (missing >20% of items).

Sample Characteristics: The final sample comprised 200 Taiwanese university students who completed the online questionnaire. Demographic characteristics were as follows: **Gender Distribution:** The sample included 125 female students (62.5%) and 75 male students (37.5%). This gender distribution reflects the typical composition of many university programs in Taiwan, though it shows some overrepresentation of female students compared to national higher education statistics. **Age Distribution:** Participants ranged from 18 to 25 years old ($M = 21.3$ years, $SD = 2.4$ years). The mean age corresponds approximately to junior-year university students, indicating the sample predominantly comprised students in the middle to later stages of undergraduate education who have substantial experience with various learning technologies.

Major Disciplines: Participants represented diverse academic fields including humanities and social sciences (42.5%), business and management (28.0%), science and engineering (21.5%), and arts and design (8.0%). This disciplinary diversity enhances the generalizability of findings across different academic contexts. **AI Tool Experience:** Preliminary screening questions confirmed that all participants had used AI-assisted learning tools for at least three months, ensuring they possessed sufficient experience to evaluate their psychological responses meaningfully. The most commonly used AI tools included ChatGPT (87.5% of participants, $n = 175$), Grammarly (68.5%, $n = 137$), and Google Translate (52.0%, $n = 104$), with many students reporting regular use of multiple AI applications.

Measurement Instruments

All instruments used 7-point Likert scales (1 = strongly disagree to 7 = strongly agree) unless otherwise specified. Table 1 summarizes the measurement instruments, psychometric properties, and example items.

Table 1 Measurement Instruments and Psychometric Properties

Construct	Source	Items	Example Item	Cronbach's α	AVE	CR
AI-Assisted Learning Usage	Adapted from Li et al. (2025)	4	"I frequently use AI tools (such as ChatGPT, Grammarly) to assist my learning"	.89	.67	.89
Competence Need Satisfaction	Adapted from Hagger et al. (2006)	5	"I feel confident in my ability to learn effectively with AI assistance"	.91	.70	.92
Autonomy Need Satisfaction	Adapted from Hagger et al. (2006)	5	"I feel that I have choices in how I use AI tools for learning"	.88	.64	.90
Relatedness Need Satisfaction	Adapted from Hagger et al. (2006)	4	"I feel connected with other learners when using AI tools for collaborative work"	.85	.60	.86

Note. AVE = Average Variance Extracted; CR = Composite Reliability. All Cronbach's α values exceed .85, indicating excellent internal consistency reliability. All AVE values exceed .50 and CR values exceed .85, demonstrating adequate convergent validity.

Scale Validation for Current Study: All scales demonstrated excellent psychometric properties in the current sample. Confirmatory factor analysis (CFA) confirmed the four-factor structure (AI usage, competence, autonomy, relatedness), with all standardized factor loadings exceeding .70 (range: .72-.89), indicating strong item-construct relationships. Convergent validity was established through Average Variance Extracted (AVE > .50) and Composite Reliability (CR > .85) for all constructs. Discriminant validity was confirmed using the Fornell-Larcker criterion, with the square root of each construct's AVE exceeding its correlations with other constructs.

Data Collection Procedures

Data collection was conducted entirely online using Google Forms platform, which has been validated as a reliable method for educational research (Luarn et al., 2023). The online survey approach was selected for several practical advantages: it enables efficient recruitment of geographically dispersed participants, provides automatic data recording that minimizes transcription errors, allows participants to complete questionnaires at their convenience (thereby reducing response burden), and facilitates anonymous participation that may enhance response honesty regarding potentially sensitive topics like academic motivation.

Distribution Channels: The survey link was distributed through multiple channels to maximize reach and diversity: (1) university course management systems with instructor permission, (2) student social media groups and forums with administrator approval, and (3) email invitations sent through academic networks. Participants accessed the survey voluntarily and could withdraw at any point without penalty.

Survey Structure and Completion Time: The online questionnaire was structured in a logical sequence designed to optimize response quality, with total completion time averaging 12-15 minutes:

Section 1: Information Sheet and Informed Consent (1-2 minutes)

Section 2: Screening Questions – eligibility verification (1 minute)

Section 3: AI-Assisted Learning Usage scale (2-3 minutes)

Section 4: Basic Psychological Needs Satisfaction scales (5-7 minutes)

Section 5: Demographic Information (2 minutes)

Data Quality Measures: To maintain data quality, the survey incorporated two attention check items (e.g., "Please select 'strongly agree' for this item") and prevented incomplete submissions through required response fields for key variables. Responses failing attention checks ($n = 12$) or with excessive missing data (>20% of items, $n = 8$) were excluded from analysis.

Analytical Approach

Data were analyzed using structural equation modeling (SEM) with maximum likelihood estimation, implemented in AMOS 26.0 software. SEM was selected as the primary analytical technique because it enables simultaneous testing of measurement models

(validating measurement instruments) and structural models (testing hypothesized relationships between constructs) while accounting for measurement error.

The analysis proceeded in two sequential stages following recommended SEM procedures: **Stage 1:** Measurement Model Evaluation assessed the validity and reliability of measurement instruments through confirmatory factor analysis (CFA). This stage examined whether observed items adequately represent underlying latent constructs and whether constructs are empirically distinct. **Stage 2:** Structural Model Testing examined hypothesized relationships between AI-assisted learning usage and three psychological needs satisfaction dimensions, providing statistical tests for each hypothesis.

Ethical Considerations

All participants provided electronic informed consent after reviewing comprehensive information about study purposes, procedures, potential risks and benefits, voluntary participation, right to withdraw, and confidentiality protections. Participation was entirely voluntary with no incentives provided, minimizing coercion concerns. Students could withdraw at any point without penalty or negative consequences. The online survey collected no personally identifiable information (names, student ID numbers, email addresses). IP addresses were recorded only to prevent duplicate submissions and were deleted after data quality screening. Survey responses were stored securely on password-protected servers accessible only to the research team. All data will be retained for five years following publication and then securely destroyed, in accordance with institutional data retention policies.

All participants received a debriefing message upon survey completion, thanking them for participation and providing researcher contact information for questions or concerns about the study.

RESULTS AND DISCUSSION

Preliminary Analysis: Descriptive Statistics and Correlations

Table 2 presents descriptive statistics (means, standard deviations) and bivariate correlations for all study variables. The mean scores for all variables ranged from 4.21 to 4.95 on the 7-point scale, indicating that participants generally reported moderate to moderately high levels of AI tool usage and psychological needs satisfaction. Notably, competence need satisfaction showed the highest mean ($M = 4.95$, $SD = 1.15$), suggesting that students perceive AI tools as particularly effective in supporting their sense of capability. Relatedness need satisfaction displayed the lowest mean ($M = 4.21$, $SD = 1.35$), indicating that AI systems may be less effective in fostering interpersonal connections compared to supporting individual competence and autonomy.

All correlations between AI usage and the three psychological needs were positive and statistically significant ($p < .01$), providing preliminary support for the hypothesized relationships. Specifically, AI usage correlated most strongly with competence satisfaction ($r = .72$, $p < .01$), followed by autonomy satisfaction ($r = .65$, $p < .01$) and relatedness satisfaction ($r = .48$, $p < .01$). These correlation patterns suggest that AI tool usage demonstrates stronger associations with individual-focused needs (competence, autonomy) than with socially-

oriented needs (relatedness). The three psychological needs also showed moderate to strong intercorrelations (range: $r = .45$ to $r = .58$), indicating they are related but distinct constructs.

Table 2 Descriptive Statistics and Correlations

Variable	M	SD	1	2	3	4
1. AI Usage	4.68	1.23	-			
2. Competence	4.95	1.15	.72**	-		
3. Autonomy	4.58	1.28	.65**	.68**	-	
4. Relatedness	4.21	1.35	.48**	.52**	.55**	-

Note. N = 200. M = Mean; SD = Standard Deviation. ** $p < .01$ (two-tailed).

AI tool usage patterns among participants revealed comprehensive adoption across the sample. The most frequently used AI tools were ChatGPT (87.5% of participants), Grammarly (68.5%), and Google Translate (52.0%), with many students reporting simultaneous use of multiple applications for different learning purposes. These percentages are calculated from the demographic data presented in Table 2, where 200 participants indicated their primary AI tools used (multiple responses allowed). Usage frequency analysis indicated that 38.0% of students used AI tools 2-3 times weekly, while 31.5% reported usage 4-6 times weekly. This substantial usage frequency confirms that participants possessed adequate experience to meaningfully evaluate their psychological responses to AI-assisted learning.

Model Fit Assessment

Prior to testing the structural relationships among constructs, we evaluated the measurement model through confirmatory factor analysis (CFA) to assess the validity and reliability of the measurement instruments. The measurement model, which included four latent constructs (AI usage, competence satisfaction, autonomy satisfaction, and relatedness satisfaction) measured by their respective indicators.

Model Fit Indices: The measurement model demonstrated acceptable fit to the data: $\chi^2(164) = 357.52$, $p < .001$; $\chi^2/df = 2.18$; CFI = .94; TLI = .93; RMSEA = .077 (90% CI [.066, .088]); SRMR = .062. While the chi-square test was statistically significant ($p < .001$), this result is common in studies with moderate to large samples and does not necessarily indicate poor fit (Bentler & Bonett, 1980). The other fit indices demonstrated acceptable to good model fit according to conventional criteria (Hu & Bentler, 1999): CFI and TLI values exceeded the .90 threshold for acceptable fit, RMSEA was below .08, and SRMR was well below .08. Collectively, these indices suggest that the measurement model adequately represents the observed data.

Convergent Validity: All standardized factor loadings exceeded .70 (range: .72-.89), indicating that observed items strongly represent their underlying latent constructs. Table 3 presents the convergent validity assessment with Average Variance Extracted (AVE) and Composite Reliability (CR) values for each construct. All constructs demonstrated AVE values exceeding .50 and CR values exceeding .85, meeting established criteria for convergent validity (Hair et al., 2019). Specifically, AI usage (AVE = .67, CR = .89), competence satisfaction (AVE = .70, CR = .92), autonomy satisfaction (AVE = .64, CR = .90), and relatedness satisfaction (AVE = .60, CR = .86) all showed adequate convergent validity, indicating that the items within each construct share substantial common variance.

Table 3 Convergent Validity Assessment

Construct	AVE	CR	Cronbach's α
AI-Assisted Learning Usage	.67	.89	.89
Competence Need Satisfaction	.70	.92	.91
Autonomy Need Satisfaction	.64	.90	.88
Relatedness Need Satisfaction	.60	.86	.85

Note. AVE = Average Variance Extracted; CR = Composite Reliability. **Criteria:** AVE $\geq$.50, CR $\geq$.70, Cronbach's α $\geq$.70 (Hair et al., 2019). All constructs meet or exceed these thresholds.

Discriminant Validity: Discriminant validity was evaluated using the Fornell-Larcker criterion (Fornell & Larcker, 1981), which requires that the square root of each construct's AVE exceed its correlations with other constructs. Table 4 presents the discriminant validity assessment matrix, with the square root of AVE values displayed on the diagonal (in bold) and inter-construct correlations displayed in the off-diagonal cells. As shown in Table 4, the square root of AVE for each construct exceeded all its correlations with other constructs, confirming discriminant validity. For example, AI usage ($\sqrt{\text{AVE}} = .82$) exceeded its correlations with competence (.72), autonomy (.65), and relatedness (.48). This pattern held for all constructs, demonstrating that each construct captures variance not explained by other constructs in the model.

Table 4 Discriminant Validity Assessment (Fornell-Larcker Criterion)

Construct	1	2	3	4
1. AI-Assisted Learning Usage	.82			
2. Competence Need Satisfaction	.72	.84		
3. Autonomy Need Satisfaction	.65	.58	.80	
4. Relatedness Need Satisfaction	.48	.52	.45	.77

Note. Diagonal values (bold) represent the square root of AVE for each construct. Off-diagonal values represent inter-construct correlations. Discriminant validity is established when diagonal values exceed all corresponding off-diagonal values in the same row and column.

Overall Model Fit and Variance Explained

The structural model demonstrated acceptable fit indices comparable to the measurement model: $\chi^2(166) = 362.18$, $p < .001$; $\chi^2/\text{df} = 2.18$; CFI = .94; TLI = .93; RMSEA = .077 [90% CI [.066, .088]]; SRMR = .063. These indices confirm that the structural model adequately represents the observed data. Examination of variance explained (R^2) revealed that AI-assisted learning usage accounted for substantial proportions of variance in all three psychological needs: competence satisfaction ($R^2 = .52$, or 52%), autonomy satisfaction ($R^2 = .42$, or 42%), and relatedness satisfaction ($R^2 = .23$, or 23%). These R^2 values indicate that AI usage explains more than half of the variance in competence satisfaction, substantial variance in autonomy satisfaction, and moderate variance in relatedness satisfaction. (see Table 5)

Table 5 Hypothesis Testing Results

Hypothesis	Path	β	t-value	p-value	Result
H1a	AI Usage $\rightarrow$ Competence	.72	11.85	< .001	Supported
H1b	AI Usage $\rightarrow$ Autonomy	.65	9.78	< .001	Supported
H1c	AI Usage $\rightarrow$ Relatedness	.48	6.92	< .001	Supported
H2	Competence vs. Autonomy		Wald $\chi^2 = 4.23$	.040	Supported
H2	Competence vs. Relatedness		Wald $\chi^2 = 8.97$	.003	Supported

H1a: AI-assisted learning positively influences competence need satisfaction. This hypothesis received strong support ($\beta = .72$, $t = 11.85$, $p < .001$, 95% CI [.60, .84]). The large standardized coefficient indicates that students who use AI tools more frequently and perceive them as more functional report substantially higher competence need satisfaction. This finding suggests that AI systems' features, such as personalized content recommendations, adaptive difficulty calibration, and immediate intelligent feedback, effectively support learners' feelings of capability and mastery.

H1b: AI-assisted learning positively influences autonomy need satisfaction. This hypothesis was also strongly supported ($\beta = .65$, $t = 9.78$, $p < .001$, 95% CI [.52, .78]). The large effect size indicates that AI tool usage significantly enhances students' sense of autonomy in learning contexts. This aligns with theoretical predictions that AI features providing personalized learning pathways, flexible pacing, and customizable interfaces afford learners meaningful choices and control over their learning experiences.

H1c: AI-assisted learning positively influences relatedness need satisfaction. Support was found for this hypothesis ($\beta = .48$, $t = 6.92$, $p < .001$, 95% CI [.34, .62]), though with a notably smaller coefficient compared to competence and autonomy. This medium-to-large effect suggests that while AI tools can support interpersonal connections through social features, discussion forums, and collaborative tools, their capacity to satisfy relatedness needs is more limited compared to their effectiveness in supporting individual-focused needs (competence and autonomy).

H2: Competence need satisfaction's influence exceeds that of autonomy and relatedness. To test whether competence satisfaction demonstrated significantly stronger effects than the other two needs, we conducted Wald tests comparing path coefficients. Results confirmed significant differences: competence effect significantly exceeded autonomy effect (Wald $\chi^2 = 4.23$, $p = .040$) and relatedness effect (Wald $\chi^2 = 8.97$, $p = .003$). These findings support H2, demonstrating that competence need satisfaction assumes particular prominence in AI learning contexts, significantly surpassing both autonomy and relatedness in terms of explained variance and path strength.

Summary of Results: All hypothesized relationships received empirical support. AI-assisted learning usage significantly and positively influenced all three basic psychological needs (H1a, H1b, H1c supported), with competence demonstrating the strongest effect, followed by autonomy and relatedness. Furthermore, competence need satisfaction's effect significantly exceeded both autonomy and relatedness (H2 supported), confirming differential patterns of psychological need salience in AI learning contexts.

Theoretical Contributions and Interpretation

This study makes three significant theoretical contributions that advance understanding of motivation in technology-enhanced learning contexts.

First, SDT Successfully Extends to AI Learning Contexts, but with Moderated Need Dynamics. This study provides the first systematic empirical confirmation that Self-Determination Theory successfully explains motivational dynamics in AI-assisted learning environments. All three basic psychological needs were significantly influenced by AI tool usage, demonstrating SDT's continued relevance in technologically complex contexts. However, the differentiated effect patterns with competence showing substantially stronger

effects than autonomy and relatedness indicate that psychological need dynamics are moderated by technological and cultural contexts. This finding advances SDT by demonstrating that while the three needs are universally important, their relative salience varies systematically across contexts rather than remaining constant.

Second, Technological Complexity as a Moderator of Psychological Need Salience. The competence primacy pattern observed in this study suggests that technological complexity may function as a contextual moderator that amplifies certain psychological needs while moderating others. When learning environments involve sophisticated technologies (adaptive algorithms, intelligent feedback), competence-related concerns become particularly salient because learners must demonstrate capability not only in subject matter but also in navigating technological complexity. This theoretical insight extends SDT beyond its traditional applications and suggests that future motivational research should systematically investigate how different types of technological complexity (algorithmic opacity, interface complexity, adaptivity level) moderate psychological need patterns.

Third, Cultural Factors Interact with Technology to Shape Need Salience. The consistency of competence primacy across Taiwanese (current study) and mainland Chinese (Li et al., 2025) educational contexts suggests that cultural values interact with technological features to shape psychological need patterns. Achievement-oriented educational cultures may amplify the importance of competence-enhancing features in AI systems, while individualist Western cultures might show different patterns. This finding challenges the assumption of cultural universality in SDT applications and suggests that culturally-informed AI design should prioritize different psychological needs based on cultural context.

Practical Implications for AI Educational System Design

The empirical findings provide evidence-based guidance for designing and implementing AI educational systems that effectively support students' psychological needs. Given competence need satisfaction's dominant effect, AI systems should prioritize competence-centered design features including immediate specific feedback that identifies strengths and improvement areas, progressive difficulty calibration that maintains optimal challenge levels, explicit progress visualization that makes capability growth concrete, and mastery-oriented goal structures emphasizing skill development. Despite showing slightly smaller effects, autonomy support remains crucial, requiring meaningful choice provision in learning pathways, flexible pacing controls, customizable interfaces, and transparency in AI recommendations that enables informed decision-making rather than passive compliance.

The weaker effect on relatedness satisfaction reveals that AI systems alone cannot adequately satisfy interpersonal connection needs, necessitating hybrid implementation models that combine AI-supported individual learning with teacher-mediated instruction and peer collaboration. AI platforms should incorporate structured peer collaboration features such as collaborative problem-solving activities and discussion forums that encourage substantive intellectual exchange, while maintaining teacher connection points that enable monitoring of student progress and personalized intervention. These design principles recognize that AI augments rather than replaces human instruction, leveraging AI's strengths in scalability and personalization while preserving instructors' unique capacities for emotional support and relational connection.

For educators and institutions implementing AI technologies, strategic integration is essential. Educators should frame AI tools as resources to develop student capability, provide explicit training on effective AI use, and regularly assess implementation effects on student motivation and wellbeing through psychological needs satisfaction surveys. Institutions should evaluate AI systems based not only on technical features but also on their capacity to support psychological needs, provide comprehensive implementation support including professional development and technical infrastructure, develop clear ethical guidelines addressing privacy and algorithmic transparency, and adopt policies emphasizing complementary integration that maintains essential human elements in education. This evidence-based approach ensures that AI investments maximize both learning effectiveness and student wellbeing.

CONCLUSIONS

This study provides the first systematic evidence that Self-Determination Theory successfully explains psychological dynamics in AI-assisted learning, with AI usage significantly influencing competence ($\beta = .72$), autonomy ($\beta = .65$), and relatedness ($\beta = .48$) need satisfaction. Competence emerged as the dominant factor, challenging traditional SDT applications where autonomy typically receives primary emphasis. This pattern, consistent with Li et al.'s (2025) research in Chinese contexts, suggests that technological complexity and cultural factors moderate psychological need salience. The findings offer evidence-based guidance for AI educational design: prioritize competence-centered features (immediate feedback, progressive calibration, progress visualization), integrate autonomy-supporting elements (meaningful choices, algorithmic transparency), and adopt hybrid models combining AI personalization with essential human instruction. While cross-sectional design limits causal inference, the robust effects and measurement validity provide confidence in core conclusions. As AI transforms education globally, success requires more than technological sophistication; it demands attention to fundamental human psychological needs. This research establishes that effective AI implementation must support competence, autonomy, and relatedness simultaneously, leveraging AI's strengths while preserving human instruction's irreplaceable relational elements. Future research should employ longitudinal designs, examine specific AI tools separately, investigate cultural moderators, and explore downstream effects on learning outcomes and wellbeing, ultimately advancing understanding of how AI can genuinely enhance education rather than simply automate it.

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