

UNLOCKING STUDENT ENGAGEMENT WITH GENERATIVE AI: NEED SATISFACTION AS THE KEY, SELF-EFFICACY AS THE GATEKEEPERYuXuan Xin¹*Mohd Shahril Nizam Shaharom¹Kenny Cheah Soon Lee¹

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Abstract: Understanding how learning environments support student engagement requires attention to the motivational processes through which learners internalize instructional resources. Drawing on Self-Determination Theory, this study examines whether perceived affordances of AI-supported learning environments promote students' classroom engagement through psychological need satisfaction, and whether students' AI self-efficacy conditions this process. Survey data were collected from 389 undergraduates and analyzed using structural equation modeling. The results indicate that perceived AI affordances positively predict behavioral, cognitive, and emotional engagement indirectly via enhanced need satisfaction, with the strongest indirect effect observed for cognitive engagement ($\beta = 0.385$). In addition, AI self-efficacy modestly strengthened the relationship between perceived affordances and need satisfaction, suggesting a meaningful boundary condition in the motivational process. These findings clarify how and for whom supportive learning environments foster engagement, highlighting the central role of psychological need satisfaction in translating contextual resources into sustained classroom involvement. From an instructional perspective, the study highlights the importance of designing learning environments, rather than focusing solely on technologies, that effectively support students' autonomy, competence, and relatedness.

Keywords: AI affordances, student engagement, need satisfaction, SEM, AI self efficacy.

INTRODUCTION

In recent years, generative artificial intelligence (Gen-AI) has moved rapidly into university classrooms and become part of students' routine academic practices. Existing research has largely focused on whether students use AI tools, the factors influencing their intentions, and the types of tasks completed with systems such as ChatGPT (Cotton et al., 2024; Lo et al., 2024). However, much less attention has been given to a fundamental pedagogical question: Does the growing presence of AI actually enhance students' engagement in learning? Without contributing to meaningful engagement, AI risks becoming yet another "technologically impressive but educationally superficial" innovation with limited instructional value.

Student engagement, including behavioral, cognitive, and emotional dimensions, is widely regarded as a key indicator of instructional quality and an important predictor of academic outcomes (Fredricks et al., 2005). Although digital technologies in higher education have demonstrated potential to enhance engagement, much of the existing work has concentrated on short-term motivation, learner attitudes, or performance on isolated tasks rather than on sustained engagement in authentic classroom settings (Bond et al., 2020; Chiu, 2021). In the context of generative artificial intelligence, most studies have similarly focused on students' usage intentions and motivational perceptions, providing limited understanding of whether and how AI contributes to engagement within classroom learning activities (Crompton et al., 2024; Lo et al., 2024). As Gen-AI becomes more deeply integrated into university teaching and learning, clarifying its actual influence on students' classroom involvement has become increasingly essential.

To understand how AI enhances engagement, this study focuses on AI affordances (AIAs), defined as the perceived possibilities for action that learners identify when interacting with AI systems (Fu et al., 2020; Zhang et al., 2024). Existing research has classified AIAs into dimensions such as interactivity, personalization, social presence, and convenience (Wang & Chuang, 2024; Xu & Li, 2024), and has shown that they can promote motivation, reduce anxiety, enhance flow experiences, and strengthen continued usage intentions (Cui et al., 2025;

Jeon, 2024; Zhang et al., 2024). Further studies have reported that AIAs positively influence behavioral, cognitive, and emotional engagement (Huang et al., 2025; Xu & Li, 2024). However, as Crompton (2024) highlights, most of these studies remain at the outcome level, offering limited insight into the psychological mechanisms through which AIAs shape engagement. This gap constrains theoretical advancement and limits evidence-based instructional design.

Self-Determination Theory (SDT) posits that students engage more deeply and persistently in learning when their fundamental needs for autonomy, competence, and relatedness are adequately supported (Reeve, 2012). From this perspective, AI affordances such as adaptive guidance, immediate feedback, and interactive assistance can function as need-supportive features that enhance learners' psychological fulfillment, subsequently promoting behavioral, cognitive, and emotional engagement in classroom environments. Although prior studies have shown that AI-based learning activities can facilitate need satisfaction (Chiu, 2022; Li et al., 2025; Xia et al., 2023), there remains limited empirical evidence on how AI affordances lead to heightened classroom engagement by fostering students' psychological need fulfillment within higher education settings.

Moreover, the effectiveness of AIAs is likely to differ across learners. Although prior studies have examined moderators such as gender or engagement profiles (Huang et al., 2025; Xu and Li, 2024), they have paid relatively little attention to AI self-efficacy (ASE), which refers to students' confidence in their ability to use AI tools effectively (Wang & Chuang, 2024). Existing research indicates that ASE can function as both a mediator and a moderator in AI-supported learning processes (Kong et al., 2025; Yi & Siquan, 2025); however, it is still predominantly conceptualized as a mediating psychological factor rather than as a boundary condition that shapes how learners interpret and benefit from technological affordances (Cui et al., 2025; Zhang et al., 2024). As a result, empirical evidence remains limited regarding whether ASE influences the extent to which AIAs are internalized as psychological need support—an essential step in the mechanism linking AI affordances to classroom engagement. Although previous studies demonstrate that ASE affects motivational and behavioral outcomes in AI-enhanced environments (Chen et al., 2025; Kim & Kim, 2024; Liu et al., 2024), its moderating role in the relationships among AIAs, need satisfaction, and engagement has not been sufficiently examined.

In light of these gaps, this study addresses three core research questions. First, it examines whether AI affordances significantly promote classroom engagement, thereby extending the antecedents of engagement and expanding the documented outcomes of AI-supported learning. Second, it investigates how AIAs influence engagement through psychological need satisfaction, revealing the motivational mechanism underlying AI-supported classroom involvement. Third, it explores whether the effects of AIAs vary according to students' AI self-efficacy, thereby identifying boundary conditions that determine for whom AI is most effective. Together, these questions integrate the whether, how, and when dimensions into a unified framework and clarify both the mechanisms and contingencies of AI-supported classroom engagement.

LITERATURE REVIEW

AI Affordance

In educational technology research, AI affordance (AIA) refers to the actionable possibilities that learners perceive when interacting with AI systems. The concept is grounded in Gibson's affordance theory (Gibson, 1979, 2014), which emphasizes how individuals recognize potential actions enabled by technological features. Building on this foundation, Leonardi (2011) highlighted that affordances arise from the interplay between system attributes and users' goals, while Hammond (2010) extended the notion to ICT education, underscoring the interactional nature of learner–technology relationships. Al-Maawali (2020) further argued that educational affordances support self-directed learner engagement. Within AI-enhanced learning contexts, AIA specifically denotes learners' perceived opportunities for use offered by AI tools (Fu et al., 2020; Zhang et al., 2024a), reflecting how AI systems make particular forms of learning activity possible.

In educational research, scholars have proposed various categorizations of AIAs. Xu and Li (2024) identified four key dimensions: interactivity, personalization, social presence, and convenience. Zhan et al. (2024) highlighted affordances related to adaptive learning, real-time feedback, and collaborative assistance. Similarly, Wang et al. (2024), through a systematic review, outlined accessibility, personalization, automation, and interactivity as the principal technological affordances of generative AI in education. Collectively, these classifications capture the

fundamental capabilities of AI systems and underscore their capacity to enhance learners' motivation and engagement.

In recent years, scholarly interest in AI affordances (AIAs) has grown rapidly, yet much of the existing work continues to emphasize technology use and learner motivation. For instance, Jeon (2024) reported that AIAs create new opportunities for language learning while simultaneously introducing challenges such as feedback reliability and increased cognitive load. Zhang et al. (2024) showed that AIAs can promote flow experiences and self-expansion, thereby reducing speaking anxiety and strengthening learners' intention to continue using AI tools. Likewise, Cui et al. (2025) found that digital literacy plays a significant role in shaping how students translate perceived AIAs into motivated learning behaviors, with foreign language enjoyment further amplifying this effect. Despite these insights, prior research has predominantly focused on AI usage patterns and motivational outcomes, offering a limited understanding of how AIAs contribute to more central learning processes such as student engagement.

Recent studies have increasingly examined how AI affordances relate to student engagement. Xu and Li (2024) found that AIAs can enhance learners' behavioral, cognitive, and emotional engagement, with particularly pronounced benefits for students who initially exhibited low levels of engagement. Similarly, Huang et al. (2025) reported positive effects across multiple engagement dimensions, noting that gender differences further shaped several of these pathways. Despite these findings, Crompton (2024) highlighted that most existing research remains largely descriptive and focuses on engagement outcomes rather than the underlying motivational processes. As a result, the field still lacks a clear understanding of the psychological mechanisms through which AI-supported learning environments foster engagement, limiting both theoretical progress and the ability of educators to design evidence-based AI-enhanced instructional practices. This gap becomes even more pressing as AI technologies are increasingly integrated into everyday classroom activities.

Student Engagement

Student engagement (SE) is widely acknowledged in educational research as a fundamental construct and a strong predictor of both learning outcomes and academic success (Fredricks et al., 2005). It is broadly defined as the behavioral, emotional, and cognitive resources that students invest in the learning process, reflecting their effort, affective attitudes, and cognitive processing levels. Specifically, behavioral engagement typically refers to attendance, attention, and task completion; EE encompasses interest, enjoyment, and affective involvement in learning activities; and CE emphasizes strategy use, deep processing, and self-regulation during learning (Reeve, 2012).

With the ongoing advancement of educational technology, scholars have increasingly explored how digital learning environments can enhance student engagement. For instance, gamification strategies (e.g., immediate feedback, competition, and reward mechanisms) have been shown to improve behavioral and emotional engagement (Sailer & Homner, 2020). Building on this line of work, recent developments in artificial intelligence have broadened the landscape of engagement research. A systematic review of 72 empirical studies by Lo et al. (2024) reported that learning environments incorporating ChatGPT generally produce mid-level gains in student engagement. Their analysis showed moderate enhancements in behavioral and emotional engagement, alongside comparatively larger effects on cognitive engagement.

Systematic evidence indicates that AI-supported learning applications primarily target the behavioral, cognitive, and emotional dimensions of engagement. For instance, intelligent tutoring systems, natural language processing tools, and chatbots have been widely adopted to stimulate motivation and enhance participation (Chen et al., 2025). AI-driven personalized learning platforms further strengthen engagement by providing individualized pathways through functions such as instant feedback, microlearning, intelligent recommendation, and virtual assistants (Nguyen et al., 2024). However, most studies have focused on the overall impact of AI on engagement, with limited attention to the specific mechanisms through which AIAs influence SE (Xu & Li, 2024). Beyond serving as a key learning outcome, SE offers important insight into how technologies, particularly AIAs, shape learning processes. Clarifying the relationship between AIAs and SE is therefore essential for identifying which AI features genuinely support meaningful engagement and for guiding more purposeful instructional design.

THEORY AND HYPOTHESIS DEVELOPMENT

Self-Determination Theory

Self-Determination Theory (SDT), introduced by Deci and Ryan (1985), serves as a central motivational perspective that emphasizes the importance of fulfilling basic psychological needs to foster intrinsic motivation and optimal functioning. SDT proposes that people have an inherent tendency toward growth and engagement, which is sustained when their needs for autonomy, competence, and relatedness are adequately met. When these needs are satisfied, learners are more likely to internalize learning behaviors, display stronger motivation, and participate actively in meaningful activities. Conversely, when these needs are thwarted, individuals may experience reduced engagement and lower levels of psychological well-being (Deci & Ryan, 2000).

SDT provides the theoretical grounding for the present study. In AI-assisted learning environments, AIAs such as personalization, feedback, and interactivity function as external supports that help learners satisfy key psychological needs, especially competence and autonomy. When these needs are met, students tend to show higher behavioral, cognitive, and emotional engagement. ASE further serves as a boundary condition that shapes how effectively learners perceive and utilize these affordances. Students with stronger confidence in using AI tools are therefore more likely to benefit from AIAs, experience greater need satisfaction, and subsequently engage more actively in learning. Overall, the proposed model aligns with SDT by illustrating how technological features, psychological needs, and individual differences jointly shape student engagement (Ryan & Deci, 2020).

AIA and SE: the mediating role of NS

The multidimensional features of AIAs provide critical pathways for satisfying learners' basic psychological needs. Chiu (2021), through a Delphi study, developed a classification tool encompassing 20 ChatGPT-supported learning activities and examined the extent to which these activities addressed students' three basic psychological needs. The findings revealed that functions such as instant feedback, answer checking, and example generation primarily enhanced competence, as they helped learners confirm understanding, build confidence, and master tasks. Meanwhile, flexible writing assistance, outline generation, and learning pace control significantly promoted autonomy, enabling learners to pursue learning in alignment with personal goals and rhythms. In terms of relatedness, human-like dialogue, simulated debates, and collaborative tasks were found to foster a sense of social connectedness. Similarly, Xia et al. (2023), through experimental research in K–12 AI education, demonstrated that need-supportive teaching practices grounded in SDT (covering autonomy, competence, and relatedness) enhanced students' learning involvement and cognition across different genders and ability levels. Furthermore, Li et al. (2025b), using network analysis, identified competence NS as the most central and influential factor in the motivational structure, surpassing both autonomy and relatedness. Taken together, these studies support the pathway from AIAs to NS, underscoring its foundational role in AI-enhanced learning contexts.

Based on the above reasoning, the following hypotheses are proposed:

H1. AI Affordances positively predict Need Satisfaction.

Self-Determination Theory (SDT) proposes that students demonstrate stronger and more persistent engagement when their core psychological needs for autonomy, competence, and relatedness are met (Deci & Ryan, 2000). When learners experience such need fulfillment, they tend to show higher behavioral involvement (e.g., completing tasks actively), employ deeper and more strategic cognitive approaches, and report greater emotional interest and enjoyment. A substantial body of research has documented this relationship. For instance, Chiu (2022) showed that digital support provided through a learning management system better satisfied students' basic needs than traditional instructional methods, which in turn improved various types of engagement. Emerging evidence indicates that similar mechanisms operate in AI-enhanced learning settings. Studies on generative AI chatbot environments reveal that psychological need fulfillment significantly predicts engagement across behavioral, cognitive, and emotional domains (Zhang et al., 2024). Overall, these studies underscore SDT's assertion that need satisfaction represents a critical foundation for fostering robust and enduring student engagement.

Together, these insights lead to the following hypotheses:

H2a. Need Satisfaction positively predicts Behavioral Engagement.

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H2b. Need Satisfaction positively predicts Cognitive Engagement.

H2c. Need Satisfaction positively predicts Emotional Engagement.

H3a. Need Satisfaction mediates the relationship between AI Affordances and Behavioral Engagement.

H3b. Need Satisfaction mediates the relationship between AI Affordances and Cognitive Engagement.

H3c. Need Satisfaction mediates the relationship between AI Affordances and Emotional Engagement.

Mediating Role of AI Self-efficacy

Self-efficacy, as conceptualized by Bandura (1997), concerns individuals' confidence in executing tasks effectively. In AI-enhanced learning contexts, AI self-efficacy (ASE) can be defined as students' perceived skills, confidence, and competence when using AI tools such as ChatGPT or DeepSeek. High levels of ASE imply that students believe they can effectively operate AI tools and resolve related challenges, thereby maximizing the value of AIA. Conversely, low self-efficacy may prevent students from leveraging AIA, thereby limiting the satisfaction of their psychological needs. Drawing on Social Cognitive Theory (SCT), individual behavior is determined not only by external environmental conditions but also by self-efficacy beliefs (Bandura, 1997). Thus, ASE may constitute a key psychological resource determining whether learners can fully benefit from AI-supported environments.

Previous research has explored ASE predominantly as either a mediating mechanism or a moderating variable within AI-supported learning contexts. For example, Kong et al. (2025) identified ASE as the explanatory link between students' AI literacy and their motivational commitment. Its moderating function is also well documented. Liu et al. (2024) found that AI efficacy determined the extent to which exposure to AI-related information translated into AI discussion, improved literacy, and policy-related attitudes. Similarly, Kim and Kim (2024) reported that strong AI-learning self-efficacy mitigated the detrimental effects of work overload on psychological contract breach. Chen et al. (2025) further showed that ASE strengthened the progression from AI learning anxiety to active learning motivation, suggesting that students with higher efficacy beliefs are better equipped to convert anxiety into constructive learning engagement.

Although existing research has demonstrated the mediating and moderating roles of ASE in motivational and behavioral pathways, its boundary effect within the AIA → NS relationship remains underexplored. Prior studies (Li & Lin, 2025; Li et al., 2025) suggest that AI tools may either support or frustrate learners' psychological needs in different contexts, particularly when students lack confidence or encounter usage barriers. This suggests that the extent to which AIAs promote need satisfaction may vary according to learners' self-efficacy levels. Drawing on Social Cognitive Theory, ASE functions as a psychological capability that strengthens the influence of AIAs on need satisfaction, whereas insufficient efficacy may limit this effect.

H4. AI Self-efficacy moderates the direct path from AI Affordance to Need Satisfaction.

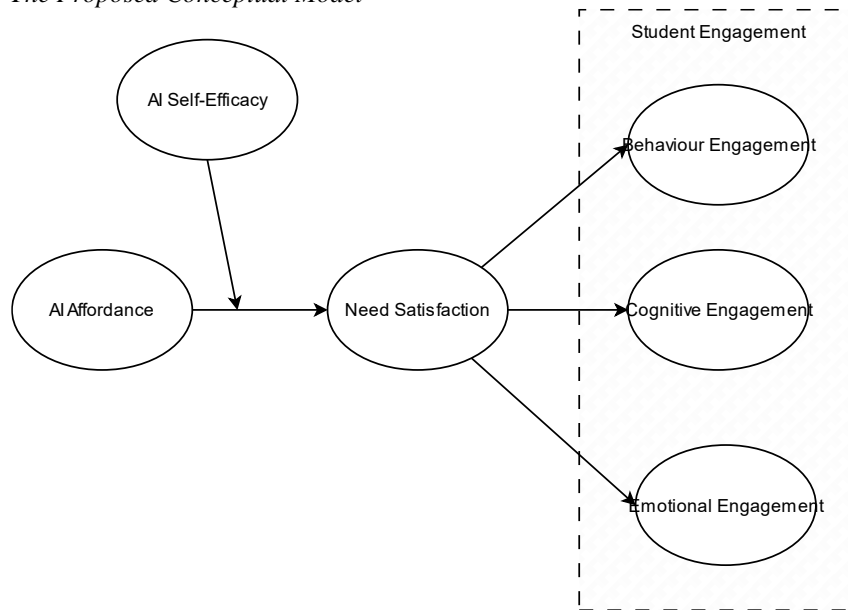
H5a. The indirect effect of AI Affordances on Behavioral Engagement through Need Satisfaction is stronger when AI self-efficacy is higher.

H5b. The indirect effect of AI Affordances on Cognitive Engagement through Need Satisfaction is stronger when AI self-efficacy is higher.

H5c. The indirect effect of AI Affordances on Emotional Engagement through Need Satisfaction is stronger when AI self-efficacy is higher.

METHODOLOGY

Figure 1.
The Proposed Conceptual Model



Instrument

The questionnaire for this study comprised four sections: AIAs, SE, NS, and ASE. The AIAs scale (AIad-S) was adapted from Zhang et al. (2024) and Fu et al. (2020). SE items were adapted from Reeve and Tseng (2011). The NS scale was derived and modified from Van den Broeck et al. (2010). The ASE scale was adapted from Wang and Chuang (2024). Following their recommendations, per Chen (2025), and consistent with the conceptualization adopted in this study, ASE was treated as a single-dimensional construct, as presented in Table 1.

The revised instrument included 40 items distributed across several dimensions. For AI affordances, convenience corresponded to items AI1 to AI4, personalization to items AI5 to AI7, social presence to items AI8 to AI11, and interactivity to items AI12 to AI15. Need satisfaction comprised competence (items 16 to 18), autonomy (items 19 to 21), and relatedness (items 22 to 24). Student engagement consisted of behavioral engagement (items 25 to 28), cognitive engagement (items 29 to 32), and emotional engagement (items 33 to 36). Finally, AI self-efficacy was measured using items 37 to 40.

Before the main study, the questionnaire underwent a pilot test with 30 students and a content validity assessment, both of which confirmed its reliability and validity. To ensure linguistic accuracy and clarity, the research team adopted a translation–back translation procedure. The English items were first translated into Chinese and then back-translated into English. Two applied linguistics experts reviewed the discrepancies, after which revisions were made, and the final Chinese version was prepared for large-scale administration.

Table 1
Questionnaire Structure

Construct	Dimensions (No. of items)	Source(s)
AIAs	Convenience (4), Personalization (3), Social presence (4), Interactivity (4)	Zhang et al. (2024); Fu, Gu, & Yang (2020)
NS	Competence (3), Autonomy (3), Relatedness (3)	Van den Broeck et al. (2010)

SE	Behavioral (4), Cognitive (4), Emotional (4)	Reeve & Tseng (2011)
ASE	_____	Wang and Chuang (2024)

Sampling and Data Collection

This study was carried out at a university in Northeast China that has implemented a campus-wide AI curriculum and integrated multiple AI tools and platforms into its teaching activities. With a diverse student population across various disciplines, the institution provided a suitable context for investigating AI's role in education. To obtain a sample with varied levels of AI experience and academic backgrounds, instructors of AI-related courses assisted with participant recruitment and questionnaire distribution.

A purposive sampling strategy was employed. Prior studies indicate that this approach strengthens the rigor of research design (Sharma, 2017), facilitates participant recruitment and data collection (Campbell et al., 2020), and is commonly used in quantitative studies (Anggraeni & Sole, 2020; Pratama et al., 2020). This cross-sectional study collected data through the Wenjuanxing online platform. Participants were assured of anonymity and confidentiality, yielding 389 valid responses.

Data Analysis

Before conducting the main analyses, the dataset underwent a rigorous quality-control procedure. First, responses submitted in under 60 seconds or with unusually long completion times were discarded, as extreme durations may signal inattentive participation (Leiner, 2019). Second, entries displaying patterned responding (e.g., selecting the same option for many items or producing longstring sequences of 15 or more identical answers) were removed to avoid satisficing or non-differentiated responding (Huang et al., 2012). Third, multivariate anomalies were screened using Mahalanobis distance ($p < .001$) and subsequently excluded. In total, 89 questionnaires were removed through these procedures, leaving 300 valid cases for analysis. Summary statistics for the final sample are reported in Table 2.

The proposed research framework was examined through Partial Least Squares Structural Equation Modeling (PLS-SEM). This analytical technique is well-suited for investigating models that incorporate multiple mediating or moderating pathways. Within educational technology and social science contexts, PLS-SEM is widely adopted because it handles deviations from normality, supports complex latent structures, and provides robust estimates for prediction and explanation. In the present study, PLS-SEM was employed to assess the combined influence of AI affordances, need satisfaction, and AI self-efficacy on students' behavioral, cognitive, and emotional engagement.

Table 2
Demographic Information

variable	category	Frequency	%
Gender	Male	135	45%
	Female	165	55%
Discipline	Arts	117	39%
	Science	183	61%
Frequency	sometimes	162	54%
	Every week	54	18%
	multiple times per week	51	17%
	everyday	33	11%

RESULTS

Measurement Model Results

AIA and NS were treated as second-order reflective constructs through item parceling, whereas BE, CE, EE, and ASE were modeled as first-order reflective constructs. The measurement model demonstrated strong psychometric

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soundness. All indicators loaded above 0.70 (Hair, 2014), confirming adequate item reliability. Composite reliability values ranged from 0.913 to 0.956, and Cronbach's alpha coefficients were all above 0.87, indicating high internal consistency. The AVE values (0.724–0.878) exceeded the recommended threshold of 0.50 (Fornell & Larcker, 1981), providing evidence of convergent validity. Discriminant validity was established using both the Fornell–Larcker criterion, where each construct's AVE square root exceeded its correlations, and the HTMT ratios, all remaining below the conservative 0.90 benchmark (Henseler et al., 2015). To check for common method variance, Harman's single-factor test was conducted, and the largest factor accounted for 41% of the variance, which is below the 50% criterion. This suggests that common method bias was not a substantial concern (Podsakoff et al., 2003).

The model quality was further assessed using explanatory power, predictive ability, and model fit indices. The R^2 values indicate that need satisfaction is strongly explained by its antecedents ($R^2=0.738$, $p < 0.001$), representing substantial explanatory power. In contrast, the explained variance of behavioral engagement ($R^2 = 0.342$, $p < 0.001$), cognitive engagement ($R^2=0.403$, $p < 0.001$), and emotional engagement ($R^2=0.273$, $p < 0.001$) ranges from weak to moderate, which is common in educational psychology research. These results suggest that while AI affordances and self-efficacy account for need satisfaction well, additional factors beyond the present model may influence students' engagement, particularly emotional engagement. The SRMR value was below the recommended threshold of 0.08 (Henseler et al., 2015; Hu & Bentler, 1999), indicating an acceptable model fit.

The PLSpredict results indicated that all Q^2 -predict values were greater than zero, confirming the predictive relevance of the model (Hair et al., 2021). Predictive validity was strong for need satisfaction (Q^2 -predict = 0.645–0.665), moderate to strong for cognitive engagement (0.321–0.377), and moderate for behavioral and emotional engagement (0.218–0.317). Additionally, the CVPAT results demonstrated that the PLS-SEM model significantly outperformed the naïve benchmark model for all endogenous constructs (BE: $\Delta=-0.162$, $t=5.303$, $p < 0.001$; CE: $\Delta = -0.215$, $t=8.176$, $p < 0.001$; EE: $\Delta = -0.160$, $t = 5.510$, $p < 0.001$; NS: $\Delta = -0.295$, $t=10.833$, $p < 0.001$). The overall CVPAT result ($\Delta = -0.202$, $t=8.707$, $p < 0.001$) further confirms the superior predictive validity of the proposed model. Taken together, these findings indicate that the proposed model demonstrates strong explanatory power, predictive relevance, and satisfactory model fit.

Table 3
The Convergent and Discriminant Validity Test

Construct	Item	loadings	VIF	Cronbach's alpha	rho_a	CR	AVE
ASE	ASE1 <- ASE	0.892	2.855	0.922	0.922	0.945	0.81
	ASE2 <- ASE	0.897	3.16				
	ASE3 <- ASE	0.919	3.849				
	ASE4 <- ASE	0.891	3.021				
BE	BE1 <- BE	0.819	1.906	0.897	0.903	0.929	0.766
	BE2 <- BE	0.924	3.757				
	BE3 <- BE	0.857	2.401				
	BE4 <- BE	0.896	3.151				
CE	CE1 <- CE	0.905	3.215	0.926	0.927	0.947	0.818
	CE2 <- CE	0.916	3.566				
	CE3 <- CE	0.909	3.216				
	CE4 <- CE	0.887	2.817				
EE	EE1 <- EE	0.902	3.542	0.922	0.93	0.944	0.809
	EE2 <- EE	0.893	3.474				
	EE3 <- EE	0.924	3.973				
	EE4 <- EE	0.879	3.206				
AIA	I-AVE <- AIA	0.891	2.588	0.873	0.886	0.913	0.724

	P-AVE <- AIA	0.881	2.808				
	SP-AVE <- AIA	0.829	2.421				
	C-AVE <- AIA	0.8	2.148				
NS	A-AVE <- NS	0.944	4.212	0.93	0.93	0.956	0.878
	R-AVE <- NS	0.938	3.932				
	CO-AVE <- NS	0.928	3.373				

Table 4
Discriminant Validity (HTMT&Fornell-lacker)

	AIA	ASE	BE	CE	EE	NS
AIA	0.851	0.707	0.579	0.632	0.522	0.737
ASE	0.707	0.9	0.66	0.767	0.768	0.767
BE	0.579	0.66	0.875	0.858	0.832	0.638
CE	0.632	0.767	0.858	0.904	0.829	0.683
EE	0.522	0.768	0.832	0.829	0.899	0.56
NS	0.737	0.767	0.638	0.683	0.56	0.937

The Structural Model Results

Hypothesis Tests and Path Analysis. Table 6 presents the structural model estimates. Perceived AI affordances showed a strong positive association with need satisfaction ($\beta = 0.607, t = 11.878, p < 0.001$), indicating that higher levels of affordance perception substantially promote students’ fulfillment of psychological needs. Need satisfaction subsequently contributed significantly to all three engagement domains—behavioral ($\beta = 0.585, t = 10.908, p < 0.001$), cognitive ($\beta = 0.635, t = 14.745, p < 0.001$), and emotional engagement ($\beta = 0.523, t = 9.078, p < 0.001$)—highlighting its pivotal role as an internal mechanism driving engagement. The moderating analysis further showed that AI self-efficacy strengthened the relationship between AIA and NS ($\beta = 0.065, t = 2.394, p < 0.05$), suggesting that learners with higher confidence in AI-related abilities benefit more from AI affordances in terms of need fulfillment. Effect size estimates revealed substantial impacts for the AIA → NS pathway ($f^2 = 0.817$) and the NS → CE pathway ($f^2 = 0.675$), whereas the other effects ranged from small to moderate. Additionally, all VIF values were below the commonly accepted threshold of 5, indicating no multicollinearity issues.

Table 5
Results of Structural Model Path Analysis

Hypothesis	Path	β	STD	<i>t</i>	<i>p</i>	f-square	VIF	Result
H1	AIA -> NS	0.607	0.051	11.878	***	0.817	1.725	Accepted
H2a	NS -> BE	0.585	0.054	10.908	***	0.519	1	Accepted
H2b	NS -> CE	0.635	0.043	14.745	***	0.675	1	Accepted
H2c	NS -> EE	0.523	0.058	9.078	***	0.376	1	Accepted
H4	ASE x AIA -> NS	0.065	0.027	2.394	*	0.019	1.025	Accepted

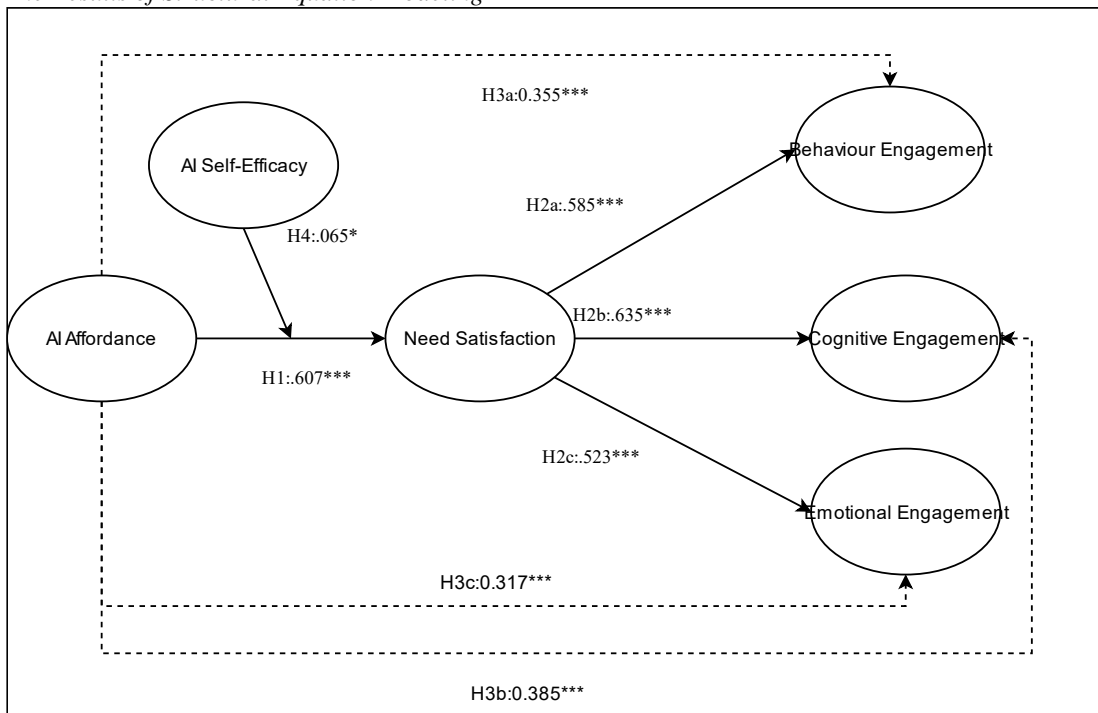
Analysis of Indirect Effects. Bootstrapping was conducted to assess the mediating role of need satisfaction. As summarized in Table 6, NS acted as a significant conduit linking AIA to each type of engagement. The indirect pathways were significant for behavioral engagement (H3a: $\beta = 0.355, p < 0.001$), cognitive engagement (H3b: $\beta = 0.385, p < 0.001$), and emotional engagement (H3c: $\beta = 0.317, p < 0.001$), thereby supporting all three mediation hypotheses. Moreover, evidence of moderated mediation also emerged. The interaction between AIA and ASE produced significant indirect effects via NS for behavioral (H5a: $\beta = 0.038, p < 0.05$), cognitive (H5b: $\beta = 0.041, p < 0.05$), and emotional engagement (H5c: $\beta = 0.034, p < 0.05$). These findings suggest that students with higher

AI self-efficacy experience stronger need satisfaction from AI affordances, which in turn enhances engagement, aligning with H5a–H5c.

Table 6
Indirect Effects and Moderated Mediation Results

Hypothesis	Indirect Path	β	STD	t	p	Result
H3a	AIA \rightarrow NS \rightarrow BE	0.355	0.039	8.993	***	Accepted
H3b	AIA \rightarrow NS \rightarrow CE	0.385	0.034	11.393	***	Accepted
H3c	AIA \rightarrow NS \rightarrow EE	0.317	0.039	8.237	***	Accepted
H5a	ASE \times AIA \rightarrow NS \rightarrow BE	0.038	0.017	2.272	*	Accepted
H5b	ASE \times AIA \rightarrow NS \rightarrow CE	0.041	0.018	2.344	*	Accepted
H5c	ASE \times AIA \rightarrow NS \rightarrow EE	0.034	0.015	2.231	*	Accepted

Figure 2.
The Results of Structural Equation Modeling



Moderation Effect of ASE. To further explore whether the mediation effect of NS between AIA and three types of engagement (BE, CE, and EE) is contingent upon the level of ASE, we conducted a conditional indirect effects analysis at three levels of ASE (mean, +1 SD, and -1 SD). As shown in Table 7, all conditional indirect paths were statistically significant ($p < 0.001$), confirming that ASE moderates the indirect relationship between AIA and the engagement outcomes via NS. Specifically, the indirect effect of AIA \rightarrow NS \rightarrow BE (H2) increased from 0.359 at low ASE (-1 SD) to 0.444 at high ASE (+1 SD), suggesting a strengthened mediation effect under higher AI Self-Efficacy. Similar patterns were found for CE (H3) and EE (H4), indicating robust moderated mediation effects and further supporting H5, as shown in Figure 3.

In conclusion, Figure 2 summarizes the structural model results. AI affordances strongly predicted need satisfaction ($\beta = .607, p < .001$), which subsequently explained behavioral ($\beta = .585, p < .001$), cognitive ($\beta = .635, p < .001$), and emotional engagement ($\beta = .523, p < .001$). AI self-efficacy further strengthened the AIA \rightarrow NS link ($\beta = .065, p < .05$). The dotted paths in the figure illustrate the indirect effects of AI affordances on engagement, with significant mediation identified for BE ($\beta = .355$), CE ($\beta = .385$), and EE ($\beta = .317$).

Figure 3.
Simple Slope Analysis

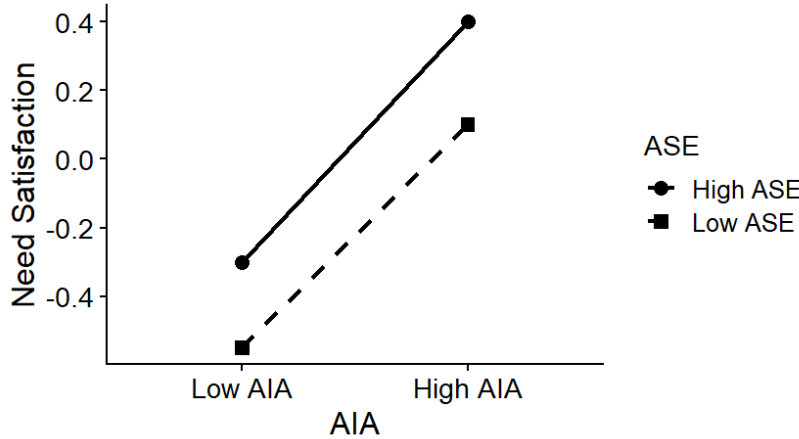


Table 7.
Conditional Indirect Effects of AIA via NS at Different Levels of ASE

Indirect path	β	SE	t	p
AIA \rightarrow NS \rightarrow BE (ASE = +1 SD)	0.444	0.054	8.237	***
AIA \rightarrow NS \rightarrow BE (ASE = -1 SD)	0.359	0.051	7.058	***
AIA \rightarrow NS \rightarrow BE (ASE = Mean)	0.402	0.049	8.277	***
AIA \rightarrow NS \rightarrow CE (ASE = +1 SD)	0.49	0.049	9.965	***
AIA \rightarrow NS \rightarrow CE (ASE = -1 SD)	0.395	0.05	7.84	***
AIA \rightarrow NS \rightarrow CE (ASE = Mean)	0.442	0.045	9.836	***
AIA \rightarrow NS \rightarrow EE (ASE = +1 SD)	0.397	0.051	7.837	***
AIA \rightarrow NS \rightarrow EE (ASE = -1 SD)	0.32	0.046	6.992	***
AIA \rightarrow NS \rightarrow EE (ASE = Mean)	0.358	0.045	8.002	***

DISCUSSION

Mediating Effects of Need Satisfaction

The findings indicate that Need Satisfaction (NS) is the key mechanism linking AI Affordances (AIAs) to students' multidimensional engagement. Rather than exerting a direct influence, AIAs promoted engagement by enhancing autonomy, competence, and relatedness. This pattern is consistent with Self-Determination Theory (SDT), which emphasizes that students demonstrate stronger behavioral, emotional, and cognitive involvement when their basic psychological needs are supported (Deci & Ryan, 2000). The results also align with prior evidence showing

positive links between AIAs and student engagement (Huang et al., 2025; Xu & Li, 2024) while extending this literature by identifying the underlying motivational process. By establishing NS as the mediating pathway, this study clarifies that AIAs foster meaningful engagement primarily through strengthening students' psychological need fulfillment.

Additionally, the results show that AIAs had the greatest impact on cognitive engagement, with comparatively smaller effects on behavioral and emotional engagement. This pattern aligns with Lo et al.'s (2024) meta-analysis, which reported that ChatGPT-enhanced learning tends to yield stronger cognitive gains than behavioral or emotional improvements. Consistent evidence from Chen et al. (2025) and Nguyen et al. (2024) further suggests that AI functions such as instant feedback, personalized guidance, and knowledge expansion promote deeper processing and strategic learning, thereby strengthening cognitive engagement. Together, these results reinforce the relevance of SDT in AI-mediated learning by illustrating how AIAs foster distinct forms of classroom engagement via need satisfaction, and they further clarify the motivational processes through which AI-supported learning experiences are internalized and manifested in students' engagement behaviors.

The Moderating Role of AI Self-Efficacy

The results show that ASE exerts a statistically significant, though modest, moderating effect on the link between AIAs and NS. From an SDT perspective, this moderation is theoretically meaningful. While AI affordances offer opportunities to support autonomy, competence, and relatedness, learners must have sufficient confidence and perceived capability to benefit from them. Students with higher ASE tend to interpret AI-driven feedback, guidance, and personalization as genuinely supportive resources, thereby experiencing greater need fulfillment. Conversely, those with lower ASE may find it difficult to process or apply AI-based information, limiting the extent to which AIAs are internalized as need-supportive. Thus, ASE operates as a boundary condition that shapes how effectively AI affordances translate into psychological need satisfaction in learning environments.

This result aligns with recent studies demonstrating that individual capability beliefs determine how learners translate technological features into motivational experiences and learning outcomes (Chen et al., 2024; Liu et al., 2024; Kim & Kim, 2024). However, other research has predominantly conceptualized ASE as a mediator rather than a moderator, overlooking its potential role in conditioning whether technological affordances can be transformed into psychological need support (Kong et al., 2025; Yi & Siquan, 2025). By empirically validating the moderating role of ASE in the AIA → NS pathway, the present study extends SDT by showing that the internalization of technological affordances into need satisfaction depends not only on the presence of supportive environmental features but also on learners' perceived capability to utilize them. This contribution complements prior international research that has largely focused on direct links between AI affordances and engagement, offering a more nuanced account of how and for whom AI promotes student engagement.

IMPLICATIONS

The findings indicate that AI affordances promote classroom engagement primarily by satisfying students' needs for autonomy, competence, and relatedness. Therefore, when integrating AI into classroom instruction, teachers and designers should prioritize features that support these psychological needs, such as personalized guidance, clear, staged feedback, adaptive prompts, and AI tools that facilitate interaction. Shifting the instructional focus from simply "using AI tools" to "leveraging AI to support psychological needs" enables AI-supported classrooms to move from passive technology use toward meaningful and sustained forms of classroom engagement.

The moderating effect indicates that students' AI self-efficacy influences how much they benefit from AI-supported learning. Learners with stronger AI self-efficacy tend to interpret AI-generated feedback and guidance as useful learning support, whereas those with lower self-efficacy may struggle to engage with or apply such feedback. To address this, teachers can build students' confidence through modeling, scaffolded guidance, and explainable AI feedback, while system designers may implement tiered interaction interfaces to support varying proficiency levels. Strengthening students' AI self-efficacy allows a broader range of learners to benefit from AI-supported instruction, ultimately enhancing overall classroom engagement.

LIMITATIONS AND FUTURE DIRECTIONS

Several limitations warrant consideration. First, the use of a cross-sectional design restricts the ability to draw strong causal inferences. Future investigations could adopt longitudinal approaches or randomized controlled trials to obtain more rigorous evidence regarding causal mechanisms. Second, as the data relied solely on self-reported questionnaires, the possibility of common method bias cannot be fully ruled out. Subsequent studies may improve measurement validity by integrating multiple data sources, such as behavioral log records from learning systems, teacher ratings, or peer evaluations. Third, the current model examined only AI affordances, need satisfaction, and student engagement, leaving out other potentially influential variables—including intrinsic motivation, teacher support, and individual learner differences. Incorporating such constructs in future research may yield a more comprehensive explanatory framework. Lastly, the sample was drawn from a single university in China, which constrains the extent to which the findings can be generalized. Comparative research across diverse institutions and cultural settings is needed to assess the robustness and transferability of the results.

CONFLICTS OF INTEREST

The authors have reported no potential conflict of interest.

DATA AVAILABILITY STATEMENT

Research data can be obtained from the corresponding author upon reasonable request.

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