CONFLUX

JOURNAL OF EDUCATION

ISSN 2320-9305 (PRINT) ISSN 2347-5706 (ONLINE)

A PEER REVIEWED JOURNAL PUBLISHED SINCE 2013

VOLUME 14 ISSUE 1 DECEMBER 2025

cjoe.naspublishers.com

CONFLUX
JOURNAL OF EDUCATION
ISSN 2320-9305 (Print)
ISSN 2347-5706 (Online)
Volume 14, Issue 1, December 2025
https://cjoe.naspublishers.com/

Effects Of Artificial Intelligence On Student Motivation

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Abstract

Artificial Intelligence (AI) is transforming educational landscapes by personalizing learning experiences, yet its impact on student motivation remains underexplored. This technical paper synthesizes recent research on how AI realizes key motivational frameworks: Self-Determination Theory (SDT), Expectancy-Value Theory (EVT), and Cognitive Load Theory (CLT). Drawing on empirical studies, we examine AI's role in fulfilling psychological needs (autonomy, competence, relatedness in SDT), enhancing expectancy and value beliefs (EVT), and managing cognitive loads (intrinsic, extraneous, germane in CLT) to boost intrinsic motivation, engagement, and persistence. Findings indicate that AI-driven tools, such as chatbots and adaptive systems, can optimize motivation when designed with theoretical principles, but risks like cognitive offloading (over-reliance) and expertise mismatches must be addressed. Implications for educators, AI developers, and policy include tailored interventions for diverse learners, emphasizing inclusion and equity. This review highlights the need for integrated theoretical approaches in AI-enhanced education to sustain long-term motivational outcomes.

Keywords: Artificial intelligence, student motivation, personalized learning, self-determination theory, expectancy-value theory, cognitive load theory, educational technology

Introduction

The integration of Artificial Intelligence (AI) in education has accelerated, offering tools like intelligent tutoring systems, generative AI (GenAI) chatbots (e.g., ChatGPT) and adaptive learning platforms (Khanmigo) that personalize content and provide real-time feedback. However, while AI enhances efficiency and accessibility, its effects on student motivation -a critical driver of learning outcomes require deeper examination. Motivation influences engagement, persistence and achievement and theories like Self-Determination Theory (SDT), Expectancy-Value Theory (EVT) and Cognitive Load Theory (CLT) provide frameworks to understand these dynamics.

Motivation-Theories

Self-Determination Theory (SDT) posits that motivation is optimized when basic psychological needs—autonomy (self-endorsement), competence (efficacy) and relatedness (connections)—are satisfied, leading to intrinsic over extrinsic motivation.

Ryan and Deci (2000) noted that extrinsically motivated behaviour can be internalized and transformed into autonomous behaviour when people find and attach personal value to the behaviour. General intrinsic motivation, stemming from interest and curiosity, is associated with psychological well-being.

ISSN 2320-9305 (Print)
ISSN 2347-5706 (Online)
Volume 14, Issue 1, December 2025
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Expectancy-Value Theory (EVT) emphasizes expectancy (belief in success) and task value (attainment, intrinsic, utility, costs) as predictors of motivational choices and intentions.

The model proposed by Eccles and colleagues, identifies two primary factors that critically impact an individual's motivation, academic performance and choice of activities: expectancies for success and task values

Cognitive Load Theory (CLT) focuses on managing working memory loads to facilitate schema construction, distinguishing intrinsic (material complexity), extraneous (poor design), and germane (learning effort) loads. Cognitive load (Sweller et al., 2011) have substantiated that limitations and constraints on what can be attended and processed exist at all levels of cognitive processing. Basically, the affordances available at any one time contain far more information than could possibly be attended, perceived and processed.

This paper explores how AI impacts motivation by realizing these theories in educational contexts. Through a synthesis of recent studies (post-2023), we discuss mechanisms, empirical evidence, challenges, and implications. The analysis reveals AI's potential to foster high-quality motivation but underscores the need for human-AI collaboration to mitigate drawbacks.

Critical Analysis of Reviewed Studies

Self-Determination Theory and AI in Motivation

SDT has been increasingly applied to AI education, where supportive designs enhance needs satisfaction and shift motivation toward autonomy. AI tools like chatbots and gamified

ISSN 2320-9305 (Print)
ISSN 2347-5706 (Online)
Volume 14, Issue 1, December 2025
https:// cjoe.naspublishers.com/

systems promote intrinsic motivation by allowing personalized interactions that fulfil autonomy (e.g., student-chosen tasks), competence (e.g., adaptive feedback) and relatedness (e.g., collaborative simulations). Duolingo is one such example. This approach aligns with Flow Theory, which posits that students become highly motivated and engaged when learning activities are game-based and enjoyable. Flow occurs when an individual's skills and abilities are well-matched to the challenge of the activity. AI systems support this by adjusting the challenge level of learning activities based on learners' performance and skill levels.

Empirical evidence supports AI's impact. A two-study experiment with Grade 9 students (N=200) found an SDT-based AI curriculum eliminated gender and achievement gaps in readiness and intrinsic motivation, with significant effects on autonomy ($\eta^2=0.38$, $p<.001$) and competence (Xia & Chiu, 2023a). Another study with Grade 10 students (N=123) using AI chatbots for English learning showed teacher-guided AI increased competence for low-expertise learners ($\beta=0.93$, $p<.001$) but reduced autonomy for high-expertise ones, indicating an expertise reversal effect (Xia & Chiu, 2023b). The AI Motivation Scale (AIMS), validated with 1,068 university students, confirmed supportive AI environments predict autonomous motivation ($\beta=0.10$–0.25), mediating emotional engagement ($\beta=0.63$, $p<.001$) (Chiu et al., 2025). These findings highlight AI's role in fostering SDT-driven motivation when tailored to learner expertise.

Expectancy-Value Theory and AI in Motivation

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ISSN 2347-5706 (Online)
Volume 14, Issue 1, December 2025
https://cjoe.naspublishers.com/

EVT explains motivation through expectancy (confidence in success) and task value (attainment, intrinsic, utility, minus costs) (Wigfield & Eccles, 2000). AI enhances expectancy via success-oriented feedback and value by emphasizing task benefits (e.g., efficiency) (Chan & Zhou, 2024). Costs, like ethical concerns or effort, can reduce motivation if unaddressed (Chiu & Lim, 2024). Certain instruments like Questionnaire of AI Use Motives (QAIUM) were designed based on EVT theory. AI tools serve as highly adaptable platforms for collecting data on motivation and testing the predictive power of EVT by isolating and manipulating the key components of expectancy and subjective value. The continued study of motivational factors in AI education, such as those related to expectancy-value beliefs, is considered crucial for informing effective interventions and academic practices.

A study with 405 Hong Kong university students validated an EVT-based instrument for GenAI use, finding perceived value strongly predicted intentions ($r=0.606$, $p<.001$), knowledge-based expectancy weakly positive ($r=0.178$, $p<.05$) and cost negative ($r=-0.295$, $p<.01$) (Chiu & Lim, 2024). In management education, AI tools increased utility and intrinsic value, mediated by expectancy ($\beta=0.45$, $p<.01$) (Chan & Zhou, 2024).

Person-centered analysis with 494 Chinese students identified three motivational profiles (low, medium, high expectancy-value), with AI-supportive environments shifting students to high profiles ($\beta=0.30$, $p<.01$), predicting stronger intentions ($M=4.43$ vs. 2.77) (Xia et al., 2024). These results confirm AI's role in enhancing EVT components, particularly value, to drive motivation.

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ISSN 2347-5706 (Online)
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Cognitive Load Theory and AI in Motivation

CLT posits that learning is optimized by managing intrinsic (material complexity), extraneous (poor design) and germane (schema-building) cognitive loads (Sweller, 2010). AI reduces extraneous load through simplified interfaces and adapts intrinsic load via personalized content, indirectly boosting motivation by enhancing efficacy (Chen & Wang, 2024; Lee & Park, 2025).

AI tools also contribute to achieving the outcomes associated with effective cognitive load management by Streamlining Tasks and Reducing Extraneous Load, Adaptive Instruction and Managing Intrinsic/Germane Load and Supporting Cognitive Engagement

A phenomenological study on ChatGPT use found it lowered cognitive load for complex problems but increased extraneous load for inputs like equations, enhancing motivation when verified (Chen & Wang, 2024). In online courses, cognitive load and intrinsic motivation predicted persistence (germane load $OR=1.979$, $p<.01$; intrinsic motivation $OR=29.907$, $p<.001$), suggesting AI's load management sustains engagement (Lee & Park, 2025). AI gamification further supports CLT by balancing loads to maintain motivation, improving retention in STEM courses (Kim & Lee, 2023). These findings underscore AI's role in optimizing cognitive resources for motivational outcomes.

Risks of AI Misuse to Cognitive Processing

ISSN 2320-9305 (Print)
ISSN 2347-5706 (Online)
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While AI is beneficial when used for scaffolding (managing load), misuse can actively undermine the goals of CLT by preventing students from engaging in necessary, effortful cognitive processing:

• Decline in Critical Thinking**:** Excessive reliance on AI for complex tasks can hinder the development of critical thinking and problem-solving skills.

• Superficial Learning**:** When AI is used as a shortcut, students might bypass genuine understanding and mastery of subjects, leading to a dependence on AI for tasks requiring critical thinking and resulting in superficial learning. This suggests that inappropriate reliance prevents the accumulation of germane cognitive load required for deep learning.

Integration of Theories

SDT, EVT and CLT intersect in AI contexts: The combination of Self-Determination Theory (SDT), Expectancy-Value Theory (EVT) and the principles derived from Cognitive Load Theory (CLT) provides a powerful, multi-faceted framework for understanding the profound implications of integrating Artificial Intelligence (AI) into learning environments.

SDT's competence aligns with EVT's expectancy, while autonomy and relatedness enhance value perceptions (Chiu et al., 2025). CLT supports these by freeing cognitive resources for motivational processes (Lee & Park, 2025). Network analyses show AI environments mediate motivation across these frameworks, with supportive designs amplifying engagement (Xia et al.,

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2024). For instance, AI's adaptive feedback boosts competence (SDT) and expectancy (EVT), while simplified content reduces extraneous load (CLT), fostering intrinsic motivation.

A questionnaire combining all three theories needed to be designed and validated for any Artificial Intelligence (AI) tools to fulfil the principles and constructs of Self-Determination Theory (SDT), Expectancy-Value Theory (EVT) and the objectives related to Cognitive Load Theory (CLT) by adapting the educational environment to meet students' motivational needs and cognitive capacities, learning outcome and Academic success.

Discussion

AI realizes SDT by supporting psychological needs, EVT by enhancing expectancy-value beliefs and CLT by managing cognitive loads, collectively promoting intrinsic motivation and equity (Xia & Chiu, 2023a; Chiu & Lim, 2024; Chen & Wang, 2024). Challenges include over-reliance undermining autonomy, biases in AI algorithms and expertise mismatches reducing efficacy (Xia & Chiu, 2023b; Chiu & Lim, 2024). Human-AI collaboration, such as teacher-guided AI, mitigates these by balancing personalization with oversight (Kim & Lee, 2023).

Implications for Practice

Educators should integrate AI with SDT (e.g., choice-based tasks), EVT (e.g., utility-focused prompts), and CLT (e.g., load-adaptive content) principles, tailoring to learner expertise (Chiu et al., 2025). This combination allows them to create highly effective, motivating and personalized learning environments that address both the psychological needs and cognitive

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ISSN 2347-5706 (Online)
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limitations of students. The findings from motivational and cognitive theories integrated via AI inform educational policies necessary to address challenges like AI misuse and the resulting decline in intrinsic motivation (SDT) and critical thinking (CLT principles)

Developers combine the principles of Self-Determination Theory (SDT), Expectancy-Value Theory (EVT) and Cognitive Load Theory (CLT) when creating AI applications—particularly Personalized Learning (PL) and Intelligent Tutoring Systems (ITS)—because these theories provide a robust and complementary roadmap for designing systems that are maximally motivating, engaging and cognitively efficient**.** The goal is to move beyond mere usage of technology, which is a poor predictor of grades, toward engagement (emotional, cognitive and behavioural), which is highly predictive of academic achievement.

Developers can embed motivational scales like AIMS for real-time adjustments (Chiu et al., 2025). Policy should prioritize AI literacy to enhance expectancy and value (Xia et al., 2024).

The integration ensures that the resulting AI tool is not only technologically advanced but also psychologically sound, fostering the intrinsic motivation that leads to high engagement and academic success

Implications for Research

Most current research is concentrated in Western countries and with specific demographics. Future studies must broaden the participant base to include diverse demographic groups across educational levels, age groups and socio-economic backgrounds to increase the

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generalizability and relevance of findings. Future studies should also employ longitudinal designs to assess sustained motivation to ensure generalizability. Integrating SDT, EVT and CLT in AI interventions can provide a holistic understanding of motivation dynamics (Lee & Park, 2025).

Need for Ethical Stewardship in Primary, secondary and senior secondary school students**:** To ensure AI fulfils the positive potential implied by combining these theories, AI integration must balance technological innovation with ethical stewardship and psychological well-being. Educational policies must emphasize ethical conduct and digital literacy to guide students away from extrinsic motivators and towards intrinsic drive. AI should serve as a complement to learning, not a substitute that encourages shortcutting.

Conclusion

AI significantly enhances motivation by realizing SDT, EVT and CLT in education. By fostering autonomy, expectancy, value and cognitive efficiency, AI promotes inclusive, engaging learning. Ethical, tailored designs are critical to maximize benefits and ensure equitable outcomes. AI realizes SDT by supporting needs through personalized, collaborative tools, eliminating disparities and fostering intrinsic motivation. AI fulfils the core assumptions of these three theories by acting as an adaptive external support that customizes the learning experience to align with both the psychological needs (SDT) and motivational beliefs (EVT) of the learner, while managing the instructional design to minimize cognitive inefficiencies (CLT principles).

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