Integrating Generative AI into Business Classrooms: Effects on Student Motivation and Learning Engagement

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Abstract

The rapid advancement of artificial intelligence is reshaping industries, workplaces, and educational systems worldwide. In higher education, generative artificial intelligence (GenAI) tools are increasingly integrated into classroom instruction, assessment, and student learning processes. Despite widespread adoption, there remains limited empirical evidence examining how these tools influence core psychological drivers of academic success, particularly student motivation. Understanding this relationship is critical because motivation mediates engagement, persistence, and achievement across disciplines.

Since late 2022, generative artificial intelligence (GenAI)—exemplified by large language models (LLMs) such as ChatGPT—has diffused rapidly into education, prompting questions about how these tools shape students' motivation to learn. Motivation matters because it mediates engagement, persistence, and achievement across disciplines. In higher education especially, GenAI can alter the learning ecology by changing task demands, perceived competence, and the feedback landscape. Recent guidance from international agencies (e.g., UNESCO; OECD) highlights both opportunity and risk, calling for human-centered designs that protect learner agency and academic integrity.

Keywords: generative AI, student motivation, higher education, instructional design, self-determination theory
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Introduction

The rapid emergence of generative artificial intelligence (GenAI) tools—epitomized by platforms such as ChatGPT, DALL·E, and Gemini—has challenged long-standing assumptions about human learning, creativity, and agency in educational contexts. Since 2022, these systems have not only reshaped various industries but have also entered classrooms and study spaces with unprecedented speed, raising critical questions about what it means to be a motivated learner in the age of algorithmic assistance.

Motivation, a central driver of academic performance, engagement, and persistence, is particularly susceptible to the affordances and risks posed by GenAI. On one hand, GenAI promises personalized feedback, reduced cognitive barriers, and enhanced creative expression—features that may bolster students' sense of competence, autonomy, and task value. On the other hand, its ability to automate cognitive labor, generate ready-made answers, and obscure the boundary between human and machine effort introduces potential threats to intrinsic motivation, learning ownership, and academic integrity. (UNESCO, 2023; OECD, 2024; Wu et al., 2025)

Literature Review

Generative AI in Higher Education

GenAI tools can generate text, code, and explanations in response to natural-language prompts. In higher education, they are used as writing aids, coding partners, language-learning tutors, and course assistants integrated into LMS platforms. Recent meta- and systematic reviews indicate that GenAI generally improves learning outcomes and perceived learning but highlight that non-cognitive variables such as motivation and engagement are only beginning to be systematically examined (Garzón et al., 2025; Xia et al., 2025).

Most GenAI–motivation studies draw on three overlapping frameworks:

Self-Determination Theory (SDT) – Motivation depends on satisfaction of autonomy, competence, and relatedness needs, which support intrinsic motivation and high-quality forms of extrinsic motivation (Deci & Ryan, 2000).

Technology Acceptance Model (TAM) / UTAUT – Perceived usefulness, ease of use, social influence, and facilitating conditions drive intention to use learning technologies (Davis, 1989).

Engagement and belonging frameworks – Motivation is closely linked to cognitive, behavioral, emotional, and agentic engagement, as well as students' sense of belonging in learning communities (Xia et al., 2025; Huang et al., 2025). HKU Repository+1

Recent work often combines SDT and TAM, examining how autonomy, competence, and intrinsic interest interact with perceived usefulness and ease of use to shape students' willingness to adopt GenAI tools and to continue using them for learning (Annamalai et al., 2025; Afzaal et al., 2025).

Zhou and Li (2023) conducted one of the earliest SDT-grounded quantitative studies on ChatGPT and learning motivation. Working with 196 university students who had been trained to use ChatGPT as an auxiliary learning tool, they used structural equation modeling to examine links between SDT-related constructs and interest–enjoyment as a proxy for intrinsic motivation. Perceived competence in using ChatGPT was positively associated with interest–enjoyment, whereas tension–pressure was negatively associated; perceived value showed a weaker and partly non-significant effect (Zhou & Li, 2023). AcadLore Library+1

This study suggests that how competent and relaxed students feel when using GenAI matters more for intrinsic motivation than simply believing the tool is valuable. Importantly, Zhou and Li note that overall use time was modest and that further training and guidance are needed to unlock ChatGPT's motivational potential.

2.2 Modified SDT model: continuous use of ChatGPT

Annamalai et al. (2025) extended SDT in a study of 324 EFL/ESL students using ChatGPT for English learning. Using PLS-SEM, they modeled motivation for continuous use as an outcome of autonomy, competence, relatedness, and perceived challenges (all influenced by initial ChatGPT use). Autonomy and relatedness predicted competence, and autonomy and relatedness were the strongest predictors of motivation for continuous use, explaining about 71% of its variance (Annamalai et al., 2025).

Taken together, SDT-based studies show that GenAI supports motivation when it:

Gives students choice and control (autonomy) over how, when, and what to ask.

Helps them feel capable of using the tool effectively (competence).

Provides a sense of connection—for example, through conversational, supportive dialogue that feels socially meaningful (relatedness).

Motivational Frameworks for Understanding GenAI Effects

Self-Determination Theory (SDT), Expectancy–Value Theory (EVT), and Achievement Goal Theory provide complementary frameworks for understanding how GenAI may shape motivation. SDT emphasizes the role of autonomy, competence, and relatedness (Deci & Ryan, 2000; Ryan & Deci, 2020). EVT highlights expectancy beliefs and task value (Eccles & Wigfield, 2002). Achievement Goal Theory distinguishes mastery from performance orientations (Dweck, 1986).

Syntheses and Meta-Analyses

Early systematic reviews suggest cautiously positive effects of GenAI on engagement and motivation, though results remain context-dependent (Xia et al., 2025; Wu et al., 2025). Meta-analytic evidence shows moderate improvements in motivation and engagement, with variation in study quality.

Field Studies in Specific Domains

Quasi-experimental and classroom research suggests that GenAI-assisted programming and writing tools can increase intrinsic motivation and reduce anxiety (Fan et al., 2025; Annamalai, 2025). However, neurocognitive evidence signals the possibility of shallow processing during AI-supported writing tasks (MIT Media Lab, 2025).

Measurement Advances

Recently developed instruments like the AI Motivation Scale (AIMS) enable more rigorous empirical testing (Li et al., 2025). These include SDT-based subscales (intrinsic, identified, external, amotivation).

In evaluating the literature, several themes were found.

GenAI has clear motivational potential.
Studies grounded in SDT and TAM consistently show that when GenAI is experienced as **autonomy-supportive**, **competence-enhancing**, and **easy to use**, students report higher intrinsic motivation, interest, and intention to keep using the tools (Zhou & Li, 2023; Annamalai et al., 2025; Afzaal et al., 2025; Huang et al., 2025).

Design matters more than the technology itself.
Motivation gains are strongest when GenAI is positioned as a **tutor, coach, or partner** that prompts thinking, asks questions, and scaffolds problem-solving, rather than as an answer-spewing oracle (Xia et al., 2025; Hanshaw et al., 2024, 2025).

Motivation is multi-dimensional.
Some studies, such as Zhou and Li (2023), show that GenAI can simultaneously reduce pressure and increase competence, but that frequency of use and proficiency moderate these relationships. Meta-analyses underscore that cognitive, behavioral, emotional, and agentic engagement do not always move together (Xia et al., 2025).

There are real risks of amotivation and dependence.
Over-reliance on GenAI, especially without clear guidelines, can encourage **shortcuts**, dulling students' sense of ownership and effort. Ethical ambiguity and technostress may further undermine intrinsic motivation and trust in assessments (Hasanein & Sobaih, 2023; Klimova, 2025).

The evidence base is still young.
Many studies are single-institution, cross-sectional, or short-term, often relying on self-report scales. There is a need for **longitudinal, mixed-methods, and experimental designs** that track motivation over time and triangulate self-reports with behavioral data (e.g., log data, persistence, task choice).

In an article by Deimel, Amzalag, Zviel and Voloch, (2025), This quasi-experimental study compared undergraduate students in AI-enhanced versus traditional instruction. Results showed that students in the AI group reported higher intrinsic motivation, greater sense of competence, and stronger engagement with course tasks. The authors interpret these results through Self-Determination Theory (SDT), arguing that AI tools can support autonomy and competence when integrated with instructor guidance. Importantly, students also demonstrated modest improvements in academic performance, suggesting potential pedagogical value beyond affective outcomes. It provides recent empirical evidence that generative AI in instruction can positively influence student motivation and engagement, which strengthens the foundation of your research.

Suh, (2025) study expanded multiple disciplines, it includes business students in project-based courses where GenAI tools were incorporated into experiential tasks. Through pre- and post-semester surveys, Suh found that students experienced significant gains in engagement, creative confidence, and motivation, particularly when AI was framed as a *collaboration partner* rather than a *shortcut tool*. Qualitative data indicated that students engaged more deeply with subject content when AI clarified concepts, enabled experimentation, and reduced cognitive load. It links student attitudes toward AI with motivational and engagement outcomes, offering theoretical grounding for your research's psychological focus.

Huang, Chen, Tian and Yim, (2025) his study blends the Stimulus–Organism–Response (SOR) theoretical framework with Self-Determination Theory (SDT) to explore how perceptions of GenAI tools (stimulus) influence internal psychological processes (organism) and learning engagement (response). Using survey data from business and management undergraduates, the authors found that positive perceptions of AI usefulness and ease of use significantly predicted autonomy and competence needs fulfillment, which, in turn, predicted higher engagement, greater creative confidence, and stronger motivation. The study highlights how psychological need satisfaction mediates the effects of AI on learner engagement. It provides theory-driven evidence showing how SDT constructs explain the motivational mechanisms underlying AI's effects — perfect for supporting your conceptual model.

Study Objectives and Hypotheses

The objective of this study is to determine whether there is a relationship between generative artificial intelligence and student motivation.

H_1: There is a relationship between Generative Artificial Intelligence and Student Motivation.
H_0: There is not a relationship between Generative Artificial Intelligence and Student Motivation.

Methodology

A 15-item Likert-scale survey (1 = strongly disagree, 5 = strongly agree) was administered to 224 participants. Questions assessed perceived AI affordances and dimensions of student motivation.

Results

Table 1

Descriptive Statistics for Survey Items (N = 224) (APA 7th Edition Table Format)

Item	M	SD
Generative AI allows me to use a wide range of skills in my IT learning.	4.18	1.03
I can apply different technical skills when working with Generative AI tools.	4.22	1.01
Generative AI helps me explore diverse problem-solving approaches.	4.22	1.01
I can clearly see the complete process of solving IT problems using Generative AI.	4.04	1.05
Generative AI helps me understand the entire workflow of a project.	4.00	1.06
I can track my progress from start to finish when using AI tools.	4.14	1.04
Generative AI makes me feel that my IT learning has a meaningful impact.	4.08	1.03
I believe Generative AI can help solve real-world technological challenges.	4.04	1.04
I have the freedom to decide how to use Generative AI in my learning.	4.17	1.02
Generative AI gives me control over my learning process.	4.10	1.03
I can independently explore and experiment with AI tools.	4.17	1.01
Generative AI provides immediate and constructive feedback on my work.	4.08	1.05
I receive clear insights about my performance through AI tools.	4.03	1.06
The feedback from Generative AI helps me improve my skills.	4.06	1.05
My work with Generative AI feels important and valuable.	4.11	1.02

Note. All items were rated on a 5-point Likert scale.

Table 2

Cronbach's Alpha Reliability Coefficients

Scale	α
AI Affordances (7 items)	.954
Motivation (8 items)	.955
Full Scale (15 items)	.974

Note. α ≥ .90 indicates excellent internal consistency.

Table 3

One-Sample t Tests Against Neutral Midpoint (3.0)

Item	M	t	p
5.1	4.22	17.65	<.001
5.2	4.21	16.53	<.001
4.5	4.03	14.01	<.001
...	...	...	...

Note. All items were significantly above neutral ($p < .001$).

Table 4

Correlation Between AI Affordances and Motivation

Variable	r	p
Affordances → Motivation	.899	<.001

Table 5

Simple Linear Regression Predicting Motivation from AI Affordances

Predictor	B	SE	β	t	p
Intercept	.515	.120	—	4.29	<.001
AI Affordances	.869	.028	.899	30.91	<.001

R^2 = .808.

Discussion

The findings demonstrate a strong positive relationship between perceived AI affordances and student motivation. Items related to AI affordances and motivation had means around 4.0-4.22, indicating strong agreement. All scale items scored significantly above the neutral midpoint, with reliability indices showing excellent consistency across items. Cronbach's Alpha was performed, and all items were with excellent reliability. A One-Sample t test was performed where it was found that all items were significantly higher than 3.0, confirming positive perceptions of AI and motivation. Pearson correlation between AI affordances and motivation indicated a very strong positive relationship. Regression analysis suggests that AI affordances explain approximately 81% of the variance in motivation.

These results reinforce theoretical predictions from SDT and EVT, which posit that autonomy, competence, and value perceptions underlie motivational responses.

Recommendations for Future Research

Conduct longitudinal studies to track motivation over time, include behavioral engagement metrics beyond self-report and test experimental instructional designs using AI scaffolding and withdrawal.

Conclusion

GenAI can function as a motivational catalyst when implemented intentionally. However, poor integration risks undermining intrinsic motivation and task ownership. Institutional guidelines, assessment redesign, and AI literacy are needed to support sustainable student engagement.

As generative artificial intelligence continues to evolve, future research must move beyond cross-sectional perception studies and toward deeper theoretical and longitudinal investigation. First, longitudinal research designs are needed to determine whether the motivational gains observed in AI-supported learning environments are sustained over time or diminish as novelty effects fade. Tracking student motivation across semesters or academic years would provide stronger evidence regarding the durability of AI's impact.

Experimental and quasi-experimental studies should examine specific instructional design strategies rather than AI usage in general. For example, researchers could compare AI used as a scaffolding tutor versus AI used primarily as an answer generator to determine differential effects on autonomy, competence, and intrinsic motivation. Such studies would allow scholars to test boundary conditions of Self-Determination Theory in AI-enhanced classrooms.

Future investigations should integrate behavioral and learning analytics data—such as time-on-task, revision patterns, persistence rates, and academic performance—to triangulate self-report motivation measures. Combining survey instruments like the AI Motivation Scale (AIMS) with objective engagement metrics would strengthen causal inference and reduce common method bias.

Research should explore moderating variables including prior AI literacy, academic discipline, generational cohort, ethical orientation, and technology self-efficacy. It is possible that AI enhances motivation for some students while undermining it for others, particularly when overreliance or dependency develops.

Future scholarship should examine institutional-level factors such as AI policy clarity, assessment redesign, faculty training, and organizational culture. Motivation does not occur in isolation; it is shaped by structural signals about acceptable AI use and academic integrity. Understanding how governance frameworks interact with psychological needs for autonomy and competence will be essential for sustainable implementation.

Collectively, these future directions call for a more rigorous, multi-method, and theory-driven research agenda capable of distinguishing short-term enthusiasm from meaningful and enduring motivational transformation in AI-integrated higher education environments.

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