Cómo referenciar este artículo / How to cite this article

Wattanavit, P., Sakdapat, N., & Ngamcharoen, P. (2026). A Comparative Analysis of Predictors for Intentional Learning Behavior among Undergraduate Students in the Age of AI: Motivation, Self-Regulation, and Classroom Environment. *Espacio, Tiempo y Educación, 13*(1), pp. 103-124. doi: http://dx.doi.org/10.14516/ete.13106

A Comparative Analysis of Predictors for Intentional Learning Behavior among Undergraduate Students in the Age of AI: Motivation, Self-Regulation, and Classroom Environment

Panawat Wattanavit
e-mail: panawat_wat@utcc.ac.th
Faculty of Humanities, University of the Thai Chamber of Commerce, Thailand

Naksit Sakdapat*
e-mail: naksit_sak@utcc.ac.th
Faculty of Humanities, University of the Thai Chamber of Commerce, Thailand.

Pannika Ngamcharoen
e-mail: pannika@g.swu.ac.th
College of Creative Agriculture for Society, Srinakharinwirot University, Thailand.

Abstract: The transformation of students' learning behaviors, instructors' roles, and the overall learning process has been derived from the integration of Artificial Intelligence (AI), Generative AI in particular, into the higher education system. This study aims to analyze and identify key predictors of students' intentional learning behaviors, focusing on three core behavioral aspects: (1) AI-assisted learning behavior, (2) classroom participation behavior, and (3) self-management in learning behavior. Three groups of predictor variables were examined—motivation, self-regulation, and classroom environment. A quantitative research design was employed using multi-stage quota random sampling. The sample comprised 874 undergraduate students. Research instruments included twelve questionnaire sets with acceptable reliability (Cronbach's α = .71–.80). Data were analyzed using Pearson's correlation coefficients and multiple regression analysis. The findings indicated that motivation, self-regulation, and classroom environment significantly predicted variance in all three learning behaviors. Specifically, the predictors accounted for 42.50% of the variance in AI-assisted learning behavior, 44.67% in classroom participation behavior, and 45.35% in self-management in learning behavior. The most influential predictors across all aspects included intrinsic motivation, future-oriented motivation, ethical AI use, and instructional environment. These results highlight that high-quality learning behaviors in the age of AI are derived from a balanced integration of psychological drive, self-regulatory capacity, and supportive learning environments. The findings correspond to three dominant theoretical foundations—Self-Determination Theory, Self-Regulation Theory, and Learning Environment Theory—indicating that sustainable learning and constructive engagement are shaped by the cooperation of intrinsic motivation, behavioral regulation, and learning environments that promote analytical thinking and ethical technology utilization.

Keywords: Intentional Learning Behavior, Motivation, Self-Regulation, Learning Environment.

1. Introduction

In the age of extensive adoption of Generative Artificial Intelligence (Generative AI) in higher education, the role of AI has extended far beyond functioning as a tool for information retrieval or content generation. It has become a transformative force that redefines learning processes, instructional approaches, and—most critically—learning behaviors of twenty-first-century university students. Contemporary undergraduate students must confront the challenge of adapting to evolving learning environments in which AI can either serve as an intelligent assistant that enhances personalized learning or, if relied on uncritically without personal cognitive input, as a potential hindrance that weakens analytical reasoning and independent thought (Baidoo-Anu & Owusu Ansah, 2023).

Understanding intentional learning behavior in the age of AI has therefore become essential. Current trends reveal that students encounter "AI disparity"—a divide characterized not merely by access to technology, but by unequal capacity to use AI effectively for learning (Gui et al., 2025; Nakayama et al., 2022). Traditional definitions of learning intention, such as attending class and maintaining attention, are evolving to emphasize skills related to self-directed learning and ongoing cognitive awareness. However, when students depend on AI shortcuts to avoid engaging analytical thinking and logical reasoning, their critical thinking skills weaken. Furthermore, many students rely on Generative AI for academic tasks in the absence of university policies or explicit monitoring mechanisms, potentially leading to superficial learning when proper guidance or instructional oversight is not provided (Chan & Hu, 2023). Understanding the predictors of learning behavior in this emerging context is therefore essential for developing teaching strategies that effectively cultivate and maintain students' learning intention in AI-driven environments.

Recent evidence also highlights multidimensional impacts, indicating that AI, when positioned as a learning companion, supports students—particularly slow learners—by offering personalized explanations and immediate feedback, thereby enhancing learning engagement (Baidoo-Anu & Owusu Ansah, 2023). In contrast, excessive cognitive offloading has raised concerns with students relying on AI to generate exam answers or essays through AI without engaging in independent analytical processes. Beyond academic integrity concerns, such practices pose long-term risks to essential critical thinking skills (Cotton et al., 2024). These contrasting scenarios underscore the need for in-depth analyses to identify the factors that predict or distinguish students' AI-related learning behaviors.

At the same time, the global landscape of higher education is increasingly aligned with the United Nations' Sustainable Development Goals (SDGs) (Bernstein, 2017), particularly SDG 4.2, which highlights a commitment to inclusive and equitable education for all. While AI is widely viewed as a pivotal tool of broadening access to learning (SDG 4.3) and enhancing future employment-related competencies (SDG 4.4) (Morandín-Ahuerma, 2024), challenges arising from inappropriate use of Generative AI, such as superficial learning and cognitive offloading—may hinder the achievement of these goals. The failure to ensure that graduates fully develop critical thinking competencies undermines the broader goal of achieving sustainable, high-quality education. Identifying the predictors of intentional learning behavior in the age of AI extends beyond innovation and has become a critical imperative for assuring graduate quality and the sustainability of higher education (Allam et al., 2025).

Within this context, identifying the predictors of undergraduate students' intentional learning behavior in the age of AI is of considerable theoretical and practical significance. Motivation, self-regulation, and classroom learning environments constitute three critical dimensions that are crucial for fostering active and meaningful learning (El Deen et al., 2026). However, existing research has not yet examined these three groups of predictors collectively within the AI-mediated context nor has it investigated their combined effects on holistic intentional learning behavior, thereby indicating a substantive gap in the existing body of research.

Accordingly, this study aims to examine intentional learning behavior in the age of AI by focusing on three key behavioral components: AI-assisted learning behavior, classroom participation behavior, and self-management in learning behavior. The study further seeks to analyze and validate three predominant groups of predictors: (1) motivational factors including intrinsic, extrinsic, and future-oriented motivation, (2) self-regulatory factors encompassing concentration in learning, distraction management, and ethical use of AI, and (3) classroom environment factors comprising physical, social, and instructional aspects. Additionally, the study includes comparative analyses intended to investigate group-based differences in these predictors across diverse student populations. A more comprehensive understanding of these predictors will enable higher education institutions to formulate evidence-informed policies and design learning environments that facilitate the effective use of AI while maintaining and enhancing the essential human elements of learning.

2. Literature Review

Understanding undergraduate students' intentional learning behavior requires an integrated perspective drawing from insights across multiple domains, including educational psychology, educational technology, and the broader sociocultural context of contemporary learning (Holmes & Miao, 2023). This integration is essential for explaining the dynamic of complex learning behaviors that evolve rapidly in response to technological advancements and the expanding role of artificial intelligence (AI). Accordingly, this review synthesizes relevant theories, conceptual frameworks, and empirical studies to construct a comprehensive analytical framework for explaining the determinants and components of intentional learning behavior. Students are conceptualized as active learners who engage ethically with technology, exercise self-regulation, and participate meaningfully in the learning process (Wattanavit & Sakdapat, 2024). Accordingly, intentional learning behavior is conceptualized as comprising three interrelated components:

2.1. AI-assisted Learning Behavior

This component refers to intentional and ethical use of AI tools to support and enhance learning activities, including information retrieval, content summarization, skill practice, and new knowledge construction. Proper integration of AI promotes deep learning and reinforces learners' capacity for autonomous knowledge development (Hu et al., 2024). Traditionally, learning intention was defined through noticeable physical behaviors. However, the emergence of generative AI has transformed this traditional conception, engendering a hybrid learning paradigm, indicated by a shift from teacher-centered learning toward human–machine collaboration (Dwivedi et al., 2023; Ngamcharoen et al., 2024).

2.2. Classroom Participation Behavior

Classroom participation involves students' cognitive, social, and behavioral engagement, including asking and answering questions, expressing opinions, contributing to discussions, and collaborating in group work (Kamran et al., 2022). Active participation signals levels of intrinsic motivation, intellectual curiosity, and eagerness to engage with learning and has consistently contributes to deeper conceptual understanding and long-term retention (Cheatham et al., 2017).

2.3. Self-Management in Learning Behavior

Self-management represents students' capacity to systematically plan, regulate, and evaluate their learning processes, including time management, goal setting, sustained concentration, and strategic adjustment when encountering learning challenges (Shapiro & Cole, 1994). Self-management reflects learners' level of self-regulation, a core competency for 21st-century learning, particularly in technology-mediated learning environments (Boekaerts et al., 2000).

Together, these three components represent a holistic conceptualization of intentional learning behavior that compasses technological (AI utilization), social (classroom participation), and psychological (self-management) aspects. They align closely with major learning theories, including motivational theory and self-regulation theory, providing a theoretically grounded framework for understanding learning behavior in the age of AI (Lorig & Holman, 2003). The key theoretical variables underlying this framework are presented as follows:

2.4. Motivation

Motivation is a psychological mechanism that drives, directs, and sustains behavior toward goal attainment (Urhahne & Wijnia, 2023). It plays a vital role in shaping learning intention, effort, perseverance, and academic achievement (Deci & Ryan, 2000). Motivation is conceptualized through subcomponents:

2.4.1. Intrinsic Motivation

Intrinsic motivation refers to inherent interest, enjoyment, and satisfaction derived from learning activities. It drives sustained learning intention and engagement without reliance on external incentives (Bandura, 1997; Rheinberg & Engeser, 2018). Key subdimensions include interest in learning content, satisfaction from learning, and a sense of pride in accomplishments (Tulis & Ainley, 2011).

2.4.2. Extrinsic Motivation

Extrinsic motivation refers to level of response to external impetus that enhances students' learning intention, encouraging learners to engage in learning behaviors for the purpose of obtaining reward or avoiding negative consequences (Brophy, 2004). Key subdimensions include motivation from rewards, motivation from social acceptance, and motivation driven by external expectations (Rogti, 2021).

2.4.3. Future-Oriented Motivation

Future-oriented motivation reflects students' awareness of the long-term value of present learning in relation to future academic or career goals (Stănescu et al., 2024). Key subdimensions include perception of the value of learning for the future, long-term educational goal setting, and future-oriented learning planning.

2.5. Self-Regulation Theory

Self-regulation theory is an educational psychological framework that explains the processes through which learners actively monitor, regulate, think analytically, plan, and assess their goal-oriented learning in pursuit of learning goals (Pintrich, 2000; Zimmerman, 1989). From this perspective, learners function as self-directed agents who consciously manage their thoughts, emotions, and behaviors to achieve effective and sustainable learning. Zimmerman (1989) emphasizes the dynamic process of self-regulation, where learners actively initiate motivation, set learning goals, and monitor progress. Recent research suggests that the use of generative AI significantly reduces analytical thinking effort, underlining the significance of concentration and distraction management as protective factors for maintaining cognitive engagement (Maharani, 2025; Zhang & Kim, 2024). Three sub-variables are examined within this framework.

2.5.1. Concentration in Learning

Concentration in Learning refers to learners' ability to maintain focused attention on academic tasks without interference from irrelevant inducements. Concentration constitutes an element of self-regulation in learning (Eloran, 2024). It serves as the foundation of effective learning strategies implementation and information processing. Subdimensions include attention during learning, sustained concentration, and use of strategies to enhance concentration.

2.5.2. Distraction Management

Distraction Management involves ability to eliminate cognitive distractions through self-regulation, time management, and learning-friendly environmental management (Sinharay et al., 2025). Subdimensions include recognition of distractions, strategies for eliminating distractions, and adjustment of learning behaviors.

2.5.3. Ethical Use of AI

Ethical use of AI involves utilizing AI tools ethically, transparently, and accountably in generating, applying and referencing AI-generated outputs with attention to academic ethics and intellectual integrity. Subdimensions include ethical awareness, responsible practices, and attribution and disclosure of AI-generated outputs (Ashok et al., 2022; Stahl, 2021).

2.6. Learning Environment Theory

Learning environment theory explains how features of the learning environment influence learners' behavior and motivation. Relevant aspects include the physical environment (media, technology, and conditions that support concentration), the social environment (interpersonal relationships), and the instructional environment (learning structure, assessment, and teaching methods) (Noori et al., 2021). Learning environments that promote cognitive engagement, emotional support, and constructive feedback foster intrinsic motivation and learning intention (Schumacher et al., 2013). These conditions are crucial for active learning and ethical AI use in the context of education in the digital age. The three sub-variables are as follows:

2.6.1. Physical Learning Environment

The physical learning environment encompasses physical aspects of learning spaces or learning contexts that are conducive to concentration, convenience, and efficiency in learning (Fraser, 1998; Moos & Moos, 1978) including light, sound, temperature, ventilation, cleanliness, seating arrangements, usable areas, and availability of learning technologies. Such factors influence learners' emotional states, satisfaction, and engagement. Subdimensions include convenience and availability of learning spaces, availability of equipment and technology, and classroom atmosphere that supports concentration and learning (Ghalia & Karra, 2023).

2.6.2. Social Learning Environment

The social learning environment refers to interpersonal relationship between learners and instructors, as well as peer interactions. Supportive social climates enhance learners' motivation, sense of belonging, and learning behaviors (Won et al., 2018). A positive social environment fosters an atmosphere of trust, emotional support, and positive interaction encouraging learners to express themselves confidently, engage actively in the learning process, and develop greater motivation for learning (Brackett et al., 2011). Subdimensions include teacher–student relationships and emotional–psychological climate.

2.6.3. Instructional Environment

The instructional environment reflects learning management, teaching methods, and assessment methods as perceived by learners to be supportive of their own learning, including clarity of learning goals, appropriateness of learning activities, learners' participation, use of technology to support learning, and constructive feedback (Sharratt, 2018). In the age of AI, the instructional environment also includes the appropriate integration of AI technology to promote active learning, critical thinking and the ethical use of AI (Almarode & Vandas, 2018). Subdimensions include clarity of learning structure and goals, teaching strategies and learning activities, integration of AI, constructive feedback and academic support.

2.6.4. Socio-demographic Background

Socio-demographic Background refers to learners' individual characteristics that reflect biological, psychological, and social differences influencing learning behavior, motivation, and adaptability. Considering these background factors enables educators to understand learners holistically across dimensions of individual characteristics, personal life circumstance, surrounding social influences and that shape individual learners' learning experiences.

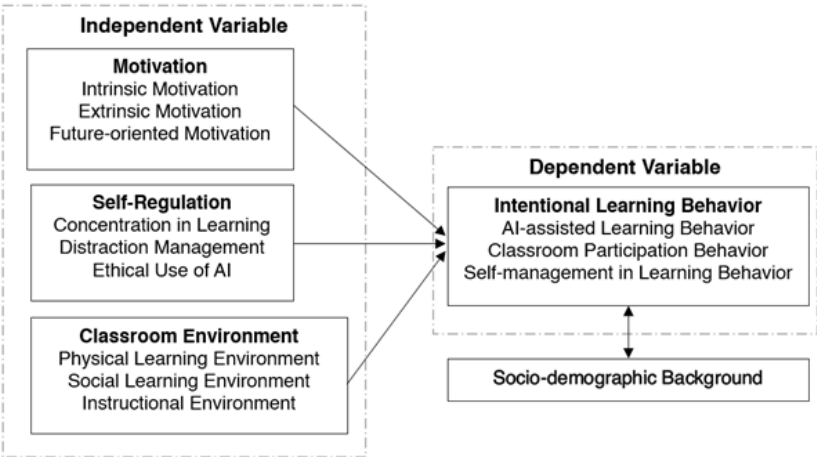
3. Hypotheses

Based on the synthesis of relevant literature, it is concluded that students' intentional learning behavior in the age of AI is influenced by the dynamic interaction between internal and external factors. Internal factors encompass motivation, self-efficacy, self-regulatory capabilities, all of which are psychological constructs that directly influence learning patterns. External factors encompass the learning environment, instructor roles, and the broader social context surrounding learners, all of which have undergone significant transformation in response to technological advancement and the increased adoption of digital learning tools.

Grounded in these theoretical foundations and synthesized insights, the following conceptual framework and research hypotheses were developed to examine the structural relationships among the variables:

H1: The motivation variable group is significantly and positively correlated with intentional learning behavior.
H2: The self-regulation variable group is significantly and positively correlated with intentional learning behavior.
H3: The classroom environment variable group is significantly and positively correlated with intentional learning behavior.
H4: The motivation, self-regulation, and classroom environment variable groups significantly predict the variance in AI-assisted learning behavior.
H5: The motivation, self-regulation, and classroom environment variable groups significantly predict the variance in classroom participation behavior.
H6: The motivation, self-regulation, and classroom environment variable groups significantly predict the variance in students' self-management in learning behavior.

Figure 1: Conceptual Framework.



4. Methodology

4.1. Research design and Ethical Considerations

This study utilized a quantitative research design aimed at investigating the relationships and predictive capabilities of psychological variable sets related to undergraduate students' learning. These included motivation, self-regulation, and classroom environment variables. Based on a comprehensive review of literature, these factors significantly influence students' intentional learning behavior, particularly within the context of the AI era, where educational environments and learner behaviors are rapidly evolving. The findings are expected to contribute to the academic understanding regarding factors influencing students' learning intention and provide practical guidance for designing instructional activities and educational policies that align with the needs and characteristics of contemporary learners.

The research project was approved by the Institutional Review Board under project code UTCCEC/Expedited018/2024. All procedures strictly adhered to ethical principles in human research to ensure compliance with international standards of academic responsibility and to comprehensively protect the participants' rights, safety, and dignity.

Systematic and rigorous measures for participant care were established, prioritizing informed consent. This enabled participants to make truly voluntary decisions without coercion, influence, or inappropriate incentives. In addition, the principles of confidentiality and anonymity were strictly maintained, preventing unauthorized access to participants' data unless explicit permission was granted by the participants. All collected data were used for academic and research purposes and were not disclosed or used in any manner that could cause harm or negative impacts on the participants, ensuring that all procedures adhered to principles of integrity, ethics, and professional responsibility.

4.2. Sample

The sample for this study comprised undergraduate students. The sample size was systematically determined in accordance with statistical principles to ensure the validity and academic significance of the results. G*Power software was utilized to calculate the appropriate minimum sample size, based on a 95% confidence level and a 5% margin of error, consistent with standard criteria for highly reliable quantitative research (Faul et al., 2009).

The calculation from the G*Power program indicated that the minimum sample size required for statistically significant data analysis was at least 800 participants. However, to account for potential errors resulting from incomplete or unresponsive responses, a preventive plan was implemented by adding approximately 5% to the minimum, resulting in a total target sample size of approximately 840 students.

A multi-stage quota random sampling method was employed to select participants (Burger & Silima, 2006). This method was selected to ensure diverse representation across various geographical regions and institutional types, facilitating a comprehensive and balanced representation of the national target population.

Thailand was divided into six geographical regions: North, Northeast, West, Central, East, and South. A data collection quota was assigned for each region at approximately 140 students per region to ensure balanced spatial distribution.

Table 1: Socio-demographic Background of the Sample.

Category	Background of the sample			
Sample group	874 undergraduate students			
Questionnaire set	Set A (429 respondents) (49.08%) Set B (445 respondents) (50.92%)			
Gender	Male = 307 (35.13%)		Female = 567 (64.87%)	
Grade point average index (GPAX)	3.32 (S.D = 0.62)			
Average age (years)	20 years 2 months			
Year level	Year 1 = 221 (25.29%)	Year 2 = 207 (23.68%)	Year 3 = 217 (24.83%)	Year 4 = 229 (26.20%)
University Type	Public 448 people (51.26%) Private 426 people (48.74%)			
Basic Sciences	148 (16.93%)			
Health Sciences	144 (16.48%)			
Engineering	146 (16.70%)			
Social Sciences	143 (16.36%)			
Humanities	145 (16.59%)			
Education	148 (16.93%)			

Note: Missing values are excluded.

Within each region, two types of institutions, public and private universities, were randomly selected. Data collection within each institution was then distributed equally across six major academic disciplines: Basic Sciences, Health Sciences, Engineering, Social Sciences, Humanities, and Education. The implementation of these steps ensured the representation of disciplinary diversity and socio-demographic backgrounds of students from educational institutions nationwide (Table 1).

4.3. Data Analysis

This study employed quantitative data analysis centered on two main types of inferential statistics:

1. Pearson Product-Moment Correlation Analysis was utilized to explore the relationships between independent and dependent variables. This analysis determined direction and magnitude of the correlations between each pair of variables, offering understanding of statistical connections between psychological factors and students' learning behaviors (Obilor & Amadi, 2018; Sedgwick, 2010).
2. Multiple Regression Analysis was conducted to determine the predictive capabilities of multiple independent variables on the dependent variable through two main approaches (Stolzenberg, 2004):

2.1 Enter Method: All independent variables were concurrently imported to the regression model to assess their collective influence on the dependent variable while controlling the effects of other variables in the model.

2.2 Stepwise Method: An automatic variable selection technique, in which independent variables were individually and sequentially imported into the model based on their statistical contribution to explaining the statistically significant increase in the variance of the dependent variable in each step.

4.4. Instruments

The research instrument consisted of 12 summated rating scale questionnaires, with questions presented in two versions (Set A and Set B) to mitigate potential order effects (Spector, 1992). The questionnaires were developed through a synthesis of relevant concepts, theories, and prior studies. Each item was rated on a six-point Likert scale, ranging from "Strongly Agree" to "Strongly Disagree." The instruments underwent a systematic three-stage validation process (Table 2) as follows:

1. Content Validity: The alignment of each item with research objectives, conceptual variables, and theoretical frameworks were evaluated by five experts in education, curriculum and instruction, and behavioral sciences related to undergraduate students' learning. The Index of Item-Objective Congruence (IOC) was calculated to assess quality of the items and yielded values between 0.80 to1.00, indicating high content validity (Kemper, 2020).
2. Item Analysis: After incorporating feedback from the experts, the revised instruments were piloted with 120 participants resembling the actual sample. Key indicators included Item Discrimination and Corrected Item-Total Correlation to ensure the ability of the items to differentiate respondent perspectives and their consistency with the overall questionnaire structure. Items with quality and appropriate correlation were selected for the final instrument.
3. Construct Validity and Reliability: Confirmatory Factor Analysis (CFA), following Harrington (2009), was conducted to verify that observed variables accurately

Espacio, Tiempo y Educación, v. 13, n. 1, January-June / Enero-junio 2026, pp. 103-124
ISSN: 2340-7263

represented latent constructs. Model fit was confirmed using at least three of five goodness-of-fit indices: Chi-square, RMSEA, CFI, TLI, and SRMR (Taasoobshirazi & Wang, 2016). Once the structure was confirmed, Cronbach's alpha was used to assess internal consistency, ensuring reliability for the subsequent data collection.

Table 2: Quality of Measurement Instruments.

Variables	No	α	CFA						
			χ^2	df	P-value (p>0.05)	RMSEA (≤0.06)	CFI (≥0.95)	TLI (≥0.95)	SRMR (≤0.08)
1. AI-assisted Learning Behavior	14	0.76	81.06	73	0.18	0.04	0.97	0.96	0.06
2. Classroom Participation Behavior	14	0.80	76.94	72	0.13	0.04	0.97	0.96	0.07
3. Self-management in Learning Behavior	14	0.75	73.25	62	0.21	0.03	0.96	0.95	0.05
4. Intrinsic Motivation	12	0.73	75.43	71	0.22	0.04	0.97	0.96	0.05
5. Extrinsic Motivation	12	0.77	65.32	67	0.24	0.04	0.97	0.96	0.06
6. Future-oriented Motivation	12	0.72	68.65	62	0.15	0.03	0.96	0.95	0.06
7. Concentration in Learning	14	0.75	73.94	65	0.16	0.04	0.97	0.96	0.05
8. Distraction Management	14	0.76	71.26	70	0.12	0.05	0.96	0.95	0.07
9. Ethical Use of AI	14	0.72	65.42	64	0.18	0.04	0.96	0.95	0.07
10. Physical Learning Environment	12	0.71	62.53	52	0.17	0.03	0.96	0.96	0.06
11. Social Learning Environment	14	0.73	67.15	63	0.16	0.04	0.96	0.95	0.05
12. Instructional Environment	12	0.78	72.43	59	0.18	0.04	0.97	0.96	0.07

Note: This research emphasizes t-values more than r-values. The criteria for item selection are t ≥ 2.00 and r ≥ 0.20, CFA passes 3 out of 5 criteria, especially when the χ^2 value is not statistically significant.

5. Results

The analysis of mean scores and standard deviations for the twelve research variables (N=874) is presented in Table 3. The mean scores ranged from 50.24 to 63.85, while standard deviation ranged from 8.23 to 12.72, indicating a moderate level and appropriate response dispersion across the questionnaire. The variable with the highest mean score was AI-assisted learning behavior (M = 63.85, SD = 12.72), followed by instructional environment (M = 62.29, SD = 8.37) and self-management in learning behavior (M = 61.59, SD = 11.47). These findings indicate that students demonstrate high levels of learning behaviors in the age of AI, particularly in AI technology integration and self-regulation. In contrast, concentration in learning obtained the lowest mean score (M = 50.24, SD = 10.91), suggesting that digital distractions may hinder sustained focus for some students. The future-oriented motivation (M = 54.98, SD = 8.23) had the lowest standard deviation, revealing consistency in students' perception of long-term learning goals. In contrast, higher standard deviations in AI-assisted learning and ethical use of AI highlight individual differences in technological proficiency and approach.

The Pearson correlation coefficients (r) indicated significant positive correlations among all variables, ranging from moderate to relatively high ($r = .31 – .66$, $p < .01$), with a few pairs gaining $p < .05$. This confirms directional relationships among motivation, self-regulation, and learning environment. In detail, it appears that AI-assisted learning behavior was strongly correlated with self-management in learning behavior ($r = .66$, $p < .01$) and classroom participation behavior ($r = .61$, $p < .01$), and moderately to highly correlated with future-oriented motivation ($r = .57$, $p < .01$) and social learning environment ($r = .57$, $p < .01$). These findings indicate that students with strong self-management, active participation, and supportive learning environments are more likely to employ AI tools creatively and effectively.

Table 3: Means, Standard Deviations, Correlation Coefficients of Various Variables in the Total Group (N=874).

Variable	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12
1.	63.85	12.72	1											
2.	60.26	10.53	.61**	1										
3.	61.59	11.47	.66**	.62**	1									
4.	54.87	8.93	.54**	.56**	.52**	1								
5.	58.43	10.51	.48**	.51**	.53**	.47**	1							
6.	54.98	8.23	.57**	.54**	.64**	.49**	.56**	1						
7.	50.24	10.91	.59**	.52**	.56**	.42**	.54**	.58**	1					
8.	61.53	11.98	.54**	.49**	.57**	.45**	.42**	.45**	.54**	1				
9.	59.27	12.53	.58**	.43**	.53**	.58**	.53**	.54**	.56**	.53**	1			
10.	56.82	9.72	.46**	.42**	.48**	.43**	.48**	.49**	.47**	.42**	.45**	1		
11.	59.35	10.94	.57**	.58**	.50**	.56**	.47*	.50**	.43**	.31**	.39**	.38**	1	
12.	62.29	8.37	.59**	.58**	.55**	.49**	.40**	.41**	.44**	.36**	.42**	.40**	.46**	1

Note: *p<.05, **p<.01
Variable: 1. AI-assisted Learning Behavior 2. Classroom Participation Behavior 3. Self-management in Learning Behavior 4. Intrinsic Motivation 5. Extrinsic Motivation 6. Future-oriented Motivation 7. Concentration in Learning 8. Distraction Management 9. Ethical Use of AI 10. Physical Learning Environment 11. Social Learning Environment 12. Instructional Environment

The motivation variables were positively correlated with all intentional learning behaviors, supporting Hypothesis 1. In particular, future-oriented motivation (Variable 6) illustrated high correlations with self-management in learning behavior (r = .64, p < .01), concentration in learning (r = .58, p < .01), and AI-assisted learning behavior (r = .57, p < .01), highlighting that long-term goal-oriented motivation is a significant psychological factor fostering self-regulation, determination, and purposeful use of learning technologies. Intrinsic and extrinsic motivations showed moderate correlations with learning behaviors and environment variables (r = .40 – .56, p < .01), confirming that both personal interest and external incentives positively promote students' learning behaviors.

As regards concentration in learning (Variable 7), correlations were moderately high with self-management in learning behavior (r = .56, p < .01) and future-oriented motivation (r = .58, p < .01), supporting Hypothesis 2. This suggests that students with better concentration are more inclined to plan, self-regulate, and use learning technologies effectively. Distraction management (Variable 8) displayed moderate correlations with most variables (r = .31–.57, p < .01), particularly self-management in learning behavior (r = .57, p < .01), revealing learners' ability to maintain concentration despite distractions.

Ethical use of AI (Variable 9) was moderately to highly correlated with AI-assisted learning behavior (r = .58, p < .01), intrinsic motivation (r = .58, p < .01), future-oriented motivation (r = .54, p < .01), and self-management in learning behavior (r = .53, p < .01). This indicates that highly motivated and self-regulated students are prone to use AI responsibly and creatively, adhering to the concept of AI literacy, which integrates ethical competence with technology use.

The learning environment variables—physical learning environment (Variable10), social learning environment (Variable 11), and instructional environment (Variable12)—were positively correlated with other variables at moderate to high levels (r = .36 – .59, p < .01), supporting Hypothesis 3. In particular, the instructional environment (variable12) showed high correlations with AI-assisted learning behavior (r = .59, p

< .01), classroom participation behavior (r = .58, p < .01), and self-management in learning behavior (r = .55, p < .01), reflecting that participatory and technology-assisted instructional practices significantly enhance positive learning behaviors. The social learning environment (Variable11) was correlated with classroom participation behavior (r = .58, p < .01) and intrinsic motivation (r = .56, p < .01), indicating the role of in-class social interactions in reinforcing motivation and learning intention.

Overall, the significant positive correlations across all variables, particularly the motivation, self-regulation, and learning environment variable groups, underscoring their importance in fostering learning intention. Students possessing positive motivation, long-term learning goals, concentration in learning, and self-management in learning behavior within a technology-enabled learning environment are better positioned to utilize AI tool creatively and ethically. This represents a significant trend in the age of AI-driven education.

Table 4: The Multiple Regression Results for Predicting AI-assisted Learning Behavior using Motivation, Self-regulation, and Classroom Environment as Predictors.

Ordinal	Group	N	1st Predictive Set (1 - 9) AI-assisted Learning Behavior		
			% Predictor	Significant Predictors	Beta
1.	Total	874	42.50	1, 3, 9, 6, 8	.35, .33, .34, 32, .28
2.	Male	307	41.75	3, 1, 2, 9	.39, .31, .28, .26
3.	Female	567	40.12	3, 1, 9, 6	.32, .29, .27, .24
4.	Year 1 - 2	428	34.14	1, 3, 8, 9, 6	.34, .30, .28, .23, .21
5.	Year 3 - 4	446	36.73	1, 3, 9, 8, 6, 5	.42, .41, .38, .32, .21, .20
6.	Basic Sciences	148	41.25	3, 1, 6, 9, 8	.42, .39, .37, .29, .28
7.	Health Sciences	144	45.37	1, 6, 3, 9, 8	.33, .29, .28, .26, .23
8.	Engineering	146	42.13	3, 1, 6, 9, 8	.34, .32, .31, .28, .22
9.	Social Sciences	143	37.58	3, 1, 5, 8, 6	.31, .27, .25, .17, .13
10.	Humanities	145	36.54	3, 2, 8, 9, 6	.37, .35, .32, .29, .28
11.	Education	148	34.12	3, 1, 8, 6, 9	.32, .28, .23, .20, .19

Note: All beta values were statistical significance at 0.05 and had a percentage difference of 5.0% or higher. Predictors: 1. Intrinsic Motivation 2. Extrinsic Motivation 3. Future-oriented Motivation 4. Concentration in Learning 5. Distraction Management 6. Ethical Use of AI 7. Physical Learning Environment 8. Social Learning Environment 9. Instructional Environment

For the total sample, the predictor variables explained 42.50% of the variance in AI-assisted learning behavior, providing support for Hypothesis 4. The significant predictors, in order of influence, were intrinsic motivation (β = .35), instructional environment (β = .34), future-oriented motivation (β = .33), ethical use of AI (β = .32), and social learning environment (β = .28).

In the subgroup analysis, health science students exhibited the highest explained variance (45.37%), with crucial predictors ordered as intrinsic motivation (β = .33), ethical use of AI (β = .29), future-oriented motivation (β = .28), instructional environment (β = .26), and social environment (β = .23).

For the total sample, the predictor variables accounted for 44.67% of the variance in classroom participation behavior, supporting Hypothesis 5. The primary predictors, in order of influence, included extrinsic motivation (β = .39), future-oriented motivation (β = .36), social learning environment (β = .35), instructional environment (β = .31), intrinsic motivation (β = .29), and distraction management (β = .27)

Table 5: The Multiple Regression Results for Predicting Classroom Participation Behavior using Motivation, Self-regulation, and Classroom Environment as Predictors.

Ordinal	Group	N	2nd Predictive Set (1 - 9) Classroom Participation Behavior		
			% Predictor	Significant Predictors	Beta
1.	Total	874	44.67	2, 3, 8, 9, 1, 5	.39, .36, .35, 31, .29, .27
2.	Male	307	45.84	3, 8, 9, 2, 5	.43, .39, .29, .27, .24
3.	Female	567	43.89	3, 9, 4, 8, 2	.41, .38, .31, .28, .26
4.	Year 1 - 2	428	39.97	5, 3, 8, 9	.42, .40, .37, .34
5.	Year 3 - 4	446	45.43	5, 3, 9, 8	.39, .35, .34, .28
6.	Basic Sciences	148	36.84	3, 9, 5, 8, 6, 1	.37, .36, .34, .32, .31, .30
7.	Health Sciences	144	37.39	5, 3, 9, 8, 1	.38, .37, .36, .32, .29
8.	Engineering	146	36.58	3, 5, 8, 9, 2	.39, .37, .28, .27, .26
9.	Social Sciences	143	49.35	3, 9, 5, 8	.36, .35, .33, .30
10.	Humanities	145	48.59	3, 8, 5, 1, 9	.38, .34, .32, .27, .25
11.	Education	148	47.46	3, 8, 2, 5, 9	.42, .41, .39, .37, .35

Note: All beta values were statistical significance at 0.05 and had a percentage difference of 5.0% or higher. Predictors: 1. Intrinsic Motivation 2. Extrinsic Motivation 3. Future-oriented Motivation 4. Concentration in Learning 5. Distraction Management 6. Ethical Use of AI 7. Physical Learning Environment 8. Social Learning Environment 9. Instructional Environment

In the subgroup analysis, social sciences subgroup demonstrated the highest explained variance (49.35%), with major predictors ordered as future-oriented motivation (β = .36), instructional environment (β = .35), distraction management (β = .33), and social learning environment (β = .30).

Table 6: The Multiple Regression Results for Predicting Self-management in Learning Behavior using Motivation, Self-regulation, and Classroom Environment as Predictors.

Ordinal	Group	N	3rd Predictive Set (1 - 9) Self-management in Learning Behavior		
			% Predictor	Significant Predictors	Beta
1.	Total	874	45.35	1, 3, 4, 5, 9	.34, .33, .30, 27, .26
2.	Male	307	36.49	1, 5, 4, 3, 8	.33, .32, .29, .27, .25
3.	Female	567	42.53	5, 1, 3, 8, 4	.35, .34, .33, .31, .30
4.	Year 1 - 2	428	40.98	5, 3, 1, 8	.37, .36, .35, .33
5.	Year 3 - 4	446	45.76	1, 3, 5, 8	.38, .35, .32, .29
6.	Basic Sciences	148	42.83	3, 1, 5, 4, 9	.38, .36, .35, .34, .33
7.	Health Sciences	144	43.44	3, 5, 1, 8, 4	.37, .36, .29, .28, .27
8.	Engineering	146	41.69	1, 5, 3, 8, 4	.35, .34, .32, .27, .25
9.	Social Sciences	143	39.74	5, 3, 1, 8	.33, .32, .31, .29
10.	Humanities	145	37.63	5, 1, 3, 8	.38, .37, .28, .27
11.	Education	148	32.85	1, 5, 8, 3	.36, .35, .32, .31

Note: All beta values were statistical significance at 0.05 and had a percentage difference of 5.0% or higher. Predictors: 1. Intrinsic Motivation 2. Extrinsic Motivation 3. Future-oriented Motivation 4. Concentration in Learning 5. Distraction Management 6. Ethical Use of AI 7. Physical Learning Environment 8. Social Learning Environment 9. Instructional Environment

For the total sample, the predictor variables predicted 45.35% of the variance in self-management in learning behavior, substantiating Hypothesis 6. The key predictors, in order of influence, comprised intrinsic motivation (β = .34), future-oriented motivation (β = .33), concentration in learning (β = .30), distraction management (β = .27), and instructional environment (β = .26).

In the subgroup analysis, Year 3–4 students revealed the highest explained variance (45.76%), with main predictors ordered as intrinsic motivation (β = .38), future-oriented motivation (β = .35), distraction management (β = .32), and social learning environment (β = .29).

6. Conclusion and Discussion

The findings of this study indicate that motivation, self-regulation, and the classroom environment are significant determinants of undergraduate students' intentional learning behavior, encompassing three dimensions: AI-assisted learning behavior, classroom participation behavior, and self-management in learning behavior. Results from multiple regression analyses revealed that these three groups of variables collectively explained a significant portion of variance in learning behavior, particularly in self-management in learning behavior, which accounted for the highest explained variance at 45.35%. This highlights the dynamic of learning in the age of AI, where learners require intrinsic drive, self-regulatory capacity, and a supportive learning environment that supports technology-enabled learning (Kamberovic, 2025).

The analysis showed that motivation, self-regulation, and classroom environment variables explained 42.50% of variance in AI-assisted learning behavior. This finding is consistent with Self-Determination Theory (Deci & Ryan, 2000), which suggests that intrinsic motivation and future-oriented goal-directed motivation drive learners to engage in meaningful and sustainable learning. Learners driven by intrinsic motivations, such as interest in content or awareness of its future relevance of their studies—are more likely to utilize AI technologies ethically and creatively. In addition, the results align with the AI Literacy Framework (Morandín-Ahuerma, 2024), indicating that ethical awareness alongside responsible technology use is an integral part of 21st-century learning, particularly among students in health sciences who systematically utilize technology in their studies.

The study found that motivation, self-regulation, and classroom environment variables accounted for 44.67% of the variance in classroom participation behavior. This indicates that participant is fueled both by external incentives, such as peer acceptance and positive peer pressure, and by future-oriented motivation, which encourages students to perceive the connection between current studies and long-term life goals. Moreover, participation is strongly influenced by the social learning environment, aligning with Fraser (1998) and Moos and Moos (1978), who underlined that the classroom social atmosphere encourages motivation and academic assertiveness. Students who feel accepted and maintain positive relationships with peers and instructors are inclined to engage more actively in class.

The distraction management ability appeared as a significant predictor, emphasizing the role of self-regulation in maintaining concentration. This finding supports Self-Regulation Theory (Zimmerman, 1989), which assumes that learners who can manage distractions and regulate their own behavior signify higher participant and academic achievement. Notably, students in the social sciences exhibited the highest explained variance (49.35%), likely reflecting the interactive and discussion-oriented nature of their discipline, where social factors and extrinsic motivation exercise a stronger influence.

Regression analyses further revealed that motivation, self-regulation, and classroom environment variables explained 45.35% of the variance in self-management in learning behavior. This reflects the importance of intrinsic and future-oriented motivation in fostering self-regulatory behavior. Learners driven by clear future goals and personal interest-driven motivation can effectively manage time, maintain concentration, and employ learning strategies efficiently. These findings are aligned with Pintrich (2000) and Tohidi and Jabbari (2012), who highlighted that motivation is the essence of learning self-regulation. The concentration in learning and distraction management were also significant predictors, reflecting behavioral self-control skills that enable sustained learning in environments with technological distractions. For third- and fourth-year students, who demonstrated the highest explained variance (45.76%), this reveals the matured self-regulation resulted from diverse learning experiences and future career preparation.

Overall, future-oriented motivation consistently turned up as a prime predictor across all three learning behaviors, aligning with Future Time Perspective Theory (Husman & Lens, 1999), which asserts that learners who perceive a connection between current learning and future outcomes show greater determination and effort. Concurrently, self-regulation in concentration, distraction management, and ethical use of technology support sustainable learning behaviors. In the age of AI dominance, ethical technology use is not merely a moral issue but also a vital competency for lifelong learners. In addition, a supportive classroom environment, particularly instructional and social learning environments, acts as a systematic enabler, maximizing the impacts of motivation and self-regulation, consistent with Learning Ecology Theory, which conceptualizes learning as a product derived from interactions among individuals, technology, and social context.

These findings have significant implications for learning development in the age of AI, confirming that "technology alone is not sufficient to enhance learning without learners' motivation and self-regulation." Promoting learning intention requires both the psychological dimension (mindset) and the social dimension (learning climate). Higher education institutions are required to foster a learning culture that emphasizes ethical responsibility in AI use alongside long-term motivational strategies, enabling learners to transcend mere knowledge acquisition, transforming it into the capabilities to utilize technology for sustained personal and societal development.

7. Recommendations

This study highlights the significant role of motivation, self-regulation, and learning environment in undergraduate students' intentional learning behaviors in the age of AI, particularly in AI-assisted learning behavior, classroom participation behavior, and self-management in learning behavior —vital 21st-century skills (Sakdapat et al., 2025). Based on the findings, policy and practice recommendations are proposed as follows:

1) Institutional Policy Recommendations

1.1. Formulate an ethical Generative AI policy: The study identified ethical AI use as a main predictor of intentional learning behavior. Clear guidelines regarding permissible AI use, referencing methods, transparency in reporting AI-assisted work, and the role of AI in academic tasks should be established. Such policies should be widely disseminated and integrated into learning evaluation to raise awareness of academic responsibility and prevent overreliance on AI.

Espacio, Tiempo y Educación, v. 13, n. 1, January-June / Enero-junio 2026, pp. 103-124
ISSN: 2340-7263

1.2 Develop AI literacy programs: Given the prominence of AI-assisted learning, AI literacy courses or modules covering foundational AI knowledge, effective educational applications, analytical evaluation of AI outputs, and ethical competencies—to cultivate knowledgeable and critical AI users should be offered.

1.3. Design hybrid learning environments: The study highlighted the importance of instructional and social learning environments in promoting classroom participation. Hybrid learning spaces—combining on-campus and online learning, such as active learning classroom, digital classroom, online learning platforms—to enhance collaborative group activities, analytical thinking, social connections, and sense of classroom belonging should be created.

2) Instructor-focused recommendations

2.1. Adopt active learning to mitigate cognitive offloading: Since some students exhibited low concentration caused by overreliance on AI, instructors should employ strategies to stimulate analytical thinking, such as case studies, open-ended questioning, in-depth discussions, and requiring students to explain reasoning or thinking process before using AI. These strategies prevent students from cognitive offloading and maintain learning concentration.

2.2. Deliver timely and high-quality feedback: Due to variability in self-management and AI-assisted leaning behaviors, instructors should provide quality guidance that guides self-regulation, such as providing detailed feedbacks, highlighting areas for improvement, and recommending appropriate AI use. Consistent feedback refines students' learning behaviors and enhances academic accountability.

2.3. Integrate future-oriented motivational activities: Since future-oriented motivation was the strongest predictor across behaviors, instructors should connect class content to real-world career pathways through expert talks, career skill-linked assignments, and student-created career roadmaps. These integrations raise students' awareness of future-relevant learning.

3) Learner-focused recommendations

3.1. Develop self-regulation and focus skills: Given the low concentration mean score, students should adopt strategies, such as Pomodoro Technique, distraction-free spaces, weekly goal-setting, and learning journals to enhance concentration and reduce dependency on AI.

3.2. Use AI as a supportive tool, not a shortcut: Students should treat AI as a co-thinking partner rather than a task completer, employing it to generate questions, analyze options, and provide additional perspectives, fostering deeper learning and critical thinking.

4) Recommendations for future research and educational systems

4.1. Develop AI usage tracking systems: Systems should be developed to monitor students' AI use each semester, allowing institutions to identify AI use patterns and provide guidance for those at risk of AI overreliance.

4.2. Design discipline-specific learning support activities: Since different disciplines exhibited varied predictor patterns, interventions should be tailored to specific disciplines, for example, emphasizing AI ethics and analytical thinking in health sciences, discussion and social engagement and social learning environment in social sciences, and systematic problem-solving with AI in engineering—to enhance the effectiveness of learning support programs.

8. Limitations

This study has several limitations that should be considered when interpreting and applying the results in other contexts as follows:

1. Linear analysis constraints: Although standard statistical techniques, including multiple regression, were employed, linear analysis may not completely capture the complex non-linear interactions among variables, such as interactions between intrinsic motivation and social learning environment or indirect effects of AI use on cognition. Mixed-methods research is recommended for a more comprehensive understanding.
2. Scope of variables: This study focused on three predictor groups—motivation, self-regulation, and learning environment—which are critical for academic engagement. However, other additional factors, such as digital literacy, technology experience, and peer and family influences, including attitudes toward AI, were not included but may also impact learning behaviors in the age of AI.

9. Acknowledgment

This research was supported by a research grant under academic collaboration with the Association of Political Science, funded by the Sustainable Development Goals (SDGs) research funding program in the field of education, SDG 4: Quality Education (Grant No. #0401-2567). The authors express their sincere appreciation to the Association for both their financial and academic support.

In addition, this research was supported by a publication grant from the University of the Thai Chamber of Commerce (Grant No. 193/2565), which was instrumental in the dissemination of this study. The authors gratefully acknowledge the University for its financial support and academic opportunities. Finally, the authors would like to thank all participating universities for their kind cooperation and assistance in the data collection process. Their support was essential to the successful completion of this research.

References

Allam, H. M., Gyamfi, B., & AlOmar, B. (2025). Sustainable Innovation: Harnessing AI and Living Intelligence to Transform Higher Education. *Education Sciences, 15*(4), 398. https://doi.org/10.3390/educsci15040398

Almarode, J., & Vandas, K. (2018). *Clarity for Learning: Five Essential Practices That Empower Students and Teachers*. Corwin Press. https://www.corwin.com/books/teacher-and-student-clarity-257635

Ashok, M., Madan, R., Joha, A., & Sivarajah, U. (2022). Ethical framework for Artificial Intelligence and Digital technologies. *International Journal of Information Management, 62*, 102433. https://doi.org/10.1016/j.ijinfomgt.2021.102433

Baidoo-Anu, D., & Owusu Ansah, L. (2023). Education in the Era of Generative Artificial Intelligence (AI): Understanding the Potential Benefits of ChatGPT in Promoting

Teaching and Learning. *Journal of AI, 7*(1), 52–62. https://doi.org/10.61969/jai.1337500

Bandura, A. (1997). *Self-Efficacy: The Exercise of Control*. W.H. Freeman.

Bernstein, S. (2017). The United Nations and the Governance of Sustainable Development Goals. In N. Kanie & F. Biermann (Eds.), *Governing through Goals: Sustainable Development Goals as Governance Innovation* (pp. 213–239). The MIT Press. https://doi.org/10.7551/mitpress/10894.003.0016

Boekaerts, M., Pintrich, P. R., & Zeidner, M. (2000). Self-Regulation: An Introductory Overview. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 1–9). Academic Press. https://doi.org/10.1016/B978-012109890-2/50030-5

Brackett, M. A., Reyes, M. R., Rivers, S. E., Elbertson, N. A., & Salovey, P. (2011). Classroom Emotional Climate, Teacher Affiliation, and Student Conduct. *Journal of Classroom Interaction, 46*(1), 27–36. https://www.rulerapproach.org/wp-content/uploads/2019/04/pub319_Brackettetal_2011_JCI.pdf

Brophy, J. (2004). *Motivating Students to Learn*. Routledge. https://doi.org/10.4324/9781410610218

Burger, A., & Silima, T. (2006). Sampling and sampling design. *Journal of Public Administration, 41*(3), 656–668. https://doi.org/10.10520/EJC51475

Chan, C. K. Y., & Hu, W. (2023). Students' voices on generative AI: perceptions, benefits, and challenges in higher education. *International Journal of Educational Technology in Higher Education, 20*(1), 43. https://doi.org/10.1186/s41239-023-00411-8

Cheatham, J. M., Ozga, J. E., St. Peter, C. C., Mesches, G. A., & Owsiany, J. M. (2017). Increasing Class Participation in College Classrooms with the Good Behavior Game. *Journal of Behavioral Education, 26*(3), 277–292. https://doi.org/10.1007/s10864-017-9266-7

Cotton, D. R. E., Cotton, P. A., & Shipway, J. R. (2024). Chatting and cheating: Ensuring academic integrity in the era of ChatGPT. *Innovations in Education and Teaching International, 61*(2), 228–239. https://doi.org/10.1080/14703297.2023.2190148

Deci, E. L., & Ryan, R. M. (2000). The "What" and "Why" of Goal Pursuits: Human Needs and the Self-Determination of Behavior. *Psychological Inquiry, 11*(4), 227–268. https://doi.org/10.1207/S15327965PLI1104_01

Dwivedi, Y. K., Kshetri, N., Hughes, L., Slade, E. L., Jeyaraj, A., Kar, A. K., Baabdullah, A. M., et al. (2023). Opinion Paper: "So what if ChatGPT wrote it?" Multidisciplinary perspectives on opportunities, challenges and implications of generative conversational AI for research, practice and policy. *International Journal of Information Management, 71*, 102642. https://doi.org/10.1016/j.ijinfomgt.2023.102642

El Deen, A. A. M. M. A., Albasis, H. H., & Mohamed, A. M. (2026). Teacher charisma and AI-mediated education: Effects on EFL learners' attitudes and self-efficacy.

Acta Psychologica, 263, 106244. https://doi.org/10.1016/j.actpsy.2026.106244

Eloran, A. P. H. (2024). The Effect of Learning Concentration on Improving the Quality of Student Human Resources in the Digital Era. *SSRN.* https://doi.org/10.2139/ssrn.5345312

Faul, F., Erdfelder, E., Buchner, A., & Lang, A.-G. (2009). Statistical power analyses using G*Power 3.1: Tests for correlation and regression analyses. *Behavior Research Methods, 41*(4), 1149–1160. https://doi.org/10.3758/BRM.41.4.1149

Fraser, B. J. (1998). Classroom Environment Instruments: Development, Validity and Applications. *Learning Environments Research, 1*(1), 7–34. https://doi.org/10.1023/A:1009932514731

Ghalia, N. H., & Karra, S. Y. (2023). Teacher Readiness and Learner Competency in Using Modern Technological Learning Spaces. *Sustainability, 15*(6), 4928. https://doi.org/10.3390/su15064928

Gui, M., Gu, B., Siraj, S. B., & Razak, R. B. A. (2025). Enhancing Chinese EFL College Students' Engagement in Academic English Writing Through AI-Supported Tools: Student Experiences and Insights. *Pegem Journal of Education and Instruction, 15*(3), 132–144. https://doi.org/10.47750/pegegog.15.03.14

Harrington, D. (2009). *Confirmatory Factor Analysis*. Oxford University Press. https://doi.org/10.1093/acprof:oso/9780195339888.001.0001

Holmes, W., & Miao, F. (2023). *Guidance for Generative AI in Education and Research*. UNESCO Publishing. https://unesdoc.unesco.org/ark:/48223/pf0000386693

Hu, J., Huang, Z., Li, J., Xu, L., & Zou, Y. (2024). Real-Time Classroom Behavior Analysis for Enhanced Engineering Education: An AI-Assisted Approach. *International Journal of Computational Intelligence Systems, 17*(1), 167. https://doi.org/10.1007/s44196-024-00572-y

Husman, J., & Lens, W. (1999). The role of the future in student motivation. *Educational Psychologist, 34*(2), 113–125. https://doi.org/10.1207/s15326985ep3402_4

Kamberovic, M. (2025). AI-Assisted Learning. In *Proceedings of the 33rd ACM Conference on User Modeling, Adaptation and Personalization* (pp. 374–378). Association for Computing Machinery. https://doi.org/10.1145/3699682.3727571

Kamran, F., Afzal, A., & Rafiq, S. (2022). Teachers' Behavior Influencing the Classroom Participation of University Students. *Journal of Social Research Development, 3*(2), 173–192. https://doi.org/10.53664/JSRD/03-02-2022-05-173-192

Kemper, C. J. (2020). Face Validity. In V. Zeigler-Hill & T. K. Shackelford (Eds.), *Encyclopedia of Personality and Individual Differences* (pp. 1540–1543). Springer International Publishing. https://doi.org/10.1007/978-3-319-24612-3_1304

Lorig, K. R., & Holman, H. R. (2003). Self-management education: History, definition, outcomes, and mechanisms. *Annals of Behavioral Medicine, 26*(1), 1–7. https://doi.org/10.1207/s15324796abm2601_01

Maharani, A. (2025). Examining the Interaction Between Behavioral and Emotional Engagement on Cognitive Engagement: A Mediation Analysis. *LEOTECH: Journal of Learning Education and Technology, 2*(2), 35–46. https://doi.org/10.70152/leotech.v2i2.316

Moos, R. H., & Moos, B. S. (1978). Classroom Social Climate and Student Absences and Grades. *Journal of Educational Psychology, 70*(2), 263–269. https://doi.org/10.1037/0022-0663.70.2.263

Morandín-Ahuerma, F. (2024). *UNESCO proposal for the use of Generative AI in Education: Eight Challenges and Seven Actions*. CONCYTEP. https://doi.org/10.31219/osf.io/78d3j

Nakayama, L. F., Kras, A., Ribeiro, L. Z., Malerbi, F. K., Mendonça, L. S., Celi, L. A., Regatieri, C. V. S., et al. (2022). Global disparity bias in ophthalmology artificial intelligence applications. *BMJ Health & Care Informatics, 29*(1), e100470. https://doi.org/10.1136/bmjhci-2021-100470

Ngamcharoen, P., Sakdapat, N., & Bhanthumnavin, D. E. (2024). Development and Evaluation on Cybersecurity Behaviour Measurement Instruments for Undergraduate Students. *International Journal of Cyber Criminology, 18*(1), 130–147. https://www.cybercrimejournal.com/menuscript/index.php/cybercrimejournal/article/view/351

Noori, A. Q., Orfan, S. N., & Nawi, A. M. (2021). Students' Perception of Lecturers' Behaviors in the Learning Environment. *International Journal of Education and Literacy Studies, 9*(3), 64–69. https://doi.org/10.7575/aiac.ijels.v.9n.3p.64

Obilor, E. I., & Amadi, E. C. (2018). Test for Significance of Pearson's Correlation Coefficient (*r*). *International Journal of Innovative Mathematics, Statistics & Energy Policies, 6*(1), 11–23. https://www.researchgate.net/publication/343609693

Pintrich, P. R. (2000). The Role of Goal Orientation in Self-Regulated Learning. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of Self-Regulation* (pp. 451–502). Academic Press. https://doi.org/10.1016/B978-012109890-2/50043-3

Rheinberg, F., & Engeser, S. (2018). Intrinsic Motivation and Flow. In J. Heckhausen & H. Heckhausen (Eds.), *Motivation and Action* (pp. 579–622). Springer International Publishing. https://doi.org/10.1007/978-3-319-65094-4_14

Rogti, M. (2021). Behaviorism as External Stimuli: Improving Student Extrinsic Motivation Through Behavioral Responses in Algerian College Education. *Global Journal of Human-Social Science, 21*(1), 29–41. https://socialscienceresearch.org/index.php/GJHSS/article/view/3523

Sakdapat, N., Yuangngoen, P., Ngamcharoen, P., Kongtraipop, V., & Bhanthumnavin, D. E. (2025). An Exploration of Predictors of STEM Knowledge Integration among Generation Z Students: Focusing on 21st Century Skills. *Foro de Educacion, 23*(2), 84–110. https://doi.org/10.14201/fde.23205

Schumacher, D. J., Englander, R., & Carraccio, C. (2013). Developing the Master Learner: Applying Learning Theory to the Learner, the Teacher, and the Learning Environment. *Academic Medicine, 88*(11), 1635–1645. https://doi.org/10.1097/ACM.0b013e3182a6e8f8

Sedgwick, P. (2010). Independent samples *t* test. *BMJ, 340*, c2673. https://doi.org/10.1136/bmj.c2673

Shapiro, E. S., & Cole, C. L. (1994). *Behavior Change in the Classroom: Self-Management Interventions*. Guilford Press.

Sharratt, L. (2018). *Clarity: What Matters Most in Learning, Teaching, and Leading*. Corwin Press. https://www.corwin.com/books/clarity-253484

Sinharay, M., Karmakar, A., & Mukherjee, S. (2025). Self-directed Learning Sessions in Medical Students: Small yet Crucial Steps to a Long Journey of Lifelong Learner. *Mymensingh Medical Journal, 34*(4), 1234–1244. https://www.researchgate.net/publication/396054793

Spector, P. E. (1992). *Summated Rating Scale Construction: An Introduction*. Sage Publications. https://doi.org/10.4135/9781412986038

Stahl, B. C. (2021). Ethical Issues of AI. In B. C. Stahl (Ed.), *Artificial Intelligence for a Better Future: An Ecosystem Perspective on the Ethics of AI and Emerging Digital Technologies* (pp. 35–53). Springer International Publishing. https://doi.org/10.1007/978-3-030-69978-9_4

Stănescu, D. F., Frunzaru, V., & Stefanita, O. (2024). Self-regulated learning, self-efficacy and life-long learning: the mediating role of future orientation. *Kybernetes, 55*(3), 1362–1382. https://doi.org/10.1108/k-03-2024-0585

Stolzenberg, R. M. (2004). Multiple Regression Analysis. In M. Hardy & A. Bryman (Eds.), *Handbook of Data Analysis* (pp. 165–208). Sage Publications. https://doi.org/10.4135/9781848608184.n8

Taasoobshirazi, G., & Wang, S. (2016). The performance of the SRMR, RMSEA, CFI, and TLI: An examination of sample size, path size, and degrees of freedom. *Journal of Applied Quantitative Methods, 11*(3), 31–39. https://www.jaqm.ro/issues/volume-11,issue-3/pdfs/2_GI_SH_.pdf

Tohidi, H., & Jabbari, M. M. (2012). The effects of motivation in education. *Procedia - Social and Behavioral Sciences, 31*, 820–824. https://doi.org/10.1016/j.sbspro.2011.12.148

Tulis, M., & Ainley, M. (2011). Interest, enjoyment and pride after failure experiences? Predictors of students' state-emotions after success and failure during learning in mathematics. *Educational Psychology, 31*(7), 779–807. https://doi.org/10.1080/01443410.2011.608524

Urhahne, D., & Wijnia, L. (2023). Theories of Motivation in Education: an Integrative Framework. *Educational Psychology Review, 35*(2), 45. https://doi.org/10.1007/s10648-023-09767-9

Wattanavit, P., & Sakdapat, N. (2024). Causal Models Related to the Development of Self-Directed Learning Behaviour Among Undergraduate Students in Thailand. *Eurasian Journal of Educational Research (EJER),* (110), 312–325. https://doi.org/10.14689/ejer.2024.110.19

Won, S., Wolters, C. A., & Mueller, S. A. (2018). Sense of Belonging and Self-Regulated Learning: Testing Achievement Goals as Mediators. *The Journal of Experimental Education, 86*(3), 402–418. https://doi.org/10.1080/00220973.2016.1277337

Zhang, X., & Kim, H.-J. (2024). Exploring the Factors Influencing Student Engagement in University English Classes. *English Teaching, 79*(1), 121–143. https://doi.org/10.15858/engtea.79.1.202403.121

Zimmerman, B. J. (1989). A Social Cognitive View of Self-Regulated Academic Learning. *Journal of Educational Psychology, 81*(3), 329–339. https://doi.org/10.1037/0022-0663.81.3.329